Firm Adaptation and Reallocation under Rationing: Evidence from South Africa

Rowan Clarke, Chris Eaglin, Zachary Kuloszewski, and Jun Wong

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Abstract

Rationing policies are frequently implemented due to equity concerns. We study whether equitable-exposure rationing rules deliver equal economic impacts in the context of the 2021–2023 power crisis in South Africa. We leverage shocks to outage intensity and a rotational assignment system to generate quasi-random variation in electricity outage exposure, and we combine detailed hour-level outages with geocoded transactions data from a leading payment platform in Cape Town. Although we find that aggregate daily sales do not change on outage days, there is substantial heterogeneity across the firm distribution. Revenue is reallocated through consumers substituting between firms: baseline high-performing firms able to invest in defensive technology capture the spending displaced from their competitors, gaining roughly nine percent in daily sales while the latter lose a similar share. Unequal effects are amplified when firms are able to anticipate electricity outages. The results suggest the impacts of rationing are not equal despite equitable exposure.

Clarke: Harvard Business School, Harvard University (rclarke@hbs.edu); Eaglin: Fuqua School of Business, Duke University (chris.eaglin@duke.edu); Kuloszewski and Wong: University of Chicago (kuloszewski@uchicago.edu and junwong@uchicago.edu). The authors gratefully acknowledge financial support from Harvard Business School, the Digital Data Design (D^3) Institute at Harvard, and J-PAL King Climate Action Initiative. The authors thank the Financial Technology partner as well as survey partners–particularly John Pienaar and Tim Treagus–for data sharing and exceptional support. We thank Juan Alcacer, James Anton, Ashish Arora, Ines Black, Fiona Burlig, Ronnie Chatterji, Leila Doumi, Michael Greenstone, Dan Gross, Koichiro Ito, Tarun Khanna, Rem Koning, Isaac Norwich, Omar Olivarez, Dominic Russel, Claire Shi, Andy Wu, Lorry Wu, Yifei Wu, and Dennis Yao, as well as seminar participants at the Duke Fuqua Summer Faculty seminar series, Wharton Management in Emerging Markets seminar, and Washington University at St. Louis Olin School of Business Strategy seminar series, for helpful comments and suggestions. All errors and views are our own.

Policymakers often ration key essential services, such as electricity, water, and health supplies using equitable exposure rules (Lund and Reed 1995; Hunt, Stilpen, and de Freitas 2018). Rationing creates ex-ante "equal" rules to allocate scarce resources, in contrast to market-based mechanisms that allocate based on willingness to pay. However, equal allocation of resources does not necessarily imply that the *impact* of such rationing is equal. Adaptation capabilities may be heterogeneous and markets may reallocate activity away from constrained users, potentially transforming equal treatment into unequal outcomes. Whether such rules yield equal outcomes is ultimately an empirical question.

We study this question among firms and consumers and their interaction in markets, in the context of a well-known example of rationing: electricity shortages in South Africa.[1] In 2023, the average South African experienced a total of 744 hours without power (BusinessTech 2023). To address these shortages, policymakers implement "load shedding"—where the state utility, Eskom, divides areas into electricity-feeder determined geographic blocks and cycles outages across these blocks based on published preset schedules. Whenever there is a mismatch between demand and supply, municipal managers are required by law to shut off these blocks according to the set rotational schedule, which balances exposure during peak hours and weekends, with the explicit goal of creating equitable rationing (NRS 2019).

We pair rich transaction-level data between 2021 and 2023 from South Africa's leading small business payments platform with outage data from the City of Cape Town to assess the causal impact of electricity rationing on firm performance and its mechanisms. The data include over 53 million transactions, covering 17,315 firms, and 1.2 million consumers in Cape Town.[2] The data allows us to geolocate each firm, which we use to recover the firm's history of electricity rationing since the rationing rule depends on the physical location of the firm. Transaction-level data allow us to construct objective measures of firm performance, while card identifiers allow us to track consumer behavior across firms and over time.

We leverage exogenous variation in the exposure to electricity shortages induced by the rationing schedule to identify the causal effect of electricity outages. Our research design exploits the facts that (1) the severity of outages are set at the national level, which are often due to unplanned generator failures and (2) the rationing rule is defined at a coarse geographic level and follows a pre-determined schedule. The municipal schedule dictates which geographic block will receive an electricity outage when there is a shortfall

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

[2] The platform processes approximately ZAR 38 billion (USD 2.1 billion) annually across nearly 250,000 merchants, roughly ten percent of the formal business sector, and 25 million consumers, over half of consumers aged 15 and over in the country.

in electricity supply. The construction of the blocks that the schedule rotates over is constrained by the network of feeders.[3] This unique institutional setting generates a natural experiment where on any given day, a firm's exposure to electricity outages is plausibly exogenous to any other determinants of firm performance.

Our main result is that electricity blackouts have no average effect on aggregate firm revenue or transaction volumes. But this null result masks the distributional effects of blackouts by baseline firm performance, which we define as whether the firm's average daily revenue is above or below median. Blackouts reduce daily revenue by 8.8 percent for below-median performers while increasing revenue by 7.1 percent for above-median firms—a 15.9 percentage-point gap that is economically large and statistically significant.

We find that these distributional effects are driven by consumers reallocating their spending toward above-median firms and those with defensive technology investments. We consider two complementary research designs to measure consumer substitution. First, we exploit the geographic nature of the rationing rule to estimate the effect of adjacent firm's outage on own firm's outcomes. Firms that are close to the border of a block experiencing a blackout see an increase in daily revenue while firms that are further away from the border do not. Second, we estimate the reallocation of spending *within* consumers by including card fixed effects. We find that when a consumer's frequented lower-performing firm experiences an outage, they shift their spending to higher-performing competitors. There are minimal changes in spending shares when high-performing firms are affected by the outage.

Differential adaptation behavior by low- and high-performing firms can explain this distinct pattern of consumer substitution. The transactions data allows us to identify whether a given firm has electricity during an electricity outage.[4] We find that higher-performing firms located in wealthier neighborhoods are much more likely to have electricity during an outage, indicating some form of adaptive behavior and defensive technology investment. To assess whether adaptation of defensive investment is distinct from baseline firm performance, we use an event study research design to estimate the causal effects of adopting a defensive technology on the effects of an electricity outage. Adaptation can fully explain the disparities between below- and above-median firms, suggesting that the pattern of consumer substitution that we see is driven by substitution toward firms with the ability to serve customers. Ultimately, we find suggestive evidence that these short-run effects

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

[4]We do so by exploiting the fact that we observe whether a transaction was conducted over WiFi or cellular network. If a firm conducts a transaction during an outage using WiFi, we consider this as a firm having some access to electricity that allows them to keep at least their WiFi network running.

accumulate into consolidation of the market around higher-performing firms. Leveraging variation in cumulative outage exposure at the block-month level, we find increased exit rates and lower entry rates among below-median performing firms in the medium run.

Despite its intended purpose of creating equitable exposure to shortages, we find that the rationing rule generated unequal effects among low- and high-performing firms. What features of the policy can explain these unequal outcomes? We show that anticipation and early announcement are key drivers with two additional research designs. First, we exploit the difference in outage probability across the rationing schedule with a regression discontinuity design (RDD) to estimate the effect of an electricity blackout among firms on the margin of receiving a power outage. We find that the differential effect of an electricity outage between low- and high-performing firms attenuate by 50% in this design, suggesting the importance of the ability to anticipate an outage. Second, we test this directly using a subset of outage events for which we were able to obtain Eskom announcements and their timing relative to the outage. The differential effect of an electricity outage between low- and high-performing firms is 224% higher when an outage is announced with at least one day of notice.

This suggests a sharp trade-off for the design of rationing policy. When shortages are announced in advance, this allows agents to adapt but amplifies differential adaptation capacity. Without advance notice, the effect of a ration is less unequal (still far from equal) but is on average, more negative. As climate change–related shortages of essential services become more frequent, policies to allocate resources will be increasingly important to evaluate and design (Reguant, Wagner, and Weber 2025).

Our main contribution is to offer one of the first quasi-experimental studies on the ways in which the impacts of electricity rationing are determined by how firms and consumers interact with each other in markets. Our results on the heterogeneous effects of equitably rationed outages are consistent with what prior research has documented on the differential adaptation to rationed shortages by households (Mansur and Olmstead 2012; Gadenne 2020; Abajian et al. 2025; Pallottini, Wong, and Zhang 2025) and firms (Abeberese, Ackah, and Asuming 2021; Hardy and McCasland 2021; Ryan and Sudarshan 2022) separately, our findings highlight that the ultimate impact of rationing is determined jointly by the behaviors of consumers and firms on both sides of the market. To our knowledge, this is the first paper to highlight the mechanism of consumer substitution in response to firm adaptation to electricity shortages.

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; Cisse 2025). Previous research has documented that electricity shortages (not necessarily rationed) impose significant economic costs on households and firms. Yet, we find that when shortages are rationed, aggregate daily spending (at least in the market for services) remains unchanged because consumers can reallocate their spending between firms. Relative to the existing literature that has focused on manufacturing, we generate evidence on the effects of electricity shortages in the market for services, which is dominated by small and medium-sized enterprises. A nascent literature on the policy design to foster adaptation to shortages and extreme events finds that advanced 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* does the advance notification benefit? We find that providing information and allowing agents to anticipate can lead to unequal outcomes via heterogeneous adaptation capacities, pointing to the role of complementary policies when equity is of concern.

The paper proceeds as follows. Section 1 provides background on South Africa's electricity crisis and the institutional features of load shedding that enable identification. Section 2 describes our data sources and sample construction. Section 3 outlines our empirical strategy. Sections 4 and 5 present the main results on the distributional effects of electricity rationing and its mechanisms, respectively. Section 6 shows how these short-run dynamics lead to longer-run effects on firm entry and exit. We investigate the role of anticipation as a policy feature that amplifies the unequal effects in Section 7. Section 8 concludes with policy implications and directions for future research.

1. Context and Background

South Africa's electricity shortfall originated in the years that followed democratization, when rising household connections were not matched by timely investment in generation and by adequate maintenance of the existing coal fleet. 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. As a consequence, dependable capacity has fallen short of even a largely stagnant level of demand, and the system operator now rations supply to protect the grid.[5] As a result, the number of hours South Africans go without electricity has risen by over 1,000% from 2018 to 2023 (Figure 1 panel

[5] Appendix Figure C.1 shows the aggregate electricity in South Africa from 2004 to 2021. Electricity demand in South Africa has stagnated even before frequent blackouts that started in 2021.

A).

Eskom, the state-owned utility, manages the deficit through *load shedding*, a scheme of centrally coordinated, rotational disconnections that are announced at the national level and executed by municipalities. Each "stage" represents an incremental gigawatt that must be removed from the grid: Stage 1 sheds up to 1000MW, Stage 2 up to 2000MW, and so on. At the most extreme level of supply shortage, Eskom has implemented Stage 8, for which a firm can expect 12 hours of outage within a single day. The National Control Centre sets the stage, sometimes with only minutes of warning when a large generating unit trips, and local distributors implement the published schedule.

Consumers within the City of Cape Town are assigned to sixteen feeder "blocks." Within any given stage every block is eventually disconnected the same number of times given sufficient time spent in that stage. However, stage changes have been frequent in recent years, leading to differences in the timing and total exposure across blocks. This arrangement generates sharp, schedule-driven variation in blackout exposure across load shedding "blocks." Panels B and C in Figure 1 shows the rotating nature of the load shedding schedule and the differences in stage between two consecutive days in June 2023. In Cape Town, the stage also implies the number of blocks that are experiencing an outage during any given moment. Thus, in stage 1, only one load shedding block is undergoing an outage while in stage 8, eight of the sixteen load shedding blocks do not have any electricity.

Two institutional features underpin our identification strategy. First, the assignment of feeders to blocks is fixed in advance and is determined largely by network topology rather than by socio-economic characteristics, so firms cannot move to a low-outage block without physically relocating. Second, the decision to escalate from one stage to another responds to unplanned plant breakdowns at the national level that bear little relation to local economic conditions. Together, the predetermined spatial assignment and the quasi-random temporal shocks supply within-city and within-day variation that we exploit empirically.[6]

The crisis is evident in the rising hours of enforced rationing. 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, when modest improvements in coal-plant availability and a wave of private embedded generation narrowed the supply-demand gap. 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 2024).

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

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 relief. Court rulings in 2023 obliged the state to prioritize certain facilities, yet Eskom argues that widespread exemptions would jeopardize system security. Consequently, most commercial feeders, including many that serve historically disadvantaged townships, remain subject to the full rotation.

2. Data

To study the effects of electrcity outages on firm performance, we combine detailed transactions-level data to measure firm performance and consumer spending with data on outages in the city of Cape Town.

Our primary dataset is the universe of transactions on South Africa's largest fintech payments platform for SMEs (herefter the "platform"). The platform processes about ZAR 38 billion (roughly USD 5 billion in PPP terms) in card transactions each year, reaching nearly 10 percent of South African firms. The Platform is the leading payment processing platform for SMEs in South Africa. The dataset contains details on the amount, geolocation, time, payment type (e.g. cash vs. card), payment processing machine, credit card identifier, and a merchant identifier. We merge the transaction-level data onto a dataset of firm-level information on its industry, owner characteristics, and headquarters location. We note that the cash transactions that we observe is self-reported, while the card transactions are automatically reported via the Platform. In total, we observe over 470 million transactions across 325,000 firms across South Africa from January 2021 to January 2024.

We use a publicly available dataset on the history of electricity outages from the City of Cape Town's Open Data Portal. The dataset reports any realized outages in each load shedding "block" and its duration from January 2020 to December 2023 in the City of Cape Town in two hour periods. For example, if an electricity outage occured during 1pm-2pm, we would observe that there was an electricity outage for 60 minutes during the period of 12pm-2pm in the dataset. We combine the history of realized electricity outages with a shapefile on the exact geography of load shedding blocks to accurately match whether a firm in a particular area is experiencing an electricity outage at any given time. The shapefile and outage history only covers the 75% of the areas of Cape Town where the City is the distributor of electricity.[7] This allows us to accurately measure outage exposure at any

[7] While the stage of loadshedding is set nationally, the implementation and schedule is set by the local distributing entity. However, shapefiles on loadshedding blocks to allow for the accurate measurement of outage exposure is not publicly available in many areas. To our knowledge, it is only publicly available in Cape Town. In fact, in many municipalities, the exact borders of load shedding areas are not published to its own residents—residents only have accurate information about their own load shedding block from their

given two-hour period. From the Open Data Portal, we also collect various demographic information: such as the average property values in the suburb (measured in 2015).[8]

As we discuss below, we also make direct use of the load shedding schedule in some of our analysis, which is published by the City of Cape Town.[9] Appendix Figure C.2 shows an example of the schedule. The load shedding schedule provides the order in which load shedding blocks would experience an outage if an outage of a particular severity is declared during any particular two-hour period on any particular day. We use this to construct a ranking of load shedding blocks, where the ranking is the order in which the blocks are phased into an electricity outage at any given time on any given day.[10] We construct the ranking such that the probability of an electricity outage is increasing in the constructed rank from the load shedding schedule. Each load shedding block has a different ranking depending on both the day and time of day.

Our main analysis is conducted at the firm-day level. 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. Appendix A details the data construction.

2.1. Summary statistics

Summary statistics for our firms from the platform are reported in Table 1. The median firm earns approximately R9,900 (USD544) per month in revenue, and has been on the platform for 2.8 years. Firms experience frequent outages: the median firm experiences 25.5 outages per month, with each outage being 2-hours in duration. Industry composition is reported in Table 2, showing firms are heavily concentrated in retail, hospitality, and healthcare, beauty and fitness industries. Together, firms in these industries comprise 77% of the sample. Overall, these sectors are over-represented compared to the broader economy of Cape Town and the Western Cape where retail and consumer-focused services comprise 47% of SMEs (Small Enterprise Development Agency 2023). This industry mismatch is due to the fact that the platform caters more towards businesses which sell directly to end-consumers.

own electricity meter.

[8] A suburb a level of administrative unit, which is akin to a neighborhood or a census tract in the U.S.

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

[10] There are a maximum of eight stages (e.g. eight concurrent geographic areas experiencing an electricity outage simultaneously). Suppose at a given time and day, the phasing in of the load shedding blocks is in the order of one through eight. That is, load shedding block 1 experiences an outage during stage 1. If it is stage 2, then load shedding blocks 1 and 2 experiences an outage. And on stage 8, load shedding blocks 1–8 experiences an outage. In this example, we assign load shedding block 8 to a rank of 1, and load shedding block 1 to a rank of 8. We assign all other blocks (e.g. blocks 8–12) who would not be at hazard of experiencing an outage during the time period and day to a rank of 0.

Our Cape Town sample occupies a middle ground between South Africa's numerous micro-enterprises and the larger VAT-registered segment captured in tax data. Statistics South Africa report that over half of informal firms turn over $\leq$ R1,500 per month, and most are one-person operations (Statistics South Africa 2023). By contrast, businesses in our main analysis sample report median monthly sales of around R10,000, which is well above informal benchmarks yet well below the R1 million-per-month ceiling that triggers VAT registration.

Our sample represents a sector of formalizing small, consumer-facing firms that lie just above the informal fringe but remain far smaller than the average tax-registered employer. To assess this claim, we conducted a survey of 300 SMEs across the Cape Town metropolitan area, including firms not on the platform. This sample reports median revenues in the range of R30,000-R75,000 and median employment between 11-20 employees. Our main sample is thus slightly smaller in terms of turnover than that of the SME survey, as noted by the discrepancy in median revenue compared to Table 1. Other summary statistics are reported in Appendix Table C.1. These firms, much like the broader South African economy, are on the cusp of digitization, with a small majority (52%) of firms stating they rely mostly on electronic payments, and 67% owning some form of card machine. Visa executives recently noted that contactless cards account for over 60% of face-to-face transactions in South Africa.[11] Thus, our sample mirrors prevailing adoption patterns in the country's small-business mainstream.

Firms in South Africa are also small as measured by employment; the SARS–National Treasury firm panel defines micro-enterprises as fewer than 10 employees and documents that micro and small firms together account for almost 90% of all registered businesses (Tsebe et al. 2018). We do not directly observe firm size as measured by employment, but, given the correlation between firm revenue and size (Statistics South Africa 2025), we expect our sample to average slightly below the 11-20 employee median range found in the SME survey. This aligns well with spatial tax data for the Cape Town metro area displayed in Appendix Figure C.20A, where, in most parts of the city, the majority of firms employ fewer than 10 full-time equivalents. This suggests that findings about outage resilience are most transferable to similarly structured urban SMEs, interfacing primarily with end consumers.

[11] Reuters, July 23, 2025

3. Empirical Strategy

Firm exposure to grid electricity blackouts could be correlated with other determinants of firm performance. Blackouts are a result of a mismatch between electricity supply and demand—thus if electricity demand surges as firms earn more revenue, it will cause blackouts. Further, blackouts can be assigned in ways that correlate with baseline firm performance due to various institutional factors. The unique setting in Cape Town, South Africa presents a natural experiment in the assignment of electricity outages that is a direct result of the load shedding implementation to estimate the *average* treatment effect (ATE) of exposure to an electricity outage on any given day over all of Cape Town.

As we discuss in Section 1, much of the blackouts are due to supply equipment failures and not due to any shifts in electricity demand. While it is likely that outages are more likely to occur during periods of higher economic activity (reflecting in our data as higher revenue and more transactions), it is unlikely that the outage decision from the national utility are based on firm-specific, or even geography-specific, factors. Blackout decisions are decided at a *national* rather than *regional* level—thus the decision to ration electricity by the *country* is based on the electricity demand of the whole country instead of the City of Cape Town alone. Second, the rationing schedule ensures that any institutional factors that might distort the allocation of blackouts to favor specific firms or specific geographies is not relevant, if the municipality follows the schedule. Given that firms are not mobile, we argue that for any given firm, the exposure to an electricity outage is as good as random on any given day.[12]

The natural experiment implies the following: conditional on the day, firm assignment to blackout exposure is random. Thus, we might expect that the characteristics of firms experiencing an outage are similar to firms that do not experience an outage. We verify this identifying assumption in Table 2, showing a balance table that summarizes the characteristics of firms exposed to an electricity blackout and firms who were not, conditional on date fixed effects. We find that firm characteristics are balanced across treatment (defined as *any* exposure to electricity outages) and control (defined as *no* exposure to electricity outages). We find negligible differences between all observed covariates. A test for the joint significance of all the covariates fails to reject zero effecs (p-value is 0.95, with an F statistic of 0.47 and fourteen degrees of freedom).

We also include firm fixed effects to account for any time-invariant differences across

[12] Hardy and McCasland (2021) utilized a similar empirical strategy in Ghana when load shedding was frequent.

firms. We estimate variants of the following equation:

$$y_{it} = \beta \text{ Outage}_{it} + \delta_t + \gamma_i + \varepsilon_{it} \tag{1}$$

where δ_t are date-fixed effects, γ_i are firm-fixed effects, and Outage_{it} is the treatment variable of interest, representing either a binary or continuous measure of firm *i*'s exposure to outages in day t. Our identifying assumption is thus the following: Outage exposure on any given day is random across firms conditional on date and firm fixed effects. This specification effectively combines the daily comparison between outage and non-outage areas into one coefficient, which utilizes variation from the rationing schedule that determines the outage areas.

We perform various heterogeneity analysis by interacting Outage_{it} with other time-invariant covariates X_i. We estimate the following regression:

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

where β and φ are the two coefficients of interest.

The rationing rule is geographic—given that consumers are potentially mobile across neighborhoods, spillovers might be a natural concern as it violates the Stable Unit Treatment Value Assumption (SUTVA). To address this, we remove all firms within 250 meters of the load shedding border in the main analysis sample. We choose 250 meter as the cutoff for the main analysis sample because Figure 4 shows that the spillover effect becomes statistically insignificant beyond 250 meters.[13]

4. Results

This section describes the effect of exposure to electricity outages on firm performance. We measure firm performance with two key metrics: log total daily revenue and log total daily transactions. Our main specifications consider the effect of exposure to *any* electricity outages on a given day.[14]

4.1. The effect of outages on firm performance

We report the results on the average treatment effect of electricity outages on firm performance in Table 3. We first note that the large differences in the estimated coefficients between column (1) and column (2) in Table 3 with the inclusion of date fixed effects

[13] We show robustness to alternate cutoffs in Table 6.

[14] Appendix Table C.6 shows robustness to alternative measures of electricity outages—including the number of electricity outages in a day and the total duration.

illustrate the variation in the data and how the empirical strategy addresses the potential bias from a simple comparison of firm performance between outage days and non-outage days. Column 1 confirms that outage days are likely to be correlated higher economic activity—on days with an electricity outage, the average firm has 18.5% higher daily revenue and 6% more transactions. Columns 2–6 implements the empirical strategy discussed above with the inclusion of date fixed effects.

In our baseline specification, electricity outages have virtually no effect on daily revenue (column (3) panel A) or transactions (column (3) panel B). We estimate a relatively precise null in both panels A and B: the 95% confidence interval is between a loss of 2.1 percent and a gain of 0.6 percent of daily revenue in panel A; and a loss of 0.5 percent and a gain of 0.07 percent of daily transactions.

There are two potential explanations for the null average effect. First, because of the frequent outages in South Africa, all firms are virtually unaffected by an electricity outage due to the adoption of defensive technology investments (e.g. uninterrupted power supplies, solar backup, or diesel generators). Thus, firms do not experience any decrease in revenue or transactions. On the other hand, it is also plausible that revenue is reallocated between firms—as firms that are either more productive, larger, or more able to invest in defensive technologies are able to serve unmet consumer demand during outage events. This reallocation between firms is necessarily one for one: Since the null average effect allows us to rule out that consumer demand is significantly impacted by daily electricity outages—consumer spending remains the same, on average, between outage and non-outage areas. We turn to test whether it is the case that all firms or only a subset of firms 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.[15] There are significant heterogeneity in the average effect of exposure to an electricity outage along this dimension. Exposure to an electricity outage reduces daily revenue by 8.8% among below-median firms, while outages *increase* daily revenue by 7.1% among above-median firms (column (4) panel A). Likewise for daily transactions, exposure to an electricity outage reduces daily transactions by 3.4% for below-median firms while increases daily transactions by 2.9% (column (4) panel B). The effect of an electricity outage differs significantly between low- and high-performing firms by 15.9% (p-value = 0.000) for revenue and 6.1% for transactions (p-value = 0.000). This stark pattern on the

[15]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), and also are more likely to invest in self-generation capabilities. While distinguishing between these three dimensions would be of interest, we unfortunately lack the data to do so.

unequal effects of electricity outages could be rationalized as consumers who visit the above-median firms spend *more* during outage days relative to consumers who visit the below-median firms. Alternatively, it could be that consumers are *substituting* between above- and below-median firms.

We turn to assess the role of substitutability between firms. Intuition suggests that firms are more substitutable if they are within the same market (same industry and same geographic area). Column 5 tests whether the same pattern we observe in column 4 holds when we consider a within-market measure of relative performance. If we observe the same pattern between columns 4 and 5, it suggests that substitution between above- and below-median firms is a possible explanation. Columns 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 causes a 9.2% (3.5%) decrease in daily revenue (transactions) among below-median firms and a 7.2% (2.81%) increase in daily revenue among above-median firms (column 5 panels A and B). This amounts to a 16.5% (6.3%) difference in the effect of outage exposure on daily revenue (transactions), statistically significant at the 1% level. Columns 4 and 5 in panels A and B suggest that the differential effect of outage exposure is not simply a result of differences in size or productivity, but highlights the role of *consumer substitution*. Column 6 in panels A and B suggest that both cross-firm variation in size, productivity, and ability to invest in defensive investments and consumer substitution play complementary roles.

4.2. Robustness

Sample cutoff. Table 6 shows the robustness of our main results to different cutoffs to drop firms. We replicate the specification in column 6 of Table 3. The first column includes the full analysis sample. We then drop firms within 100, 500, 1,000, and 3,000 meters of the load shedding border in columns 2–5. Across all 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.

Intensive margin outage days. Appendix Table C.5 shows the results by restricting only to days with an 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 are losing 2% of daily revenue and transactions while above-median firms are *gaining* 2% of daily revenue and transactions.

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.6. In each alternative specification of outage exposure, the overall pattern of estimated treatment effects remain the same: outage exposure has negligible average effects with underlying losses by low-performing firms and positive gains by high-performing firms.

Cash Transactions. One possible caveat to our results is that firms simply substitute to using cash transactions and do not record them. Businesses can report cash transactions on the platform, however they do so at varying rates. To understand if firms are simply opting to take transactions in cash instead of the platform, we restrict to the subset of firms who ever report a cash transaction on the platform, leaving a a sample of 6,853 firms. If firms are substituting in this manner, it is most likely to be detected within this subset. Table C.7 reports estimates of Equations 1 and 2 for this subsample, for both overall revenue and reported cash revenue. For this subsample, we see a qualitatively similar set of treatment effects. Low-performing firms experience a larger decrease in sales on outage days, and high-performing firms show a corresponding larger increase in sales. Notably, these effects are not due to any discernible changes in cash reporting, suggesting that substitution to cash transactions are not driving our main effects.

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 over-draws power). Another concern could be that the implementation of load shedding by the municipality deviates from the published schedule to favor certain areas over another. To address this potential concern, we use an instrumental variable approach using the load shedding schedule as an instrument. 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. Appendix B discusses the IV results and approach in detail. Appendix Table C.4 shows that the 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 are due to national calls for electricity rationing, and the rationing is done following the proper procedure in Cape Town.[16]

[16]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 city of Ekurhuleni due to its inability to properly follow the published schedule (see https://www.sabcnews.com/sabcnews/922739-2/). Interviews

5. Mechanisms

The results in the previous section showed the unequal effects of electricity outages among "low"- and "high"-performing firms. What drives these unequal effects? We show that consumers are reallocating their spending toward high-performing firms that have the ability to serve them and that firms are heterogeneous in their adaptation capacity.

5.1. Estimating consumer re-allocation

We show that consumers are directly substituting to firms with the capacity to serve them: either to firms that are directly not experiencing any outages via load shedding, or to "above-median" firms that are able to serve the consumers, even if they are located in an area with an outage.

5.1.1. The spillover effects of electricity access during outage days

During an electricity outage, a firm might not be able to operate or adequately serve its customers. As a result, a consumer might turn to nearby firms with power instead. The likelihood of substitution is likely to be correlated with the distance between the firms. If consumers are substituting between firms, we might expect to observe spillovers between firms. To test this hypothesis, we use the fact that the outages are assigned geographically, which results in variation in distance to neighboring region experiencing an electricity outage.[17].

We estimate the following equation among firms that are not actively experiencing an electricity outage (e.g. $\text{Outage}_{it} = 0$):

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

We estimate Equation 3 200 times—where we increase the sample each time to include firms within distance $d \in \{10, 2000\}$ from the adjacent geographic area. Figure 4 plots the estimated $\hat{\beta}$ by increasingly including firms further away from the border. Panel A shows a large positive effect (3-7% of daily revenue) of a neighboring outage on log daily revenue among firms within 250 meters of the border. The effect attenuates as we increase the sample to include firms further away from the border. The effects are no longer statistically different from zero once we include firms further away than 250 meters

with city officials suggest that they do this to favor industrial sections of the city. Such practice introduces clear selection bias when estimating Equation 1 since areas that experiences 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.

[17] Appendix Figure C.3 shows the distribution of distance to the closest adjacent load shedding block

from the border. Panel B presents similar patterns, whereby the estimated coefficient on log daily transactions nearby the border is large and attenuates as we include firms further away. However, the results on log daily transactions is less conclusive as the estimates are noisier.

Taken together, these result suggest that when outages occur, firms that are near outage areas but do not experience an outage experience increases in revenue and transactions, and that these effects decay by distance. This pattern is consistent with the interpretation that consumers are reallocating their spending from firms experiencing an outage toward firms that are not. Since the cost of substitution is higher for firms that are further away, we would not expect a firm that is far from the outage area to experience any revenue increase.

5.1.2. The effects of outage exposure on *the same consumer*

We now examine whether *the same consumer* substitutes to a different firm when the firm they intended on visiting experiences an outage. We turn to de-identified card level data in this analysis, where we assume that each unique card corresponds to an unique consumer.[18] Specifically, we first construct a measure of a "regular firm"—which is a merchant that the consumer frequents (visits more than twice) during 2021-2022. We limit the sample to cards for whom we can identify more than two regular firms and we drop firms within 250 meters of the load shedding border. We then test, conditional on transacting, whether an outage to the consumer's identified regular firm affects the consumer's spending at different firms. Specifically, we estimate variants of the following equation on an unbalanced 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 the 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 share on above-median (high-performing), below-median (low-performing), regular, new, and above- and below-median new firms.

Columns 1 and 3 of Table 5 Panel A evaluates the effect of an outage to a consumer's above-median regular firm on the consumer's spending shares at above- and below-median firms. An outage to a consumer's above-median regular firm increases (decreases) spend-

[18] Appendix Table C.3 shows the summary statistics of the card level data.

ing shares at below-median (above-median) firms by 0.2 percentage points. In contrast, Columns 2 and 4 of Table 5 Panel A suggests that an outage to a consumer's below-median regular firm increases (decreases) spending shares at above-median (below-median) firms by 4.2 percentage points, an estimate that is 21 times larger than Columns 1 and 3. These estimates suggest that consumers are much more likely to substitute when a regular firm that is "below-median" experiences an outage compared to if an above-median regular firm experiences an outage. This pattern is consistent with the interpretation that below-median firms are unable to serve their customers during outage hours (and thus consumers turn to other firms who are able to) while above-median firms continue to be able to serve their consumers.

Beyond the substitution between below- and above-median firms, we also analyze whether outages to a consumer's regular firms lead them to explore other "new" firms. A new firm is any firm that is not a regular firm. We find that consumers' spending shares at their "regular" firms decrease by 4.4 percentage points when a below-median regular firm experiences an outage, while if an above-median firm experiences an outage the consumers' spending shares increases slightly by 0.6 percentage points (Columns 5 and 6 of Table 5 Panel A). Instead, consumers are more likely (3.9 percentage points) to transact with a "new" firm when a below-median regular firm experiences an outage, but are 0.6 percentage points less likely to transact with a new firm when an above-median regular firm experiences an outage. Columns 3–6 in Table 5 Panel B shows suggestive evidence that consumers are more likely to substitute to *above-median* new firms relative to below-median firms.

5.2. Adaptation to blackouts

Heterogeneity in adaptation behavior. Why do consumers substitute to higher-performing firms instead of lower-performing ones? We have hypothesized that perhaps higher-performing firms are more able to adapt to power outages and thus are able to better serve their consumers. We empirically test this hypothesis in this subsection. We infer whether the firm has adopted any sort of defensive technology using the *type* of network the transaction was transmitted. The data distinguishes each transaction as transmitted via "WiFi" and "Cellular." A viable WiFi connection requires electricity. If we observe a firm sending a transaction with WiFi instead of a cellular connection during a power outage, we can conclude that the firm has adopted some form of defensive investment that allows their WiFi to stay online during periods of outages. Popular investments include backup generators or inverter-battery systems.[19] We cannot distinguish between the specific tech-

[19] Inverter-battery systems charges while electricity is flowing, and outputs electricity during electricity outages to specific outlets.

nologies: we can only observe if the firm's WiFi connection is operating during electricity outages.

Table 7 shows the differences in the firm characteristics of firms who we ultimately observe to have invested in any defensive technologies. We find that the firms that invest are much more likely to be high-performers: 60% of firms with a defensive technology is identified as a high-performer while only 37% of firms without defensive technology are high performers. We find some slight evidence that perhaps firms that experience more outages are more likely to adopt a defensive investments where adopting firms are 6 percentage points more likely to experience an outage. Adopting firms are more likely to be located in a wealthier neighborhood, less likely to be informal, and slightly more likely to be a service-oriented firm.

The effects of adopting defensive technologies. Whether the patterns we observe is due to differences between firm types or defensive technologies has large implications for policy design and understanding the distributional consequences of rationing policies. We turn to assessing the effects of adopting defensive technologies on the effects of electricity outages among firms for whom we observe to have ever adopted an investment.

We consider an event study design to estimate the effect of a defensive technology on firm performance. We 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 a two-way fixed effects approach:

$$\begin{aligned} y_{it} = & \sum_{k \neq -1} \alpha^k \text{ Relative Day } k_{it} + \sum_{k \neq -1} \beta^k \text{ Relative Day } k_{it} \times \text{Outage}_{it} + \\ & \sum_{k \neq -1} \kappa_1^k \text{ Relative Day } k_{it} \times \text{Above Median}_i + \omega_1 \text{ Outage}_{it} \times \text{Above Median}_i + \\ & \sum_{k \neq -1} \kappa_2^k \text{ Relative Day } k_{it} \times \text{Day of Week}_{it} + \omega_2 \text{ Outage}_{it} \times \text{Day of Week}_{it} + \\ & \sum_{k \neq -1} \kappa_3^k \text{ Relative Day } k_{it} \times \text{Adopt Year}_{it} + \delta_t + \gamma_i + \varepsilon_{it} \end{aligned} \tag{5}$$

where Relative Day k_{it} is a series of indicators that is equal to one when an observation is k days from the adoption date. We denote $k = 0$ as when the firm adopts the defensive technology. We include regressors that interact relative days and the outage indicator for the day of the week to control for any potential seasonality from different days of the week (e.g. weekends vs. weekdays). We also control for a firm's baseline performance by interacting both relative day indicators and outage indicator by an indicator for whether a firm's baseline performance is above median. Furthermore, we control for potential cohort effects (e.g. firms who adopt during periods of low power outages vs. firms who adopt during periods of high power potages) by including relative day by adoption year controls. We focus on β, which allows us to understand the differences in the effects of outages before and after the firm adopts a defensive technology.[20] Importantly, β^k is distinct from the differential effect of an electricity outage among high- and low-peformers, since that is captured by ω_1.

Figure 3 plots the estimated $\hat{\beta}^k$ coefficients from Equation 5. We focus on the 10 days prior and after the observed adoption of the defensive technology for clarity. We observe no differential pre-trends in the effects of electricity outages among the adopters and not-yet-adopters. In contrast, following the adoption of a defensive technology, we observe a persistent difference in the effects of electricity outages between adopting firms and not-yet-adopting firms. Figure 3 suggests that adopting firms experience 25% higher daily revenue (panel A) and 10% more daily transactions (panel B) during blackouts compared to not-yet-adopters. The estimated effect of adopting a defensive technology is similar to the differential effect of an electricity outage between high- and low-performers, implying that defensive technology adoption is sufficient to close the gap between a high- and low-performer.

6. Suggestive evidence on firm exits and entry

This section investigates whether the estimated short-run effects cumulate and affect longer-run firm dynamics in Cape Town.

To gauge the extensive–margin impact of electricity rationing, we collapse the data to the block–month level and estimate the following:

$$\begin{aligned} (6) \qquad y_{bt} = & \sum_{k=1}^{4} \beta_k \mathbf{1}\{\text{Firm Quantile} = k\} + \beta_5 \mathbf{1}\{\text{High Outage Month}_{bt}\} + \\ & \sum_{k=1}^{4} \eta_k \mathbf{1}\{\text{Firm Quantile} = k\} \times \mathbf{1}\{\text{High Outage Month}_{bt}\} + \delta_t + \gamma_b + \varepsilon_{bt} \end{aligned}$$

where High Outage Month$_{bt}$ is an indicator variable by block b in month t, taking value of 1 if block b in month t experienced total outage duration above a cutoff defined over the sample of block-month total outages. We perform this exercise using both the median and

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

the 75th percentile to define high exposure, to understand the degree of shock accumulation which may shift firms across the extensive margin. We partition firms into quartiles of performance based on total revenue, indexed by k. Outcomes are cumulative entries and exits of firms in a given block-month, for each quartile.[21] We include γ_b block fixed-effects, and month–year fixed effects δ_t. The coefficient η_1 therefore measures the additional impact of a high outage month for firms in the low performance category $k = 1$. Under assumptions that within month cumulative block-level exposure is as-good-as-random and firms being immobile within a month period, we interpret η_k as testing a significantly different response of quartile k firms to an increase in monthly realized outages.[22]

Figure 5 reports estimates of η_k from Equation 6 for block-month entries (top row) and exits (bottom row), as well as for varying definitions of high outage months. From the top panel, we find that high-outage months suppress bottom-quartile entries: a high outage month results in between 1.3 and 1.6 fewer bottom quartile entries ($p < 0.01$). Conversely, we see that high-outage months lead to *more* entries of above median firms. Considering firm exits, we see a complimentary pattern where higher performing firms are less likely to exit from the platform in response to high-outage months. This pattern is particularly exemplified through severe outage months, where treatment is defined by above 75th percentile exposure. In this specification, high-outage months lead to 0.61 more exits of first-quartile firms ($p = 0.011$), with fewer (but not statistically different from 0) exits for the rest of the population. Defining treatment using median monthly exposure presents a similar, but less precise, pattern of decreasing likelihood of exit across the distribution of revenue performance.

We conclude from this exercise that there is suggestive evidence of a composition shift on the extensive margin driven by outages. Firms below their industry-block median appear more susceptible to exit and less likely to enter when outages are severe, while top quartile firms appear relatively unaffected, resulting in a shift of market power to ex-ante high performers.

These results contain the caveat that entry and exits are defined as just use on the platform, and we cannot directly observe continuing transactions outside of the platform. This can likely take two forms: a firm only transacts in cash, or transitions to a competitor platform/ payment system. High-performing establishments have greater financial sophistication and are therefore more likely than smaller peers to substitute toward to other

[21] Entry is defined as an event where a firm uses the platform to transact for the first time in month t. Exit is defined as an event where the firm uses the platform to transact for the final time in the sample.

[22] Per the National Rationalized Specifications NRS-048, blocks are defined on fixed feeder areas and the rotation is set ex-ante to equalize expected exposure across customer classes and time periods, so realized variation in log(OutageHours$_{bt}$) is driven by national stage changes and unplanned plant breakdowns rather than local economic conditions.

non-cash payment systems. Consequently, the composition shifts documented in Figure 5 should be viewed as a lower bound on the extent to which load-shedding reallocates market presence toward stronger firms.

7. The role of anticipation and implications for policy design

The previous sections show that the ex-ante equal rationing of electricity outages generate 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 on the effects of rationing and discuss its implications for the design of rationing policies. We do so in two ways: first, we use the variation present in the load shedding schedule to estimate a different parameter of interest: the marginal effect of electricity outages. Second, we turn to data on the announcements of electricity outages and perform heterogeneity analysis by whether an outage was announced on the same day vs. in advance.

7.1. Regression discontinuity design (RDD) analysis

For every firm, there are uncertainties around the exact severity of the outages and thus whether the firm would actually receive an outage during that day. For example, conditional on any outages during the day, the firm that is first on the schedule will receive an outage with probability of 1, but a firm that is fourth on the schedule will receive an outage with probability of 0.125. We exploit exactly this variation with a regression discontinuity analysis around the stage of electricity rationing, where the stage is the number of neighborhoods that simultaneously experiences an electricity outage. The regression discontinuity analysis identifies the local average treatment effect (LATE) at the cutoff between neighborhoods that are on the margin of receiving an electricity outage on any given day. We compare this estimate to the average treatment effects in Section 4. The differences between the two target parameters allows us to infer how the effects of an electricity outage vary with the firm's expected outage probability.

We consider a fuzzy RDD.[23] We use the firm's ranking in the schedule (described in Section 2) and the stage of electricity outage during the two hour period to construct a

[23]The regression discontinuity design we employ is fuzzy for two reasons. First, we use the firm's rankings during its business hours to instrument for experiencing an outage for the whole 24 hours. By construction, if an outage occurs during non-business hours, then the firm's ranking during business hours would not capture this outage. We do not consider the effects of outages only during business hours as the parameter of interest since outages during non-business hours can also affect how a firm operates (e.g. during preparation hours of a restaurant before it is open to customers). Second, the municipality does not always implement the load shedding schedule due to technical realities or other reasons, leading to deviations in scheduled and realized outages.

normalized two-hourly ranking, where the marginal area that experiences an outage is of rank 1 and the marginal area that does not experience an outage (and would otherwise if the stage had escalated) has a ranking of -1. For each day, we take the maximum of the firm's normalized daily rankings. We use the daily maximum normalized rankings as the running variable. This running variable identifies the maximum probability that a firm would face an outage during the day. Figure 6 panel A shows the probability of a firm experiencing an outage by the daily maximum normalized rank. It shows a clear discontinuity between the rank -1 and 1, where the probability of experiencing an outage increases by over 80 percentage points.

Because we utilize discrete ranks as our running variable, our setting is not a classic RD where the running variable is continuous (Lee and Lemieux 2010). Our specification thus reflects a parameterized RD design (Howell 2017; Howell et al. 2025; Rose and Shem-Tov 2021). Our model includes separate linear slopes on each side of the cutoff and allow the slopes on either side to vary by the dimension of heterogeneity (X_i) that we are interested in (e.g. above- or below-median revenue firms). We estimate the following two-stage least squares specification:

$$\text{Outage}_{it} = \sum_x \xi^x \mathbb{1}(\text{Rank}_{it} > 0) + \beta_1^x \text{Rank}_{it} + \beta_2^x \text{Rank}_{it} \times \mathbb{1}(\text{Rank}_{it} > 0) + \delta_t + \gamma_i + \varepsilon_{it} \tag{7}$$

$$y_{it} = \sum_x \beta_0^x \text{ Outage}_{it} + \beta_1^x \text{Rank}_{it} + \beta_2^x \text{Rank}_{it} \times \mathbb{1}(\text{Rank}_{it} > 0) + \delta_t + \gamma_i + e_{it} \tag{8}$$

where we allow coefficients to vary by x, the dimensions of heterogeneity that we are interested in. For example, we let $x \in \{0, 1\}$ for a firm whose mean daily revenue is above- or below-median. Our main specification utilizes a bandwidth of rank 3 on either side of the cutoff, but results are robust to different bandwidth selection.[24] Appendix B describes the conditions for a valid RDD.

Table 4 shows the results from the regression discontinuity using a bandwidth of 3. The estimated LATE of an electricity outage in columns 2–4 of Table 4 Panels A and B is comparable for absolute and relative low-performers is similar to the ATE—suggesting that for low-performers, the effect of an electricity outage does not vary substantially by the probability of experiencing an electricity outage. However, the differential effect of an outage for higher-performers is diminished in the RDD—it is ∼50% smaller in magnitude compared to Table 3. This suggests that differential effects between high- and low-performers are diminishing as the probability of outage decreases.

[24] We use a triangular kernel to weight observations far from the cutoff less than those close to the cutoff, following DiNardo and Tobias (2001). Specifically, we use the formula: $\text{Kernel}_{it} = 1 - \frac{|\text{Rank}_{it}|}{\max_j |\text{Rank}_{jt}| + (0.01)}$.

7.2. Measuring anticipation using Eskom announcements

We now directly test whether the effects of electricity outages differ if the details of the outages were announced ahead of time. We scrape Eskom's announcement page on their website to collect information on each load shedding announcements. We measure the number of days in between the announcement and the outage event using the publishing date of the Eskom announcement. Appendix Figure C.6 shows an example announcement. Eskom does not necessarily publish all announcements on their websites and not all outage events are accompanied by an announcement. We therefore limit the sample to the outage events that we are able to link to an Eskom announcement. Appendix Figure C.7 shows the distribution of the days between the announcement date and the outage events in this sample.

We augment Equations 1 and 2 with an additional interaction for whether an outage event is announced at least 1 day ahead ($\mathbb{1}(\geq 1 \text{ Day Notice})_t$):

$$
\begin{aligned}
y_{it} =& \beta_1 \text{ Outage}_{it} + \beta_2 \text{ Outage}_{it} \times \mathbb{1}(\geq 1 \text{ Day Notice})_t + \beta_3 \text{ Outage}_{it} \times X_i + \\
& \beta_4 \text{ Outage}_{it} \times X_i \times \mathbb{1}(\geq 1 \text{ Day Notice})_t + \delta_t + \gamma_i + \varepsilon_{it}
\end{aligned} \tag{9}
$$

The main coefficients of interest are β_2 and β_4 that tests whether there are differential effects of electricity outages if they are announced in advance or announced on the same day for high- and low-performers. Table 8 shows the results. Columns 1 and 4 first estimate equation 9 without the indicator for high- or low-performing firm. While outages announced on the same day have a negative *average* effect on sales (4%) and transactions (1.5%); firms experience higher revenue (9%) and transactions (2.2%) outages announced with more than one day of notice (columns 1 and 4).

As in Table 3, columns 2 and 5 in Table 8 breaks down the average effect by absolute performance. Here, outages announced on the same day leads low-performers to lose 5.8% of their daily revenue and 3% of their daily transactions. We do not detect any statistically significant differences in how outages affect low-performing firms, though the coefficient in column 2 is large in magnitude (6%).

We detect slight differences in daily revenue (3.6%, not statistically significant) and transactions (3%) between low- and high-performing firms for outages that are announced on the same day. However, we find that this difference in the effect of an electricity outage on low- and high-performing firms are significantly larger when the outages are announced with more than one day's of notice. Columns 2 and 5 suggest that the differences in the effect of an outage between low- and high-performing firms differ by 13.9% for revenue and 5.7% for transactions. Columns 3 and 6 show that the pattern is similar when we examine the differential effect between relative performances.

This aligns with the results Table 4 above—for low-performers, being able to anticipate an electricity outage might not matter much if they are not able to use the information to adapt. While we are able to detect some differences between low- and high-performers during outages that were announced on the same day, the differential effect is much larger for outages that are announced one day ahead. In sum, this set of results suggest that firm's anticipation (either via advanced notice or higher probability of outages) serve to exacerbate the differential effects of electricity outages from differences in adaptive capacity, despite intentions of equally allocating the rationing of electricity. On the other hand, the results might suggest that policies that equalize adaptive capacity might be particularly helpful in mitigating the negative distributional consequences of electricity rationing.

8. Conclusion

South Africa's rotational blackout regime offers a clean setting for observing how frequent, short-duration supply shocks 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. Beneath this stable aggregate lie stark distributional effects: outages cut revenue for baseline low-performing firms by roughly nine percent while raising sales for high performers by a similar magnitude, widening an existing performance gap. The divergence stems from consumer reallocation rather than demand destruction; consumers shift spending that would have occurred at lower-performing businesses to new high-performing competitors able to keep the lights on. Advance warning intensifies this pattern, as a one-day notice more than doubles the revenue gap between low- and high-performers, consistent with differential capacity to plan and invest in defensive technology to mitigate shocks. These short-run re-allocations accumulate over time: months with higher blackout hours see fewer below-median entrants and more exits, whereas top-quartile firms are largely insulated, leading to a shift in market power and concentration.

These findings have direct implications for policy. First, formally equal rotation schedules do not yield equal outcomes, because smaller firms lack the capabilities to finance or maintain backup generation and therefore lose demand to larger incumbents. Second, adaptation support should be targeted: matching grants, concessional finance, or shared energy hubs can help vulnerable SMEs bridge the resilience gap. Third, the design of outage communication matters; long lead-time announcements improve transparency but may widen disparities unless paired with such support programs that enable disadvantaged firms to respond effectively. Our results have implications beyond Cape Town: as service SMEs grow to dominate the economy in sub-Saharan Africa in the presence of climate change-induced increasing instances of shortages in essential services, understanding how equal rationing impacts a significant portion of the growing SSA economy is of first order.

Our transaction records capture only in-store sales and cover a three-year horizon, so we cannot observe consumer welfare losses from deferred purchases or the broader general-equilibrium effects on suppliers and labor markets. Extending the analysis to longer horizons, other South African metros, and firms further up the value chain is necessary for a complete welfare analysis. In sum, blackouts in Cape Town reshuffle rather than reduce consumer spending, benefiting resilient firms at the expense of their less prepared peers. Understanding this redistribution is essential if electricity rationing is to remain a politically and economically sustainable tool for managing chronic supply shortages.

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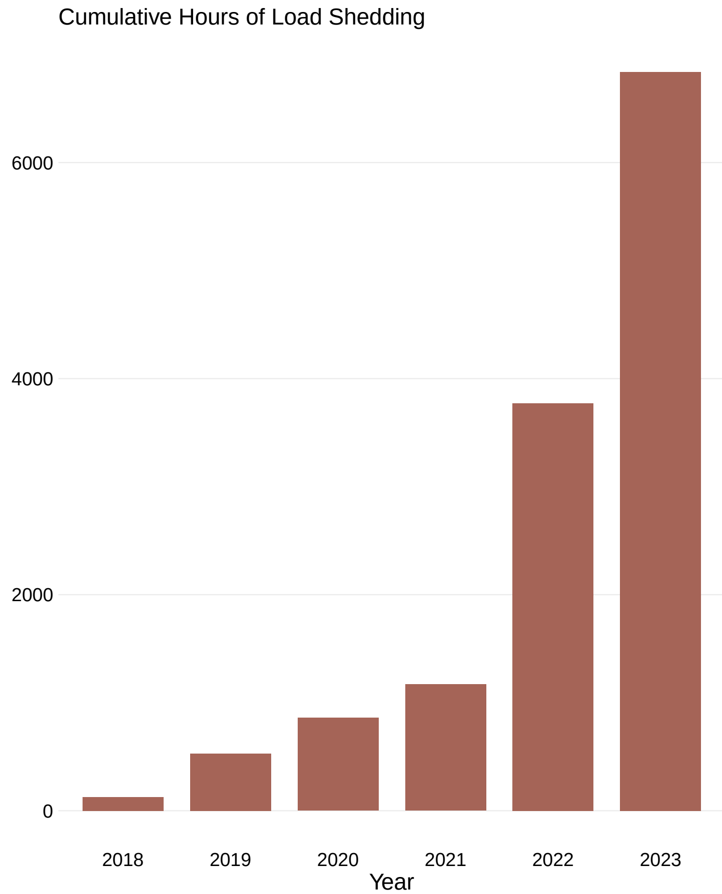
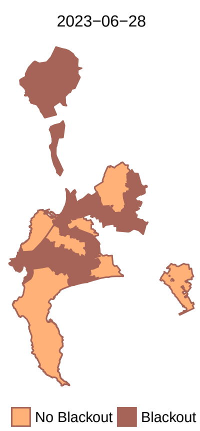
Figures

FIGURE 1. Outage Variation over Time and Space in Cape Town

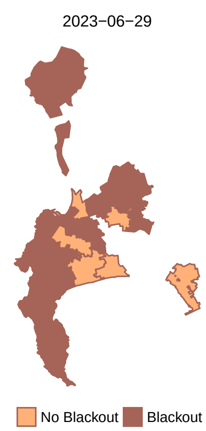
A. Hours of Blackouts in Cape Town 2018–2023



B. Areas with Outages on 2023/06/28

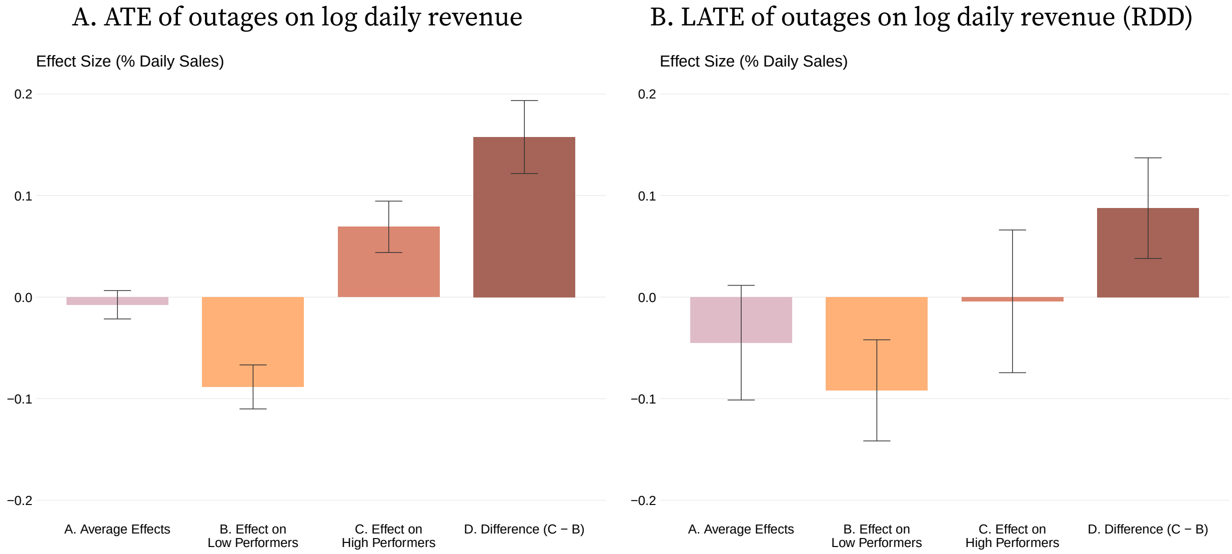


C. Areas with Outages on 2023/06/29



Note: This figure shows time-series and cross-sectional variation in outages in Cape Town. Panel A plots the cumulative hours with electricity outages from 2018–2023. Panels B and C maps the areas with an electricity outage on two days: 2023/06/28 and 2023/06/29. On both days, the severity (the "stage" which determines number of areas with an outage) and the geography (specific areas with an outage) is different.

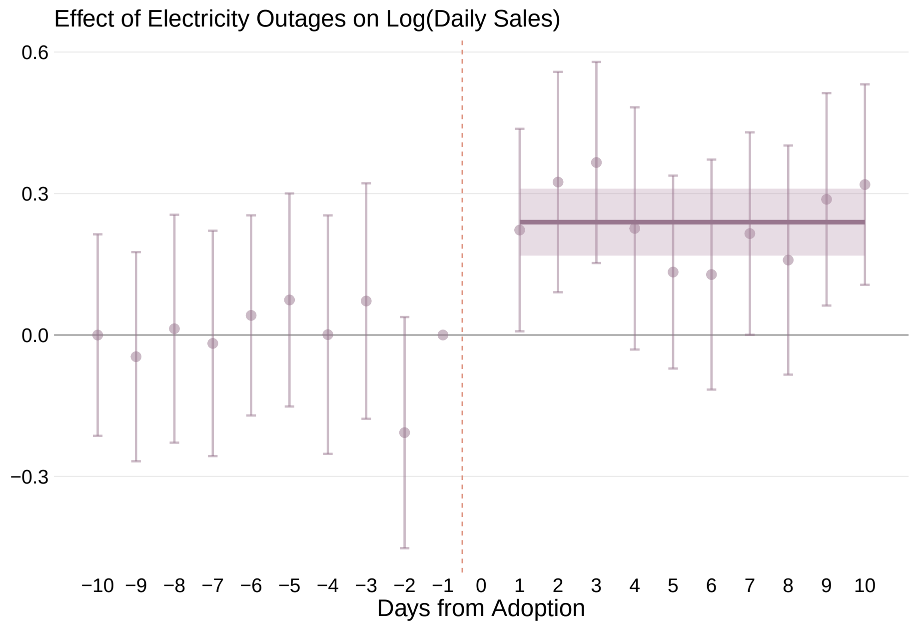
FIGURE 2. Effect of electricity outages on log daily revenue



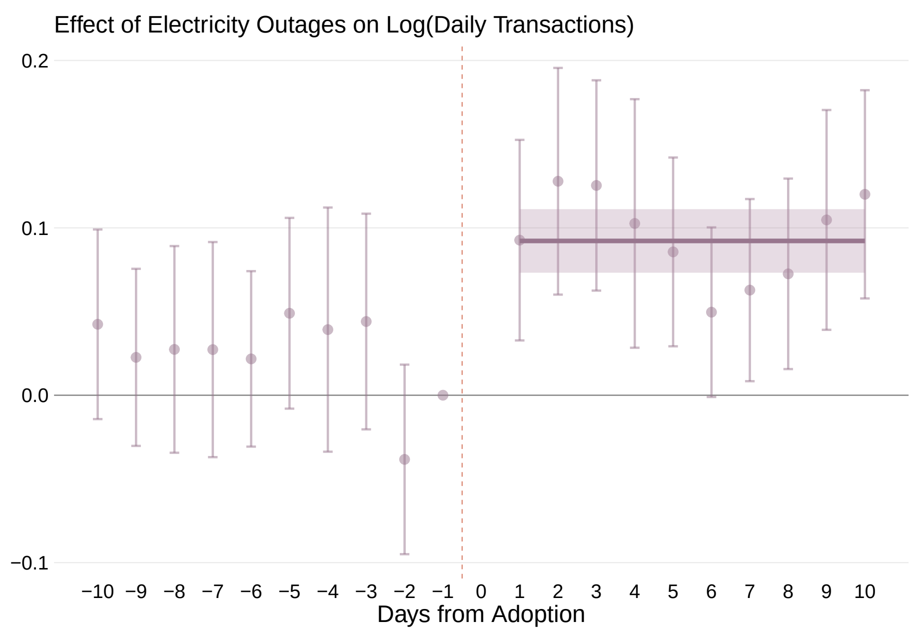
Note: This figure plots the estimates of the average treatment effects (Panel A) and local average treatment effects (Panel B) of an electricity outage on a firm's log daily revenue from the regression discontinuity design. Panel A plots estimates from Equations 1 and 2. Panel B plots estimates from Equation 8. The leftmost bar, labeled "A. Average Effects," is the average effect on all firms. The middle two bars, labeled "B. Effect on Low Performers" and "C. Effect on High Performers," show the effects of an electricity outages on low-peformers and high-performers. The rightmost bar, labeled "D. Difference (C - B)," shows the differences between the effect of an outage on high-performers from low-performers. The gray bars represent 95% confidence intervals.

FIGURE 3. Effect of defensive technology adoption on the effect of outages

A. Log Daily Sales

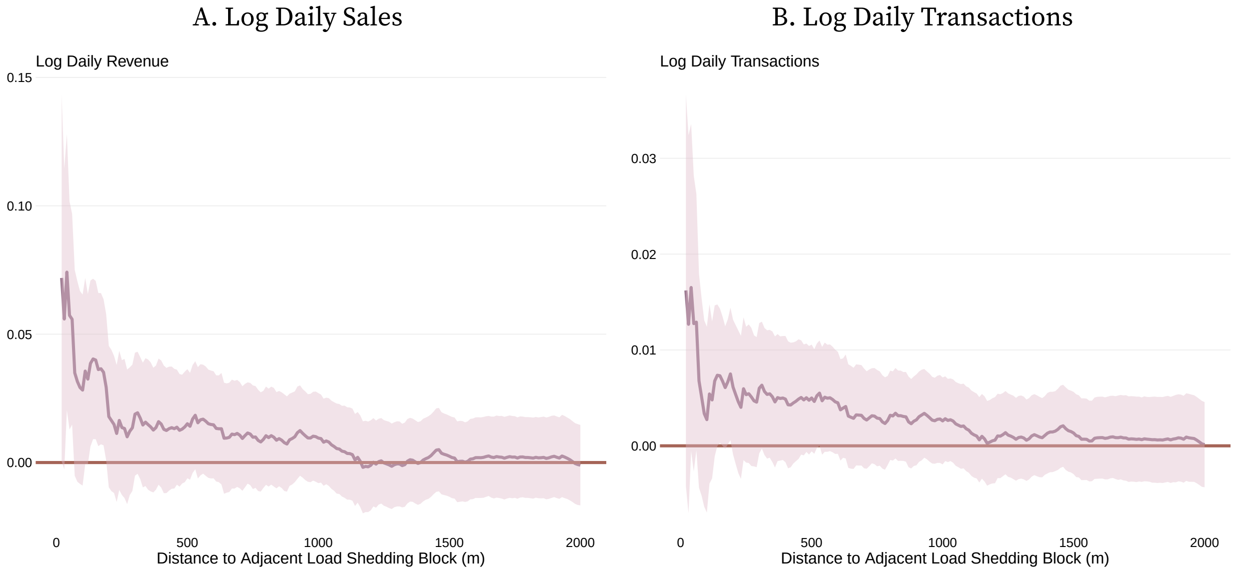


B. Log Daily Transactions



Note: This figure shows the estimated coefficients $\hat{\beta}^k$ from estimating Equation 5, relative to the day prior to adoption. "Days from adoption" indicate days relative to observed adoption of a defensive investment. Period 0 following the dashed vertical line corresponds to the adoption day. The estimated coefficients indicate the effect of a firm adopting a defensive investment on the effects of an electricity outage. Panel A shows the effects for log daily sales and Panel B reports the effects for log daily transactions. We do not report the coefficient in period 0 because we cannot disentangle for day 0, the pure effect of adoption an inverter battery system outside of the effect of an inverter battery system on the differential effect of electricity outages. The error bars indicate 95% confidence intervals. The solid line in the post-period plots the estimated average treatment effect on treated (ATT), along with its 95% confidence interval. Standard errors are clustered at the industry-block level.

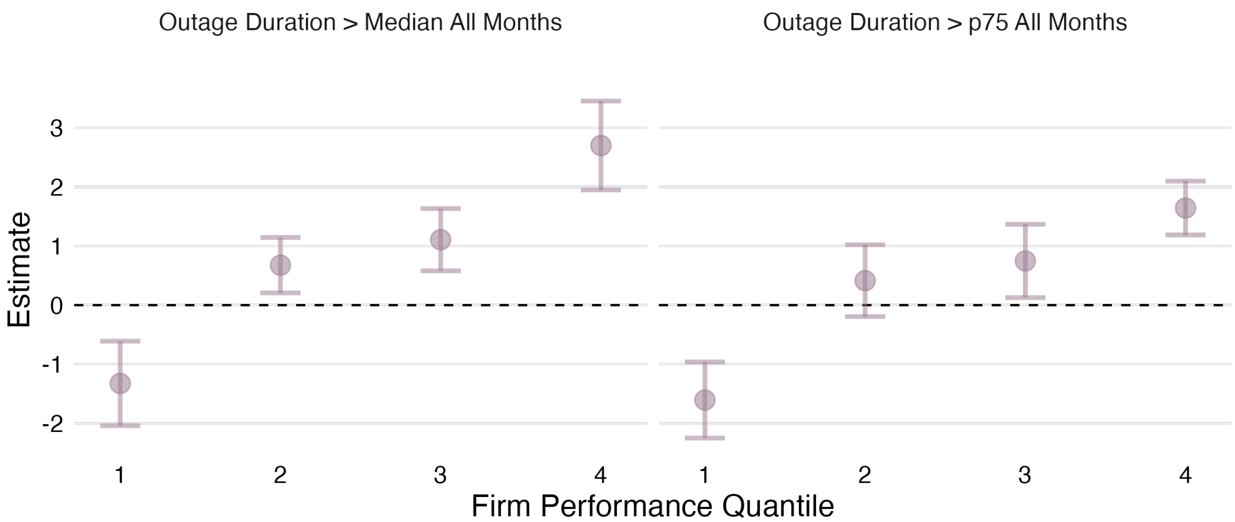
FIGURE 4. Effect of *neighboring* outages on firm performance



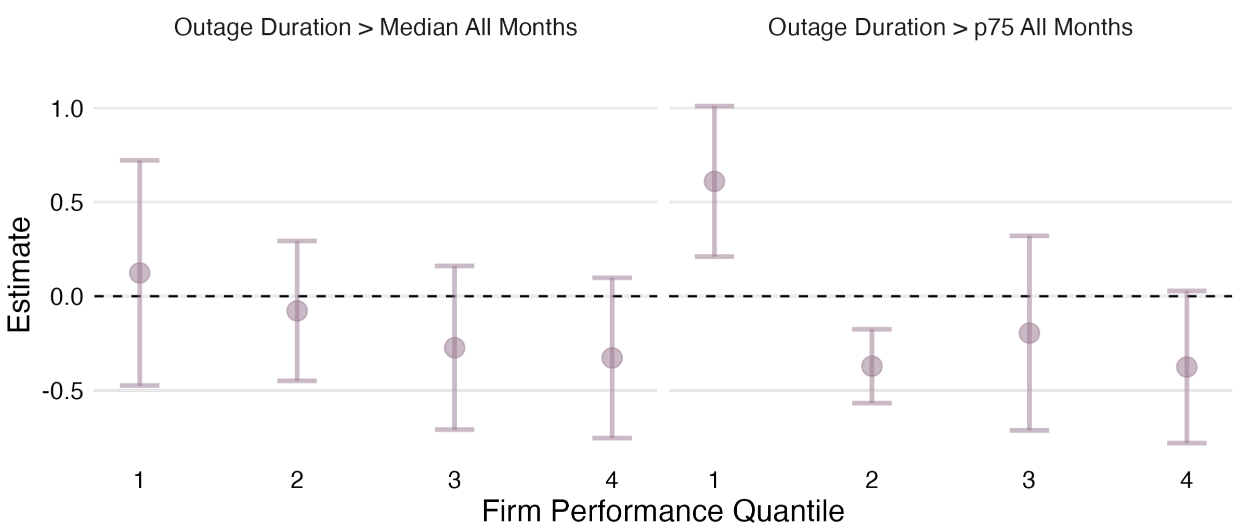
Note: This figure shows the estimated coefficients $\hat{\beta}$ from estimating Equation 3 200 times. The estimated coefficient at each point includes firms that are within $x \in \{10, 2000\}$ meters to the load shedding border. The figure connects these 200 coefficients with a line. Panel A shows the estimated coefficients on log daily sales and Panel B shows the coefficients for log daily transactions. The shaded area represent 90% confidence intervals.

FIGURE 5. Extensive Margin: Effect of outages on Firm Entry and Exit

A. Entries



B. Exits

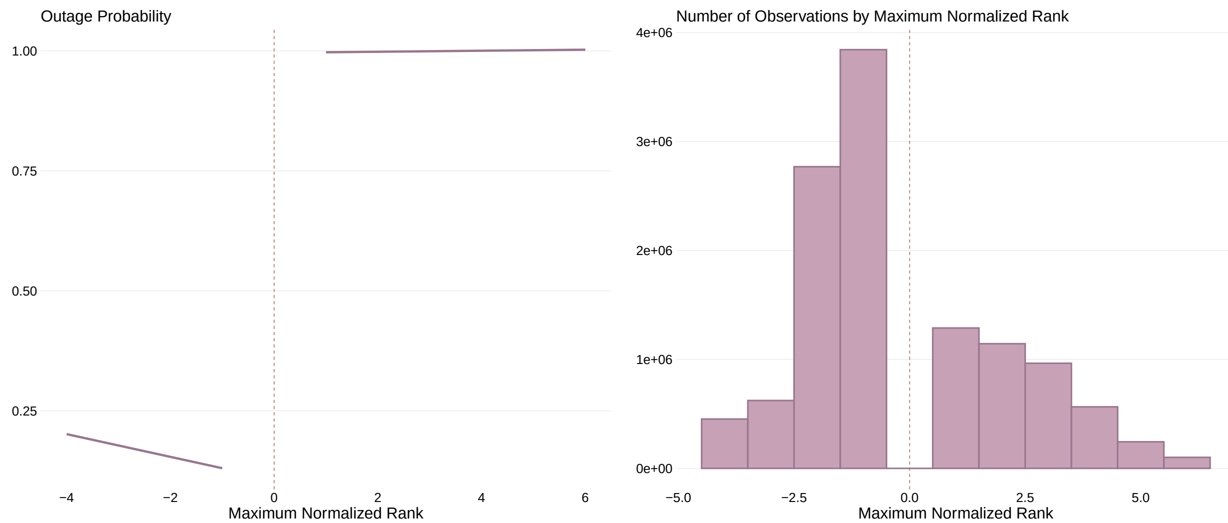


Note: This figure presents estimates of η_k from Equation 6–the coefficient on the interaction between high-outage exposure and quantile k entries/exits. Confidence intervals are computed at the 95% level using standard errors clustered at the load shedding block level. The outcome variables are the number of entries (exits) of a firm performance quantile k, calculated using total revenue.

FIGURE 6. Regression Discontinuity: First stage and density manipulation test

A. Pr(Outage) by daily maximum normalized rank

B. Density manipulation test



Note: Panel A in this figure shows the first stage on how the probability of experiencing an electricity outage changes by the firm's daily maximum normalized rank. Panel B plots the density of firms by maximum daily rank around the cutoff for all firms. There is more density overall to the left of the cutoff since we include days with no outages at all in the sample, but we observe no significant bunching around the cutoff.

Tables

TABLE 1. Summary Statistics

	N	Mean	SD	Min	P25	P50	P75	Max
Daily								
Revenue	17315	1136.53	3740.49	0.01	114.56	349.9	1023.75	318933.12
Card Revenue	17315	1101.08	3707.54	0	108.43	333.64	977.38	318933.12
Cash Revenue	17315	69.55	4236.46	0	0	0	0.57	556122.53
Transactions	17315	4.59	19.52	0	0.31	0.94	3.26	1833.91
Card Transactions	17315	4.25	19.12	0	0.29	0.89	3.02	1833.91
Cash Transactions	17315	0.34	2.43	0	0	0	0	129.64
Outages	17315	0.95	0.4	0	0.82	0.86	1.2	3.18
Monthly								
Revenue	17315	31673.63	79918.65	0.27	3203.76	9873.41	29385.13	2900284.34
Card Revenue	17315	30670.37	78748.07	0	3015	9379.9	28048.82	2900284.34
Cash Revenue	17315	2048.72	131254.49	0	0	0	16.19	17239796.17
Transactions	17315	126.13	378.95	0.05	8.6	25.92	91.13	23125.38
Card Transactions	17315	116.46	363.48	0	8.17	24.49	84.81	23125.38
Cash Transactions	17315	9.66	67.1	0	0	0	0.08	2417.51
Outages	17315	27.78	11.59	0	24.73	25.54	35.5	66.5
Lifetime								
Revenue	17315	801117.34	2313399.74	10	54719	193040.94	656439.86	89059413.43
Card Revenue	17315	776273.91	2271033.41	0	51241.59	184950	632009.78	89059413.43
Cash Revenue	17315	62922.63	4852964.18	0	0	0	388.95	637872458.46
Transactions	17315	3061.44	11489.26	2	158.02	489	1847	855638.92
Card Transactions	17315	2837.38	11084.1	0	149	459.24	1739	855638.92
Cash Transactions	17315	223.99	1730.1	0	0	0	2	56509.58
Outages	17315	668.71	332.27	0	408	867	920	945
Other Firm Characteristics								
Property Value in Suburb (Thousand Rand)	15738	2044.06	1615.02	63.86	980	1500	2985	19050
Age of Firm	17315	1135.29	647.48	31	631	1024	1556	2518
$\mathbb{1}$(Mobile Industry)	17315	0.19	0.39					
$\mathbb{1}$(Uses WiFi)	16257	0.66	0.43					
$\mathbb{1}$(Informal)	17315	0.19	0.39					
$\mathbb{1}$(Foreign-Owned)	17315	0.11	0.31					
Age of Owner	15251	47.42	12.51	19	38	47	56	98
$\mathbb{1}$(Female-Owned)	15251	0.51	0.5					

Note: This table shows the summary statistics of the 17,315 unique firms in our main analysis sample 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 are reported in the subsequent regression tables.

TABLE 2. Balance table

	No blackouts $N = 6,565,425$		Blackouts $N = 5,429,998$		
	Mean	SD	Mean	SD	p
Panel A: Firm Characteristics					
Number of Days on Platform	1478.721	602.736	1355.445	606.300	0.427
$\mathbb{1}$(Informal)	0.178	0.382	0.185	0.388	0.781
$\mathbb{1}$(Owner is Citizen)	0.893	0.309	0.888	0.315	0.629
$\mathbb{1}$(Services)	0.471	0.499	0.470	0.499	0.637
Log Rolling Non-Outage Amount	4.114	3.239	4.262	3.251	0.775
Property Value in Suburb (Thousand Rand)	2058.607	1592.603	2052.445	1627.423	0.514
Log Rolling Non-Outage Transactions	0.785	1.010	0.831	1.055	0.578
Age of Owner	48.327	12.243	48.096	12.416	0.951
$\mathbb{1}$(Female-Owned)	0.530	0.499	0.525	0.499	0.779
$\mathbb{1}$(Uses WiFi)	0.735	0.441	0.727	0.445	0.287
Panel B: Industry Composition					
Food, drink, and hospitality	0.243	0.429	0.250	0.433	0.631
Healthcare, Beauty, and Fitness	0.240	0.427	0.232	0.422	0.799
Home and Repair	0.060	0.238	0.059	0.236	0.724
Leisure and Entertainment	0.026	0.159	0.030	0.171	0.602
Personal Services	0.039	0.195	0.041	0.198	0.564
Professional Services	0.067	0.251	0.065	0.246	0.507
Retail	0.286	0.452	0.280	0.449	0.703
Transportation	0.015	0.120	0.019	0.137	0.655
Travel and Tourism	0.024	0.152	0.024	0.153	0.627

Note: This table presents a test of covariate balance across firms experiencing an electricity outage vs. firms that are 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 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.

TABLE 3. Effect of outages on firm revenue and transactions

Panel A: Log(Daily Sales)

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	0.1854***	0.0051	-0.0075	-0.0884***	-0.0905***	-0.0975***
	(0.0175)	(0.0117)	(0.0071)	(0.0111)	(0.0107)	(0.0113)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median)				0.1576***		0.0776***
				(0.0183)		(0.0253)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block)					0.1611***	0.0974***
					(0.0182)	(0.0258)
Date FE	No	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.5193	2.5193	2.5193	2.5193	2.5193	2.5193
R^2	0.00069	0.03052	0.42918	0.42929	0.42930	0.42931
Observations	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423

Panel B: Log(Daily Transactions)

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	0.0600***	0.0025	-0.0021	-0.0336***	-0.0338***	-0.0368***
	(0.0049)	(0.0055)	(0.0016)	(0.0034)	(0.0035)	(0.0038)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median)				0.0614***		0.0336***
				(0.0064)		(0.0070)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block)					0.0614***	0.0337***
					(0.0067)	(0.0083)
Date FE	No	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.64854	0.64854	0.64854	0.64854	0.64854	0.64854
R^2	0.00075	0.01876	0.55561	0.55579	0.55579	0.55581
Observations	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423

Note: This table presents estimates from Equations 1 and 2 on the average treatment effect of exposure to an electricity outage on log daily sales (panel A) and log daily transactions (panel B). All logged variables are defined as $\log(1+x)$. 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 × 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. Effect of outages on firm revenue and transactions: Regression discontinuity estimates

	(1)	(2)	(3)	(4)
Panel A: Log(Daily Sales)				
$\mathbb{1}$(Outage)	-0.0448	-0.0836***	-0.0918***	-0.0921***
	(0.0288)	(0.0251)	(0.0254)	(0.0251)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)		0.0729**		0.0031
		(0.0288)		(0.0337)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median Industry Block)			0.0876***	0.0853***
			(0.0253)	(0.0241)
Firm FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.5243	2.5243	2.5243	2.5243
R^2	0.42984	0.42994	0.42995	0.42996
Observations	10,632,635	10,632,635	10,632,635	10,632,635
Panel B: Log(Daily Transactions)				
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Outage)	-0.0110*	-0.0247***	-0.0263***	-0.0270***
	(0.0059)	(0.0053)	(0.0052)	(0.0053)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)		0.0260***		0.0069
		(0.0077)		(0.0080)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median Industry Block)			0.0289***	0.0233***
			(0.0076)	(0.0076)
Firm FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.64926	0.64926	0.64926	0.64926
R^2	0.55588	0.55604	0.55604	0.55605
Observations	10,632,635	10,632,635	10,632,635	10,632,635

Note: This table presents regression discontinuity estimates from Equation 8 on the effect of exposure to an electricity outage on log daily sales (panel A) and log daily transactions. All logged variables are defined as $\log(1+x)$. The coefficient on $\mathbb{1}$(Outage) represents the effect of an exposure to an electricity outage in column 1 of panels A and B. In columns 2–5, 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 5. Effect of outages on consumer substitution

Panel A: Substitution Across All Firms

	>P50 Firm Spending Share		≤P50 Firm Spending Share		Regular Firm Spending Share	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(>P50 Regular Firm Outage)	-0.0020**		0.0020**		0.0059***	
	(0.0008)		(0.0008)		(0.0013)	
$\mathbb{1}$(≤P50 Regular Firm Outage)		0.0419***		-0.0419***		-0.0438***
		(0.0143)		(0.0143)		(0.0140)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Card FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.94549	0.94549	0.05451	0.05451	0.32443	0.32443
R^2	0.15588	0.15590	0.15588	0.15590	0.35749	0.35749
Observations	2,515,020	2,515,020	2,515,020	2,515,020	2,515,020	2,515,020

Panel B: Substitution Across New Firms

	$\mathbb{1}$(Transacted with New Firm)		>P50 New Firm Spending Share		≤P50 New Firm Spending Share	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(>P50 Regular Firm Outage)	-0.0058***		-0.0060***		0.0002	
	(0.0014)		(0.0014)		(0.0007)	
$\mathbb{1}$(≤P50 Regular Firm Outage)		0.0386***		0.0307*		0.0131
		(0.0139)		(0.0162)		(0.0085)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Card FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.69311	0.69311	0.62992	0.62992	0.04564	0.04564
R^2	0.34355	0.34355	0.31141	0.31141	0.11620	0.11621
Observations	2,515,020	2,515,020	2,515,020	2,515,020	2,515,020	2,515,020

Note: This table presents estimates from Equation 4 on the effect of an electricity outage to a card's regular firm on six outcomes: the share of a card's daily spending on above-median firms, below-median firms, regular firms, above-median *new* firms, and below-median *new* firms, and an indicator for whether the card has transacted with a new firm. 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 card substitution across all firms and panel B examines substitution across new 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 6. Robustness

Panel A: Log(Daily Sales)

	All	$\geq$ 100m	$\geq$ 500m	$\geq$ 1km	$\geq$ 3km
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Outage)	-0.0966***	-0.0968***	-0.0966***	-0.1053***	-0.1196***
	(0.0109)	(0.0111)	(0.0119)	(0.0138)	(0.0238)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)	0.0925***	0.0863***	0.0722***	0.0812**	0.0533
	(0.0249)	(0.0249)	(0.0271)	(0.0327)	(0.0565)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)	0.0837***	0.0897***	0.1006***	0.0983***	0.1343**
	(0.0230)	(0.0238)	(0.0280)	(0.0336)	(0.0661)
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.4954	2.5022	2.5436	2.5868	2.7218
R^2	0.42829	0.42879	0.43122	0.43456	0.44444
Observations	13,376,058	12,787,104	10,875,135	8,804,265	4,142,694

Panel B: Log(Daily Transactions)

	All	$\geq$ 100m	$\geq$ 500m	$\geq$ 1km	$\geq$ 3km
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Outage)	-0.0367***	-0.0369***	-0.0370***	-0.0398***	-0.0471***
	(0.0036)	(0.0037)	(0.0041)	(0.0045)	(0.0060)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)	0.0377***	0.0362***	0.0317***	0.0349***	0.0269*
	(0.0072)	(0.0075)	(0.0074)	(0.0091)	(0.0152)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)	0.0305***	0.0321***	0.0360***	0.0358***	0.0517**
	(0.0076)	(0.0078)	(0.0090)	(0.0115)	(0.0209)
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.64102	0.64303	0.65641	0.67060	0.71543
R^2	0.55332	0.55446	0.55996	0.56541	0.57844
Observations	13,376,058	12,787,104	10,875,135	8,804,265	4,142,694

Note: This table presents estimates from Equations 1 and 2 on the average treatment effect of exposure to an electricity outage on log daily sales (panel A) and log daily transactions (panel B). We impose different sample restrictions on the firm's distance to nearest adjacent loadshedding border. Column 1 includes all firms, while columns 2–5 excludes firms that are less than 100 meters, 500 meters, 1 kilometer, and 3 kilometers away from the nearest loadshedding border, respectively. All logged variables are defined as $\log(1+x)$. 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 7. Summary statistics of firms with and without defensive technology

	No Defensive Tech $N = 4.245$		Defensive Tech $N = 9,228$		
	Mean	SD	Mean	SD	p
Panel A: Firm Characteristics					
Log Pre-Adoption Amount	5.154	1.591	5.795	1.748	0.000
Log Pre-Adoption Non-Outage Amount	5.074	1.697	5.692	1.894	0.000
Log Pre-Adoption Transactions	0.717	0.793	1.018	0.977	0.000
Log Pre-Adoption Non-Outage Transactions	0.706	0.792	0.995	0.981	0.000
$\mathbb{1}$(Above Median)	0.372	0.483	0.600	0.490	0.000
Outage Probability	0.410	0.196	0.470	0.154	0.000
Number of Days on Platform	1084.484	635.530	1296.769	661.929	0.000
$\mathbb{1}$(Informal)	0.217	0.413	0.163	0.369	0.000
$\mathbb{1}$(Owner is Citizen)	0.891	0.311	0.884	0.321	0.186
$\mathbb{1}$(Services)	0.403	0.491	0.467	0.499	0.000
Property Value in Suburb (Thousand Rand)	1900.758	1504.466	2171.364	1672.593	0.000
Age of Owner	47.036	12.788	47.335	12.267	0.233
$\mathbb{1}$(Female-Owned)	0.522	0.500	0.522	0.500	0.998
Panel B: Industry Composition					
Food, drink, and hospitality	0.288	0.453	0.283	0.450	0.556
Healthcare, Beauty, and Fitness	0.163	0.369	0.253	0.435	0.000
Home and Repair	0.060	0.237	0.051	0.220	0.038
Leisure and Entertainment	0.040	0.196	0.023	0.151	0.000
Personal Services	0.038	0.191	0.039	0.194	0.762
Professional Services	0.059	0.236	0.062	0.242	0.508
Retail	0.309	0.462	0.250	0.433	0.000
Transportation	0.024	0.152	0.013	0.115	0.000
Travel and Tourism	0.020	0.139	0.025	0.158	0.044

Note: This table presents the mean and standard deviation of firms that we observe to have ever adopted a defensive technology compared to firms who have not. We define a firm to have ever adopted a defensive technology if we observe any transactions conducted over WiFi during an outage period. We limit the sample to firms for whom we observe to have ever used WiFi on any transactions, leaving 13,473 total unique firms. 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 has ever adopted a defensive technology. Panel A shows key firm characteristics while Panel B shows the industry composition between the two groups.

TABLE 8. Effect of outages on firm revenue and transactions by announcement date

	Log(Daily Sales)			Log(Daily Transactions)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	-0.0401	-0.0583**	-0.0739***	-0.0146**	-0.0297***	-0.0336***
	(0.0326)	(0.0267)	(0.0279)	(0.0069)	(0.0064)	(0.0071)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$($\geq$ 1 Day Notice)	0.1322**	0.0604	0.0565	0.0361**	0.0069	0.0071
	(0.0582)	(0.0556)	(0.0548)	(0.0158)	(0.0150)	(0.0150)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)		0.0363			0.0298***	
		(0.0375)			(0.0101)	
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$($\geq$ 1 Day Notice) $\times$ $\mathbb{1}$(Above Median)		0.1390***			0.0570***	
		(0.0189)			(0.0063)	
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)			0.0657*			0.0369***
			(0.0357)			(0.0104)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$($\geq$ 1 Day Notice) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)			0.1478***			0.0566***
			(0.0208)			(0.0062)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.4146	2.4146	2.4146	0.63241	0.63241	0.63241
R^2	0.43001	0.43008	0.43010	0.55066	0.55082	0.55084
Observations	854,737	854,737	854,737	854,737	854,737	854,737

Note: This table presents estimates from augmented versions of Equations 1 and 2 on the average treatment effect of exposure to an electricity outage on log daily sales (columns 1–3) and log daily transactions (columns 4–6) by including an additional interaction for whether the outage event was announced with at least one day of notice. The sample limits to only days with at least one electricity outage. All logged variables are defined as $\log(1+x)$. The coefficient on $\mathbb{1}$(Outage) represents the effect of an exposure to an electricity outage that was announced on the same day in column 1. The coefficient on $\mathbb{1}$(Outage) interacted with $\mathbb{1}$($\geq$ 1 Day Notice) represents the differential effect of an exposure to an electricity outage that was announced with at least one day notice relative to outages announced on the same day in column 1. In columns 3–6, the coefficient on $\mathbb{1}$(Outage) represents the effect of an exposure to an electricity outage that was announced on the same day 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 announced on the same day for above-median firms relative to below-median firms. The coefficient on $\mathbb{1}$(Outage) interacted with $\mathbb{1}$($\geq$ 1 Day Notice) represents the differential effect of an exposure to an electricity outage that was announced with at least one day notice relative to outages announced on the same day for below-median firms. The coefficient on the interactions between $\mathbb{1}$(Outage), $\mathbb{1}$($\geq$ 1 Day Notice), and either $\mathbb{1}$(Above Median) or $\mathbb{1}$(Above Median in Industry $\times$ Block) represent the differential effect of an outage announced with at least 1 day notice for above-median firms relative to an outage announced on the same day for above-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.

Appendix A. 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.[25] 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 325,000 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.

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 54 million transactions from 17,993 distinct firms.[26] We also remove online-only firms and non-profit organizations from the main analysis sample.[27] Most of the firms in the data are service-oriented firms. This leaves over 53 million transactions from 17,315 distinct firms.

[25] 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.

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

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

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 11,995,423 observations, where we observe each of the 17,315 firms for an average of 692 days.

Appendix B. Instrumental Variables

B.1. Instrumental variables approach to main results

We describe the instrumental variable strategy that we employ in Table C.4 in detail in this section. 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 over-draws power). Another concern could be that the implementation of load shedding by the municipality deviates from the published schedule to favor certain areas over another. To address this potential concern, we use an instrumental variable approach using the load shedding schedule as an instrument.

We construct the instrument in the following manner. We first consider the assigned two-hourly rankings for each firm, which ranges from 0-8 (Appendix Figure C.4 shows the outage probability by these rankings). For each of these two-hour periods, we interact the firm's ranking with the stage of outage at which the two-hour period is at. We then aggregate the rank by stage variable to the daily level by taking the maximum. Thus, the rank by stage is an instrument that reflects the firm's maximum probability of experiencing an outage on any given day. Appendix Figure **??** shows the outage probability by the rank by stage variable. We note that this is a discrete variable and thus construct an indicator for each value of the firm's daily maximum rank by stage. This instrument is strong: the first-stage F-statistic is consistently above 30,000 (reported at the bottom of Table C.4).

B.2. Instrument validity for regression discontinuity design

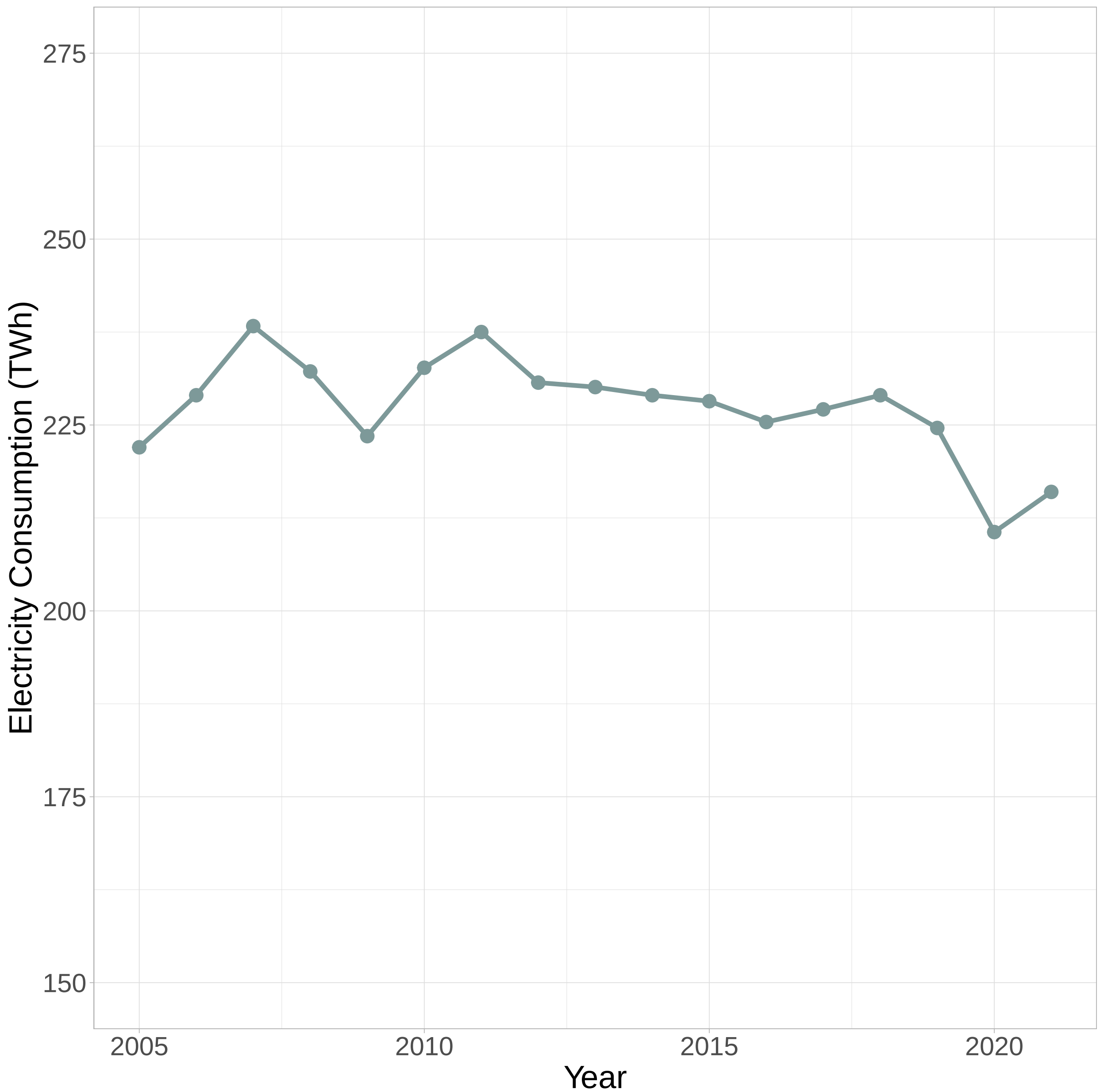
We examine the conditions for a valid fuzzy regression discontinuity design. First, the running variable must be established before treatment is assigned (i.e. the treatment cannot cause the running variable). This is mechanically the case in our setting, as the construction of the rankings is based off of a pre-published schedule and the treatment (outage) is determined each day based on national electricity demand and supply. Second, the cutoff must be independent of the running variable—the running variable cannot be manipulated around the cutoff to ensure certain load shedding areas do (or do not) receive an outage). Figure 6 panel B plots the distribution of ranks—and we find no evidence of bunching around the cutoff. This is mechanically true since firms are not mobile within any given day.

Third, covariates must be continuous across the cutoff.[28] We plot the distribution of covariates by rank, pooling both above- and below-median firms (Appendix Figures C.9–C.12), only considering above-median firms (Appendix Figures C.13–C.16), and only considering below-median firms (Appendix Figures C.16–C.19). The smoothness of firm covariates across outage thresholds is encouraging of the research design, in light of the large discontinuities in outage probabilities across the threshold.

[28]The continuity assumption is in effect the exclusion restriction. The exclusion-restriction underlying this strategy requires that the interaction of a firm's position in the published load shedding schedule with the nationally announced stage affects firm performance only by changing whether the power is actually cut (and its duration). After controlling for firm fixed effects and date (or stage-by-day) fixed effects, the schedule–stage instrument must be unrelated to any other channel that could influence sales—such as macroeconomic news embedded in the stage announcement, shifts in local demand, or operational choices firms make in anticipation of higher-stage events that do not lead to outages.

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.

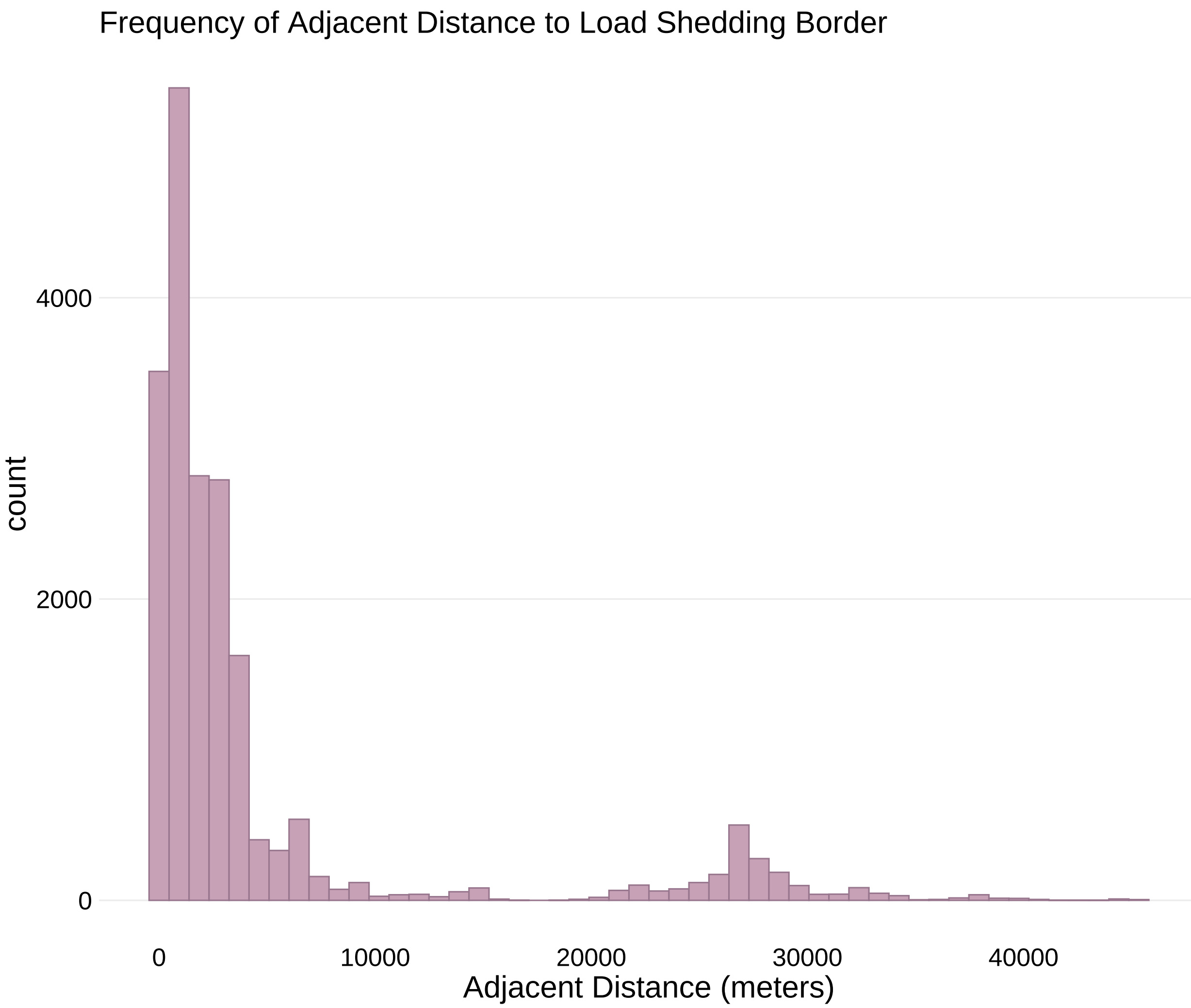
FIGURE C.2. Example of a loadshedding schedule for Stage 3

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

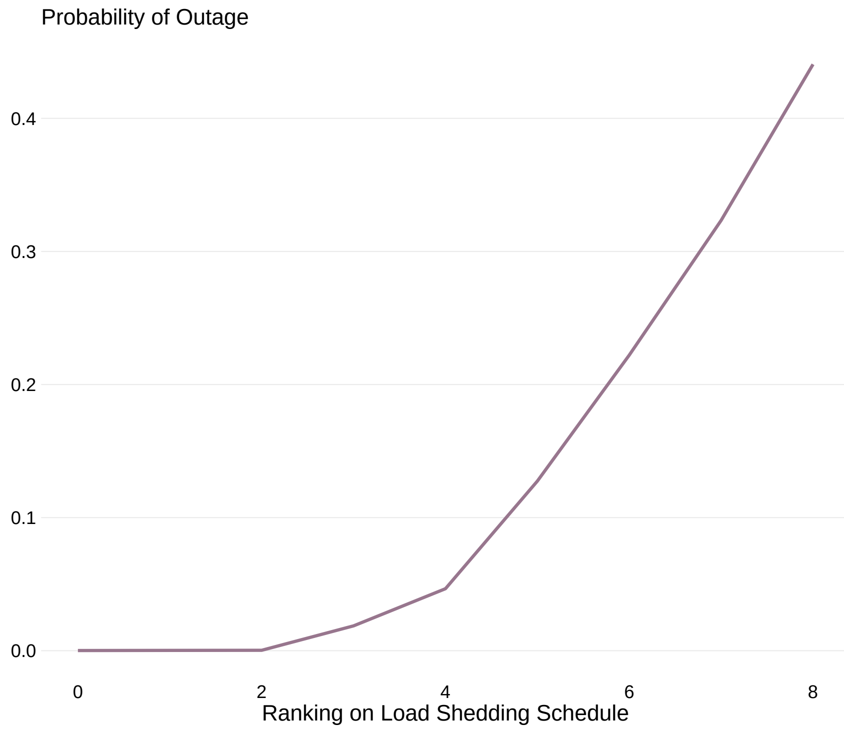
Note: This figure shows a screenshot from Cape Town's load shedding schedule. We show the schedule for stage 3, of which there are 8 total stages. Each cell indicates the load shedding block number that will experience an outage if a stage 3 outage event was declared on the days of the month indicated 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

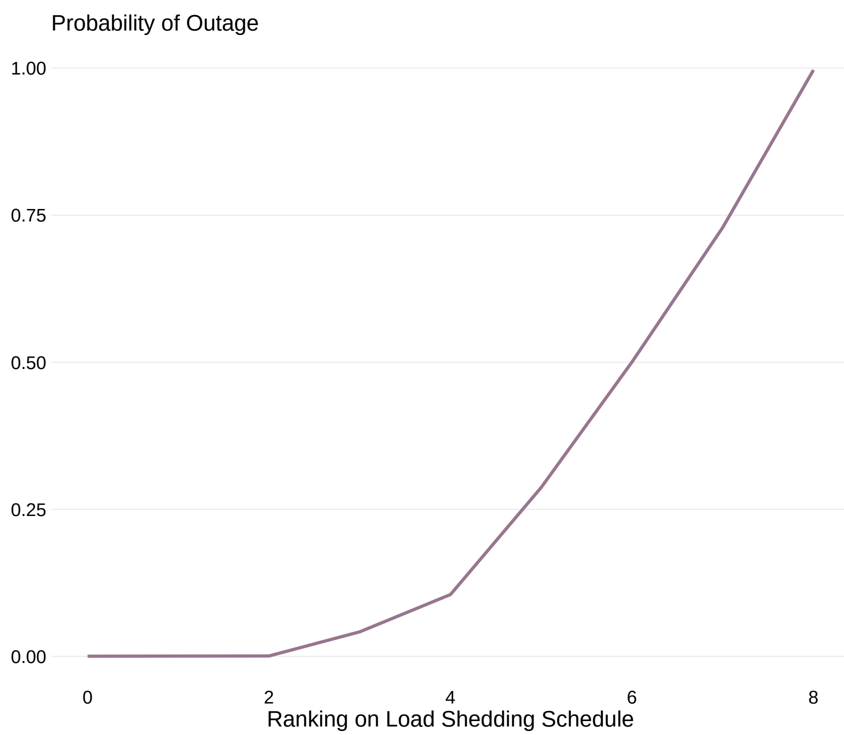


Note: This figure shows the distribution of all firms' ($N = 20,074$) distance to the nearest load shedding border.

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



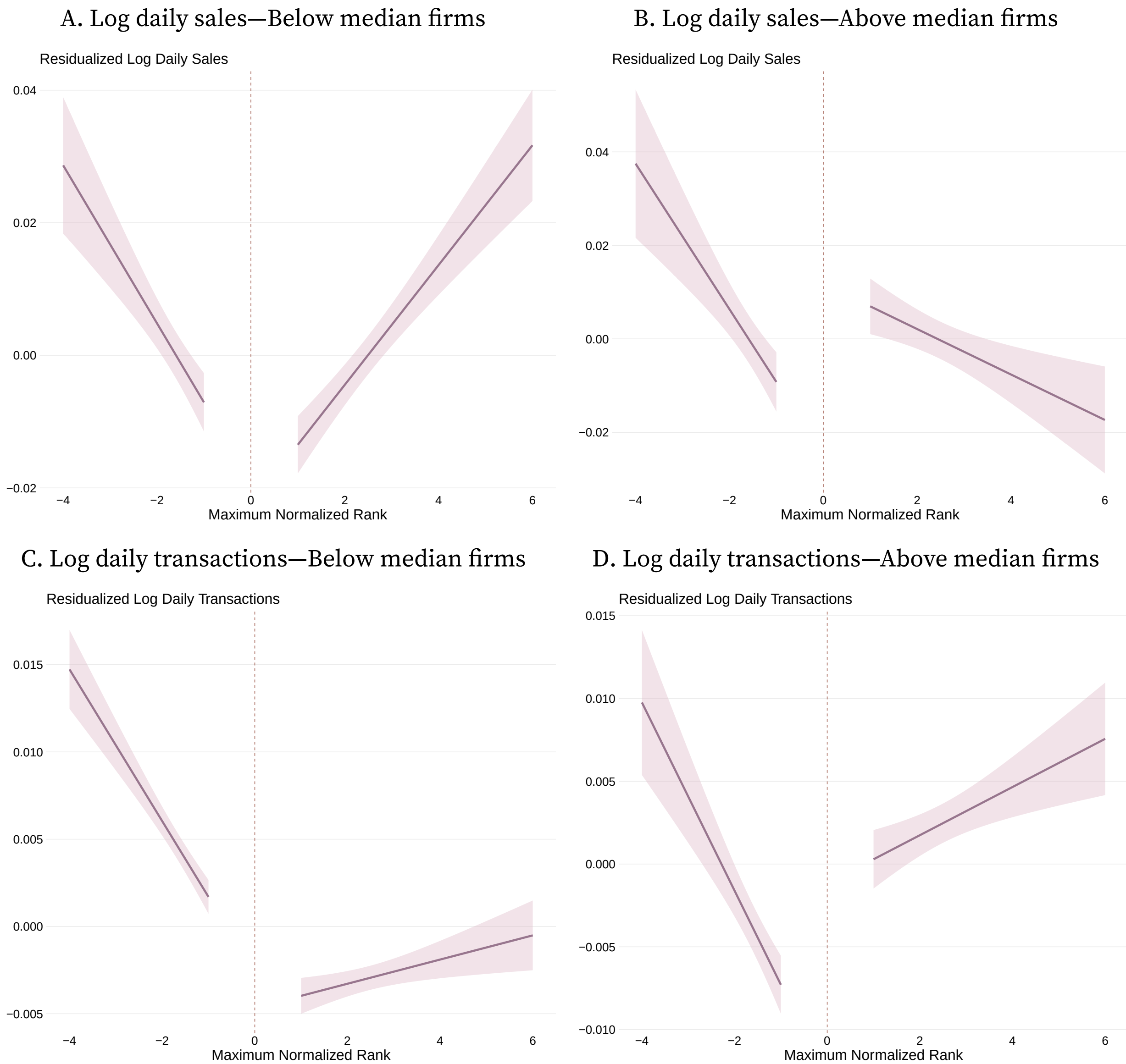
A. Outage Probability by Rank on All Days



B. Outage Probability by Rank During Outage Hours

Note: This figure reports a firm's outage probability by their load shedding schedule ranking. We transform the load shedding schedule into a ranking from 0–8, where 0 indicates that the area that the firm is located in is not scheduled to receive an outage at a particular time and day. Rank 1 indicates that the firm would only receive an outage in the most severe stage of stage 8. Rank 8 implies that the firm would receive an outage, starting from the least severe stage of stage 1. Panel A shows the outage probability across all days while Panel B restricts the sample to only hours and days in which there are electricity outages.

FIGURE C.5. Firm performance by normalized rank around cutoff



Note: This figure plots log daily sales (panels A and B) and log daily transactions (panels C and D) against the firm's daily maximum normalized rank separately for above- and below-median firms. Across all panels, we plot the firm and day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.6. 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.

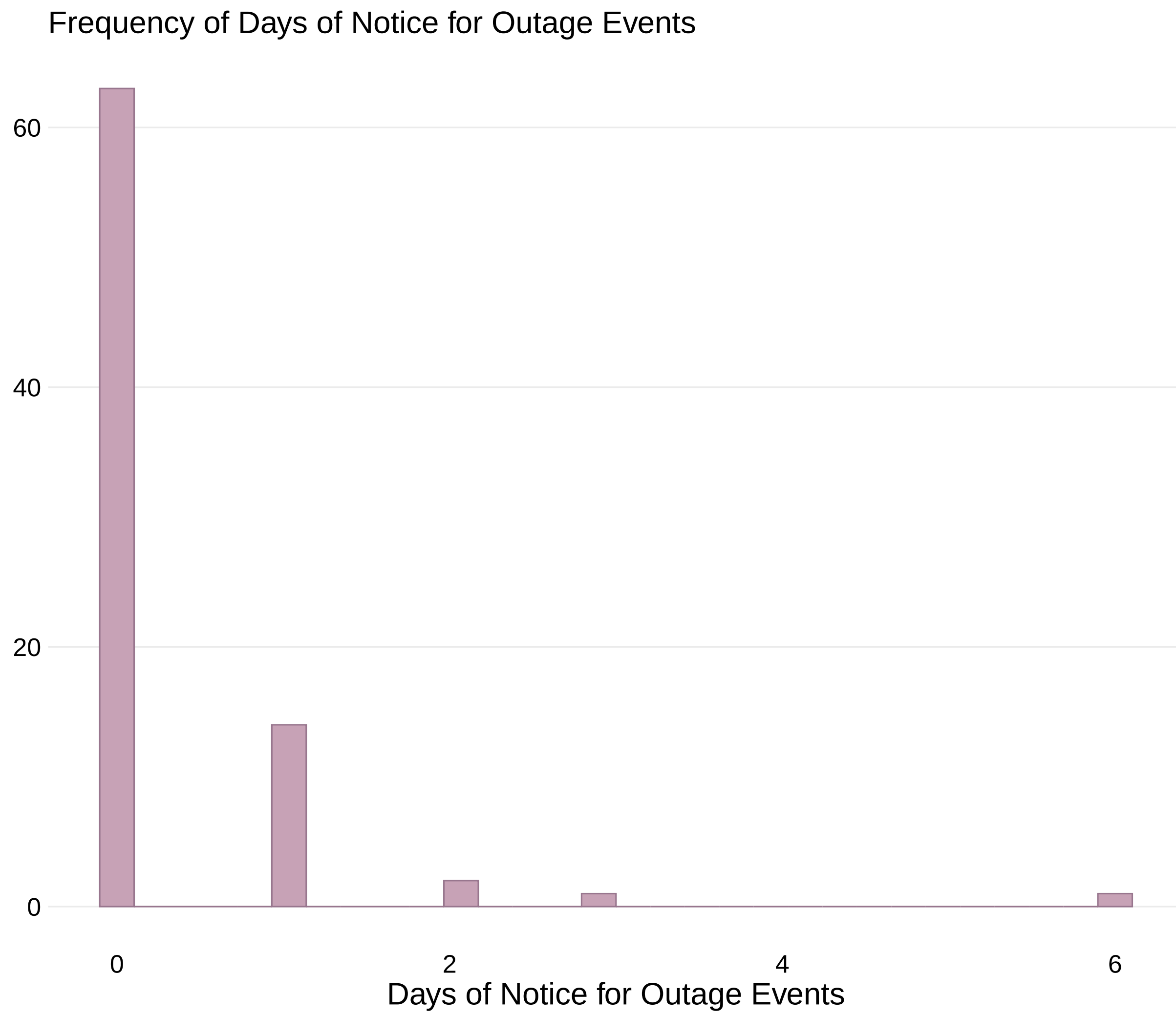
Eskom teams are working tirelessly to ensure that this additional generating units are returned to service as soon as possible.

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

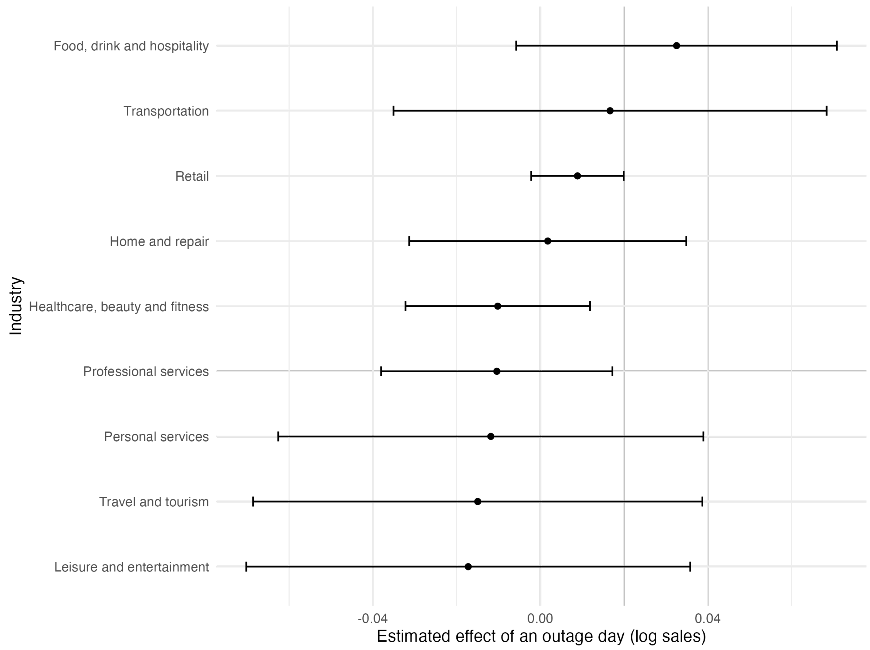
Note: This figure shows an example announcement of an escalation in outage severity from Eskom on the same day. The date of the announcement is highlighted in bold. All announcements are obtained from https://www.eskom.co.za/category/news/.

FIGURE C.7. Distribution of difference between announcement and outage days

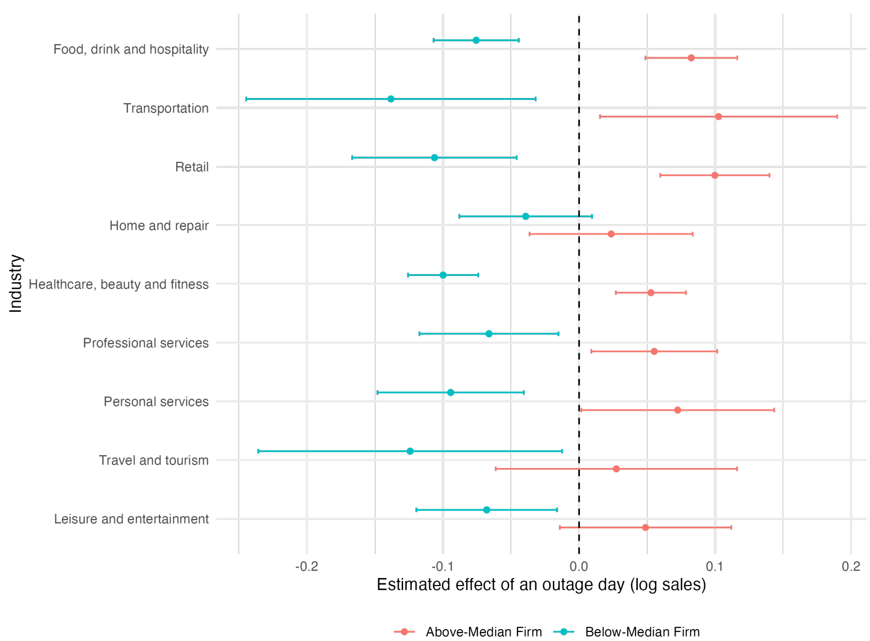


Note: This figure shows the distribution of the number of days in between the outage announcement and the outage event by Eskom for 81 distinct outage events.

FIGURE C.8. Outage Effects by Industry



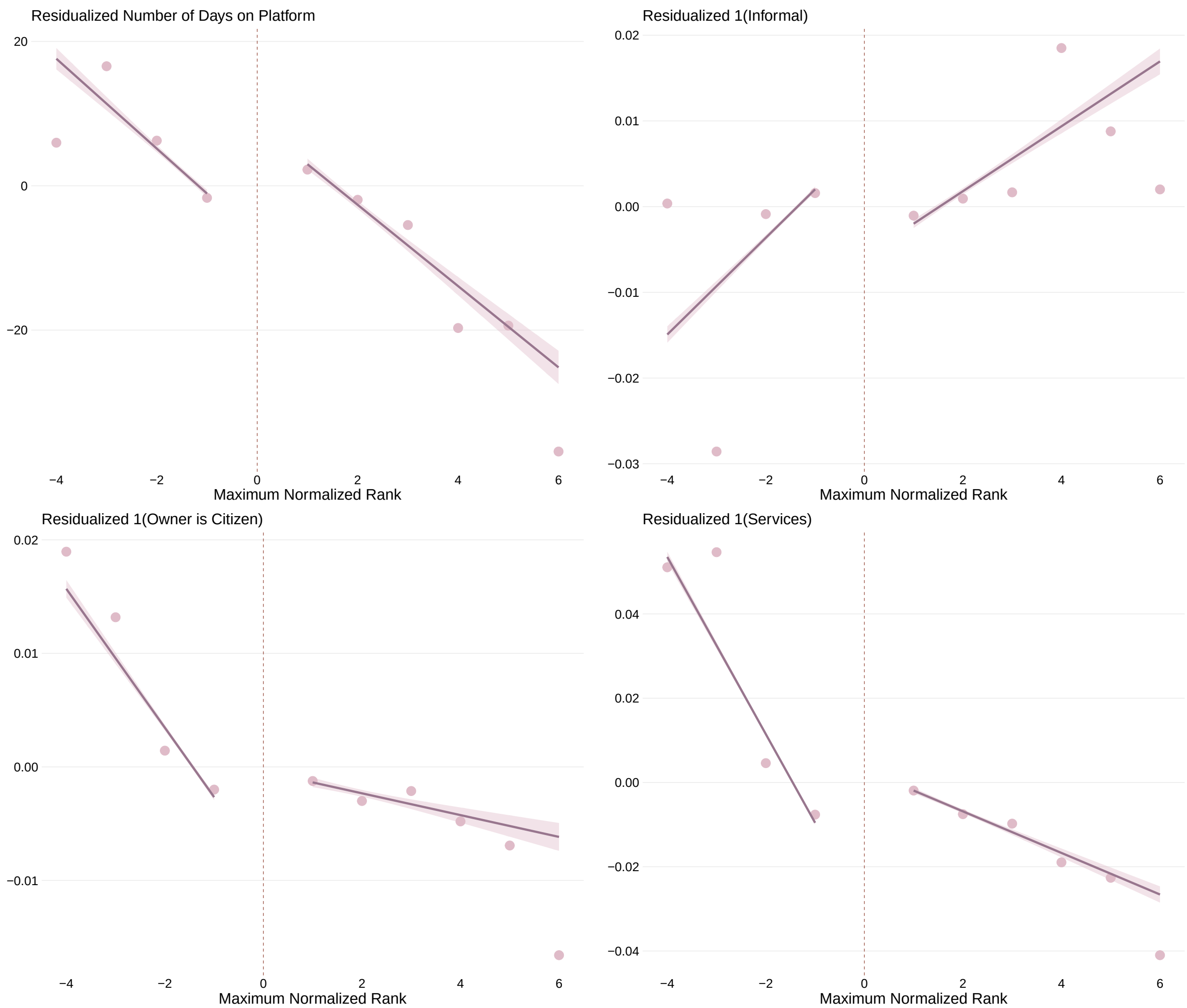
A. Overall Effects By Industry



B. Heterogeneous Effects by Industry

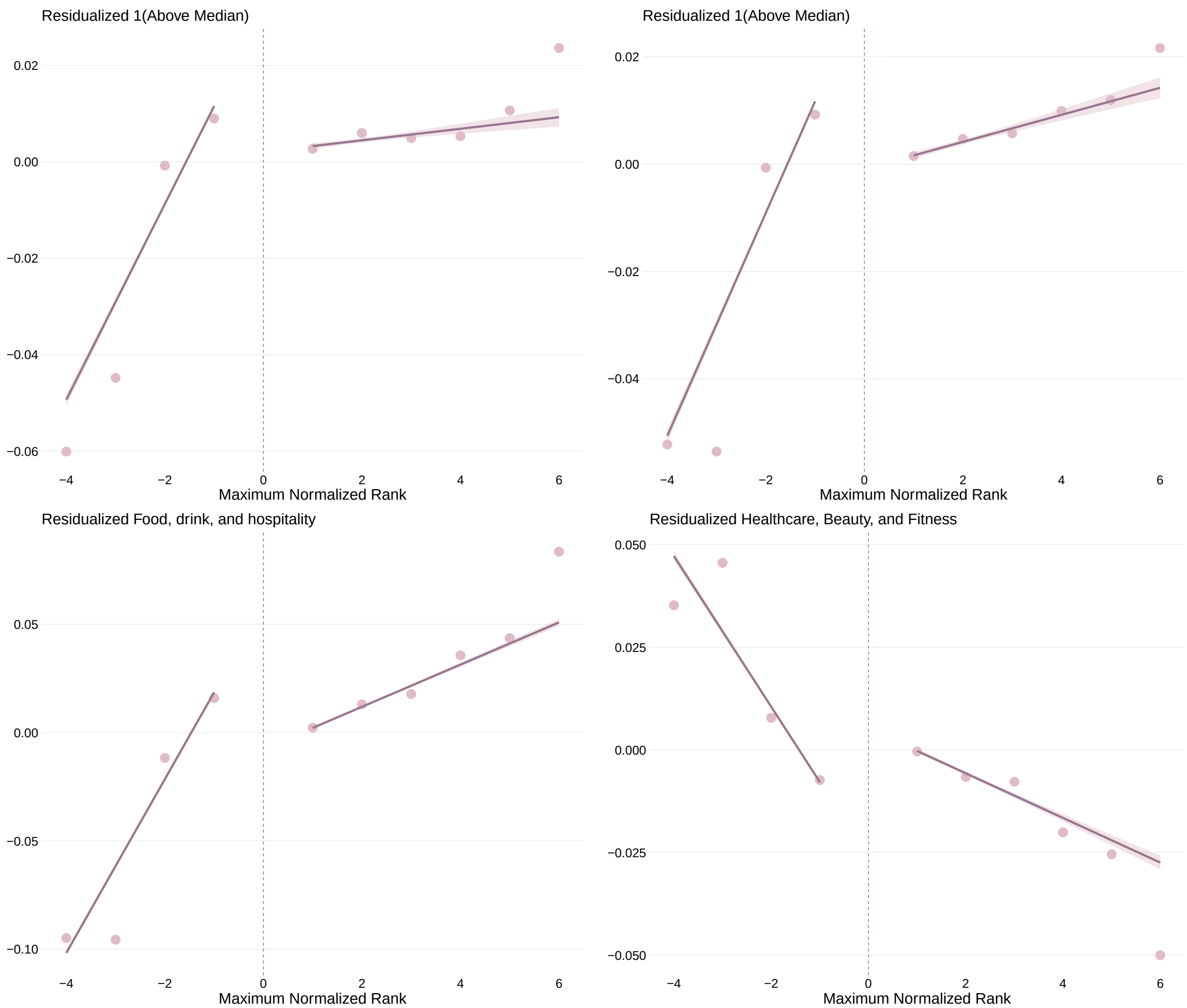
Note: This figure reports coefficient estimations of Equations 1 and 2 split by industry. Panel A reports overall effects and Panel B reports effects split by median industry performance within block. Standard errors are clustered at the block level, and used to construct the 95% confidence intervals displayed.

FIGURE C.9. Continuity



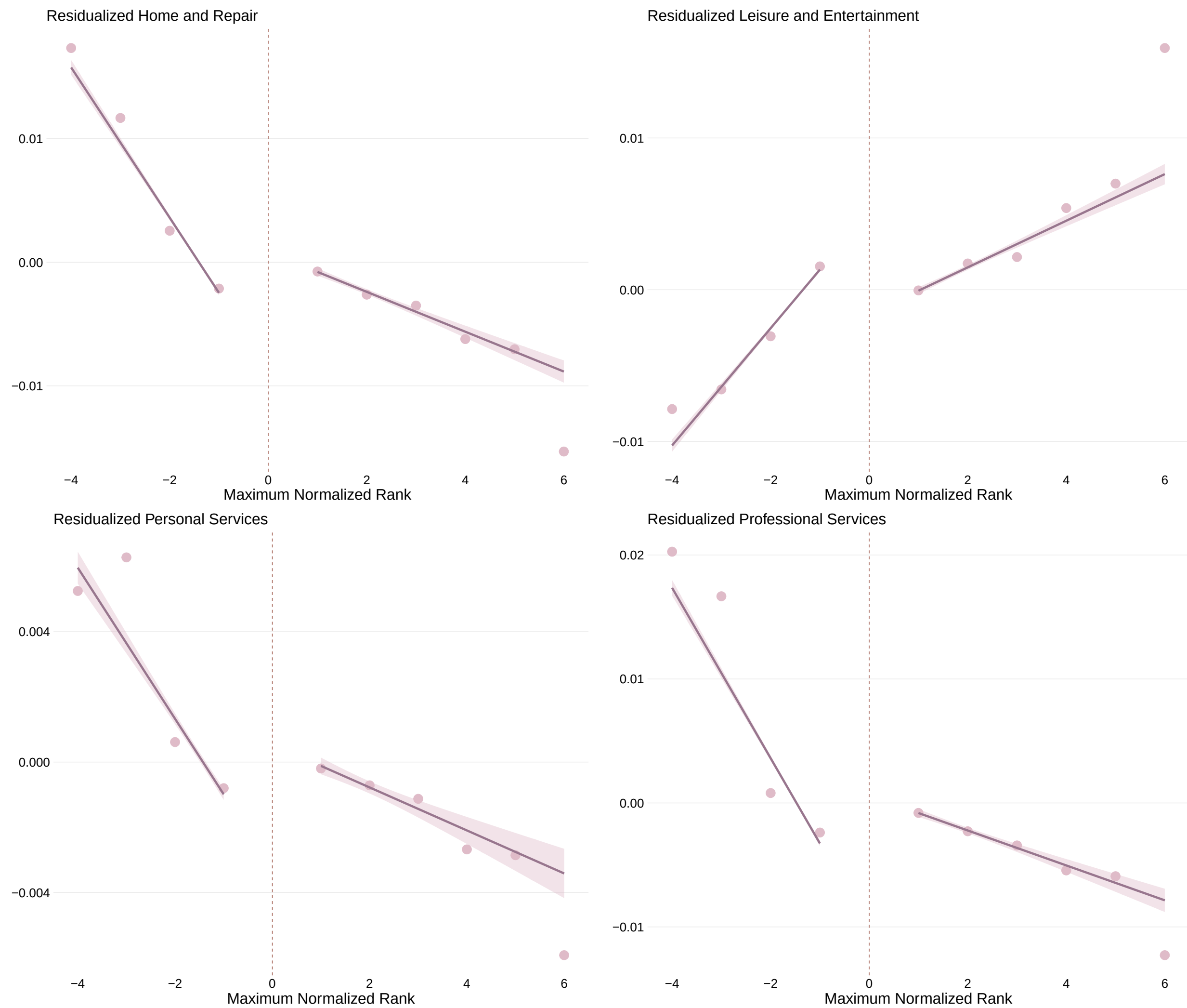
Note: This figure shows the number of days on the Platform (top left), probability that a firm is classified as informal (top right), a firm's owner is a South African citizen (bottom left), and a firm is classified as a service firm (bottom right). Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.10. Continuity



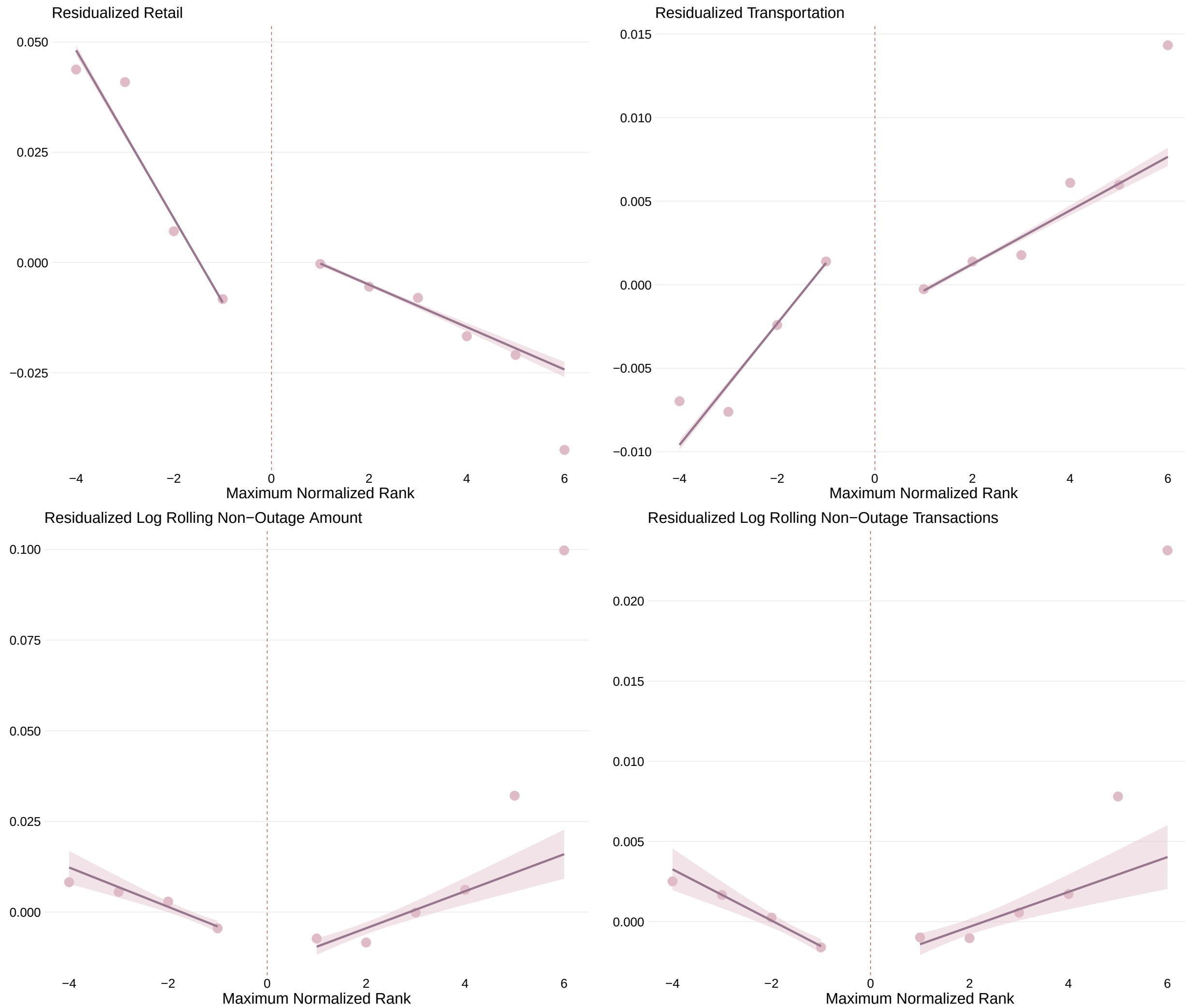
Note: This figure shows the probability that a firm is classified as above-median in daily revenue across all firms (top left) and across firms within its industry and load shedding block (top right), a firm is in the food, drink, and hospitality industry (bottom left) and in healthcare, beauty, and fitness industry (bottom right). Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.11. Continuity



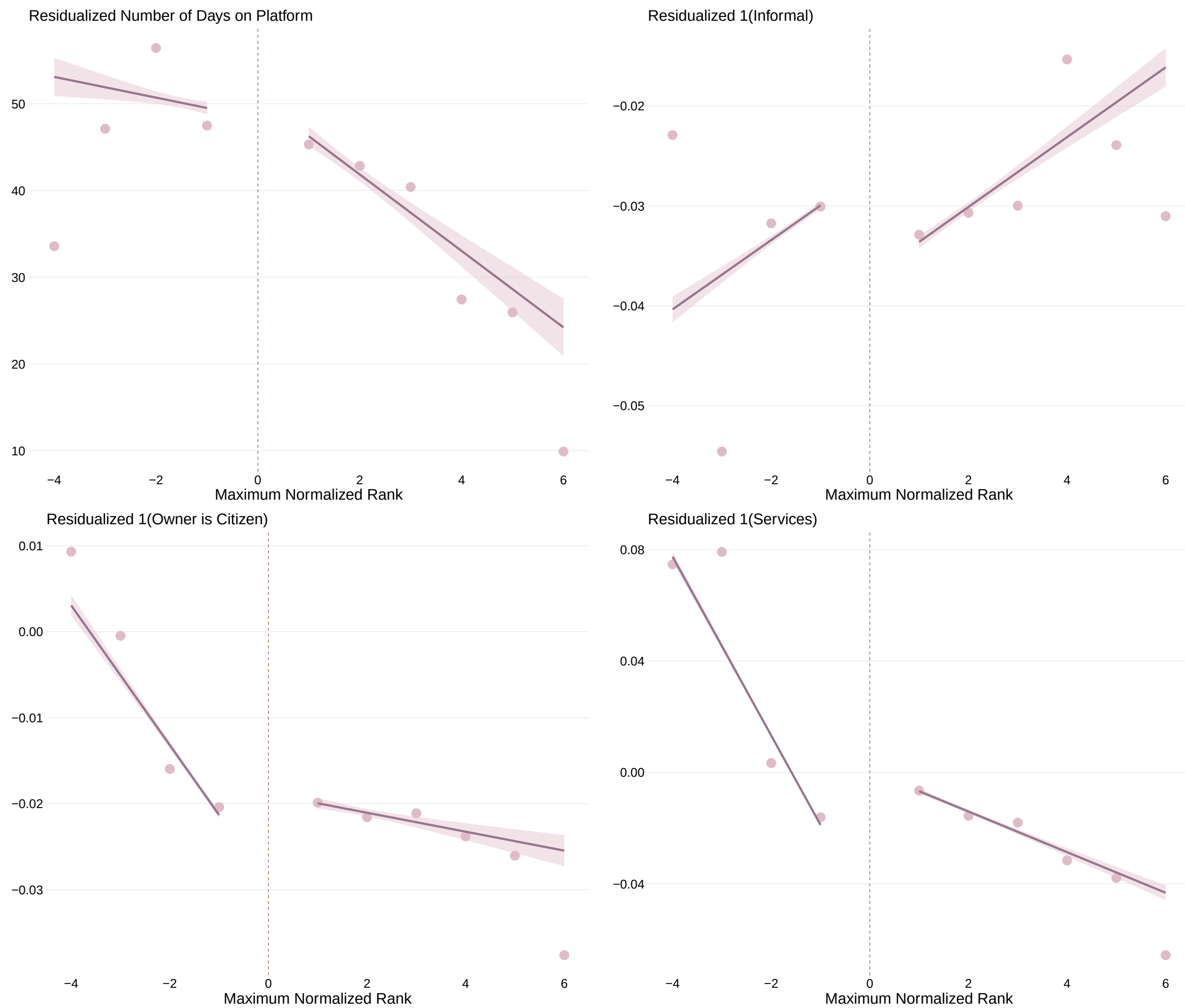
Note: This figure shows the probability that a firm is in the home and repair (top left), leisure and entertainment (top right), personal services (bottom left), and profesional services industries (bottom right). Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.12. Continuity



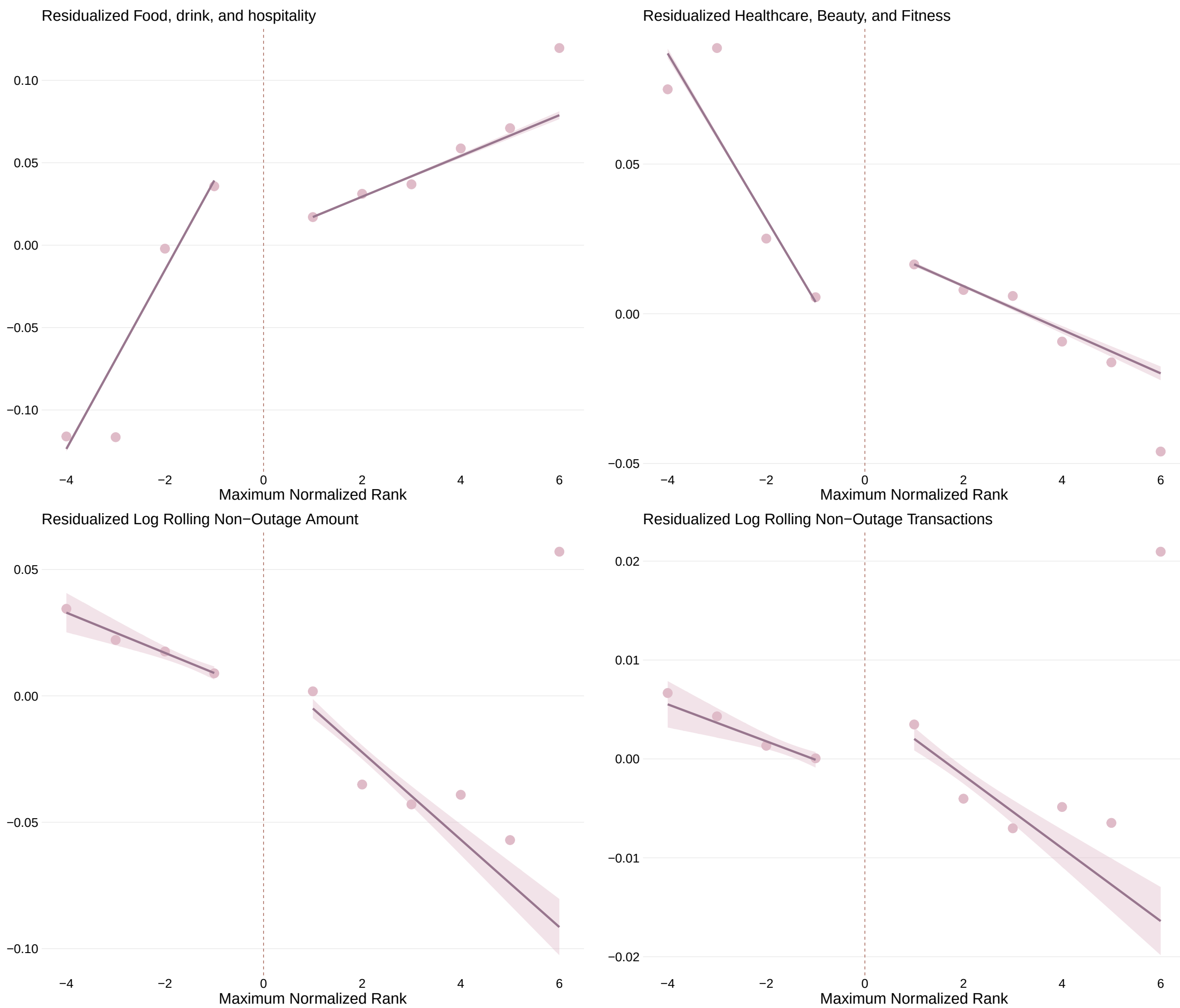
Note: This figure shows the probability that a firm is in the retail (top left) and transportation industries (top right), and the logged rolling average of daily sales (bottom left) and transactions (bottom right) over the previous three non-outage days prior to the day of interest. Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.13. Continuity



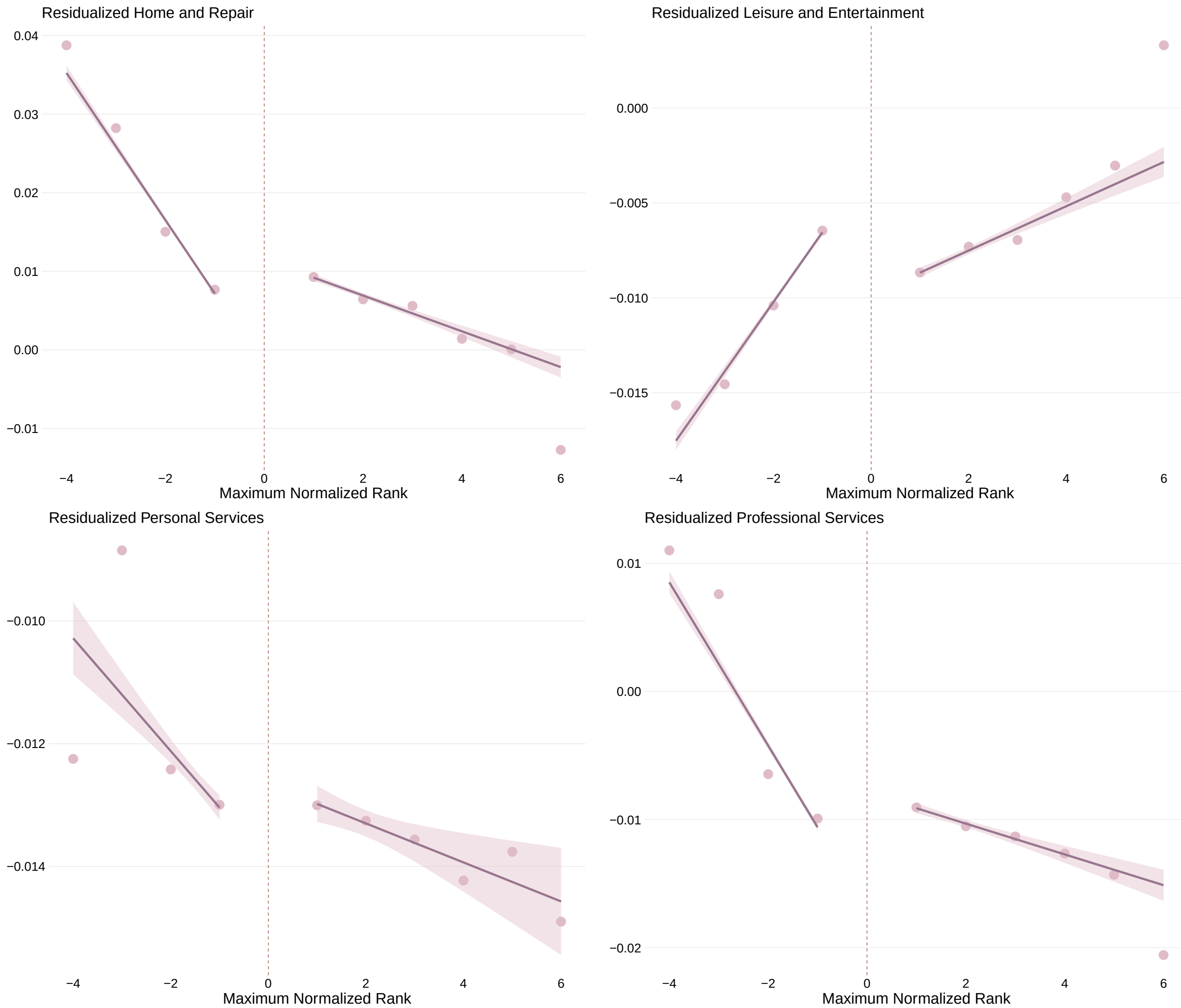
Note: This figure shows the number of days on the Platform (top left), probability that a firm is classified as informal (top right), a firm's owner is a South African citizen (bottom left), and a firm is classified as a service firm (bottom right) for above-median firms. Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.14. Continuity



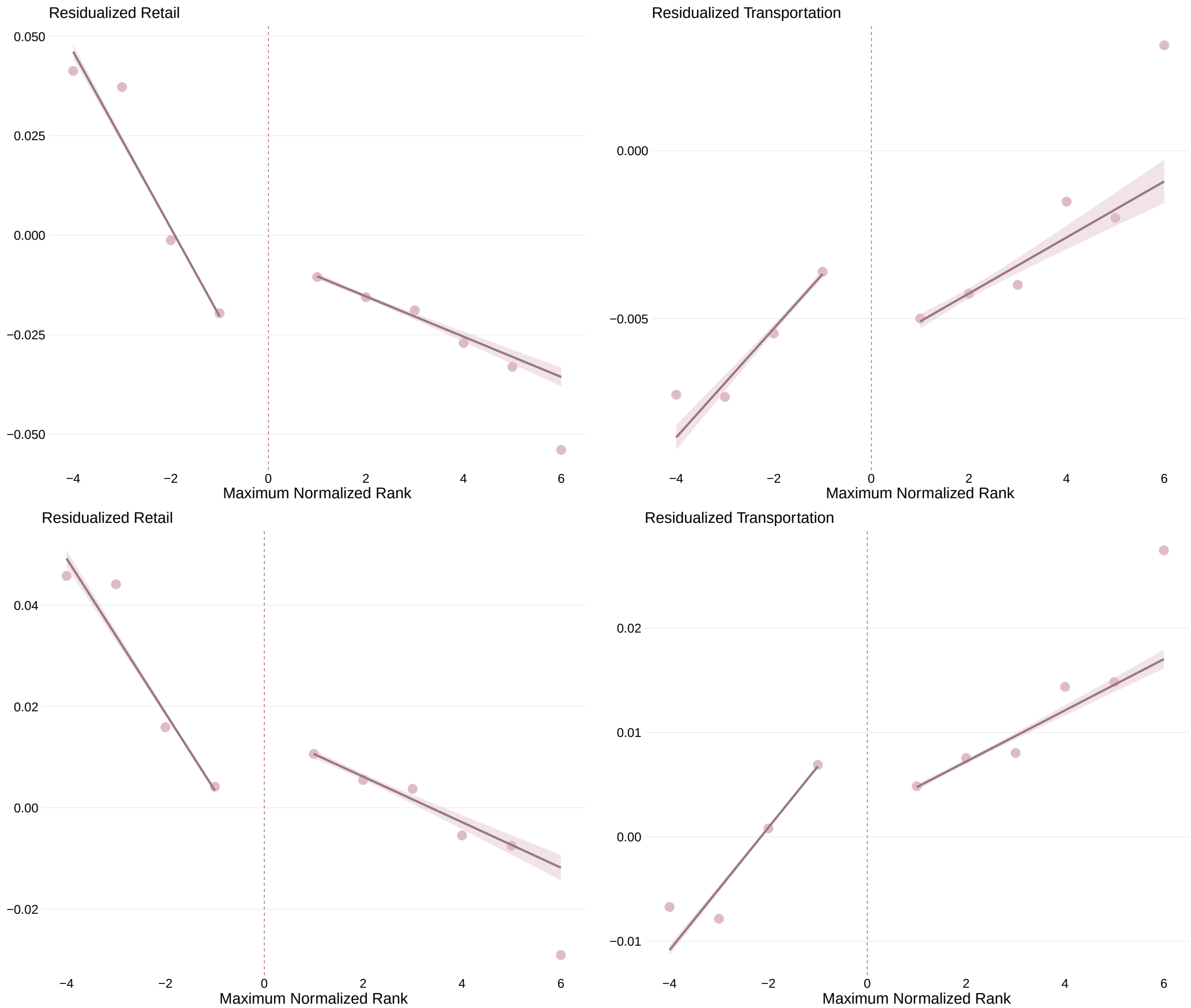
Note: This figure shows the probability that a firm is in the food, drink, and hospitality industry (top left) and in healthcare, beauty, and fitness industry (top right), and the logged rolling average of daily sales (bottom left) and transactions (bottom right) over the previous three non-outage days prior to the day of interest for above-median firms. Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.15. Continuity



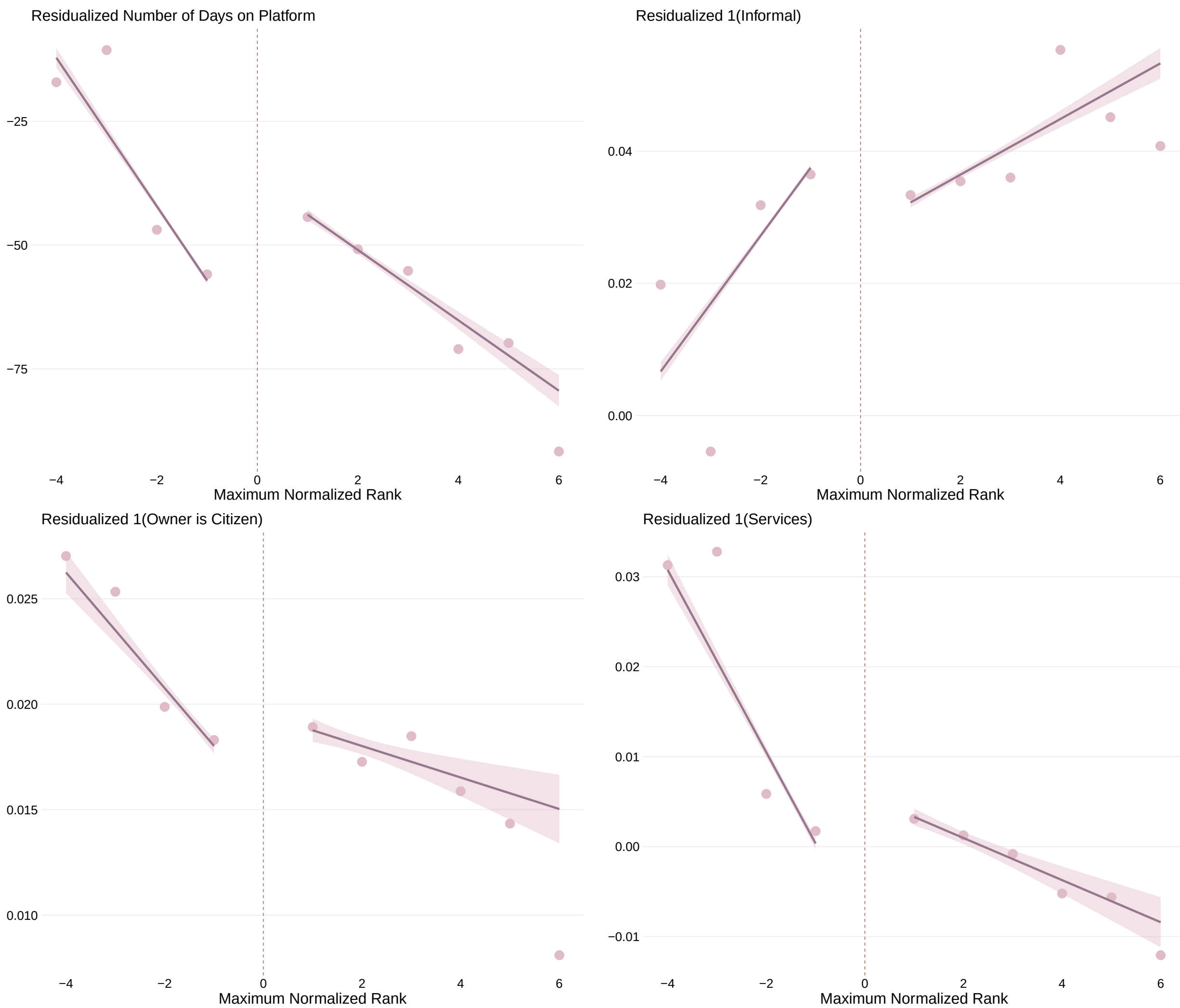
Note: This figure shows the probability that a firm is in the home and repair (top left), leisure and entertainment (top right), personal services (bottom left), and profesional services industries (bottom right). Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.16. Continuity



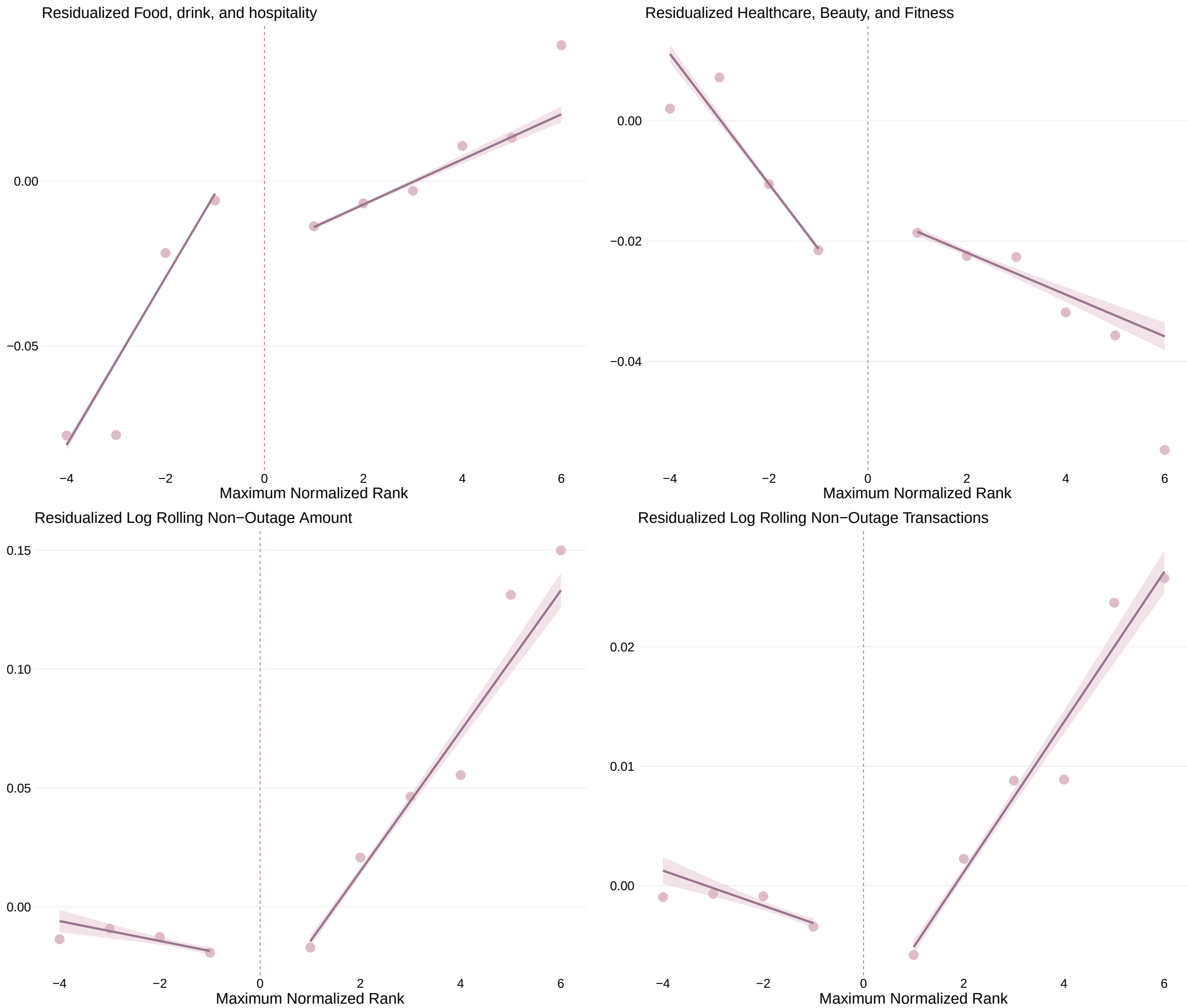
Note: This figure shows the probability that a firm is in the retail (top left) and transportation industries (top right) for above median firms; and retail (bottom left) and transportation industries (bottom right) for below median firms. Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.17. Continuity



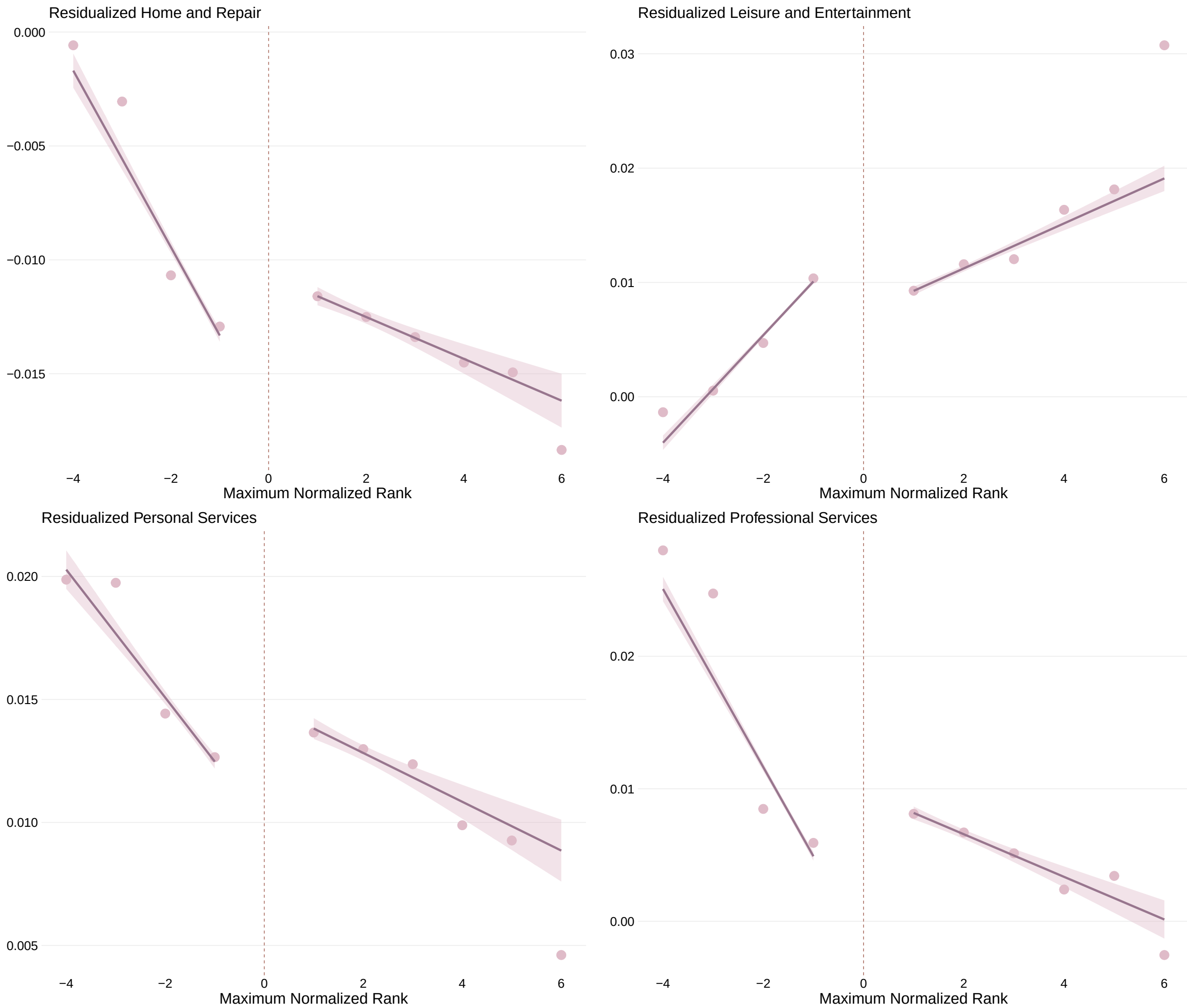
Note: This figure shows the number of days on the Platform (top left), probability that a firm is classified as informal (top right), a firm's owner is a South African citizen (bottom left), and a firm is classified as a service firm (bottom right) for below-median firms. Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.18. Continuity



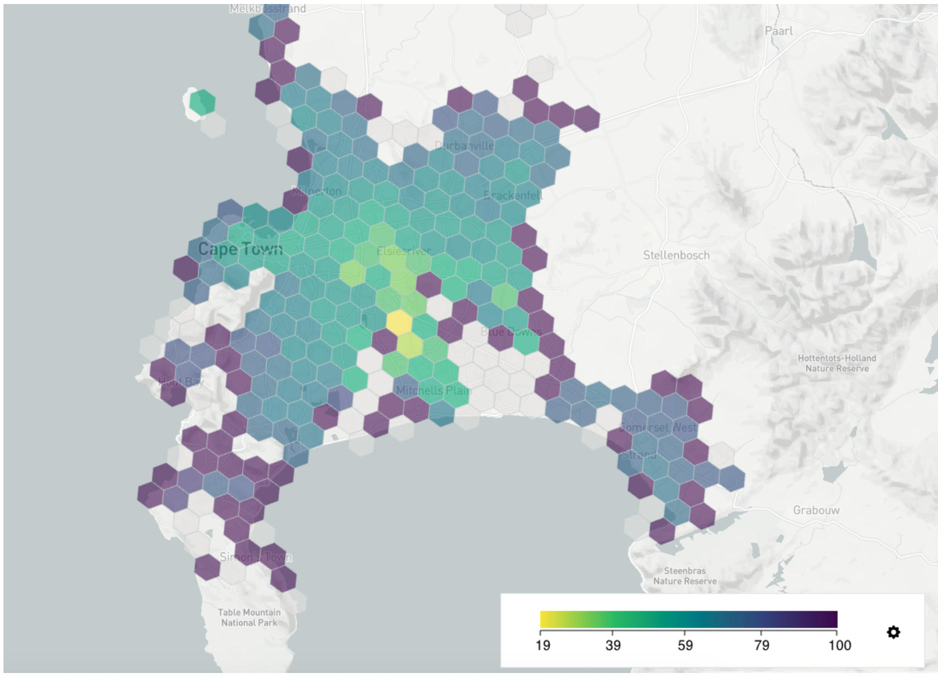
Note: This figure shows the probability that a firm is in the food, drink, and hospitality industry (top left) and in healthcare, beauty, and fitness industry (top right), and the logged rolling average of daily sales (bottom left) and transactions (bottom right) over the previous three non-outage days prior to the day of interest for below-median firms. Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.19. Continuity

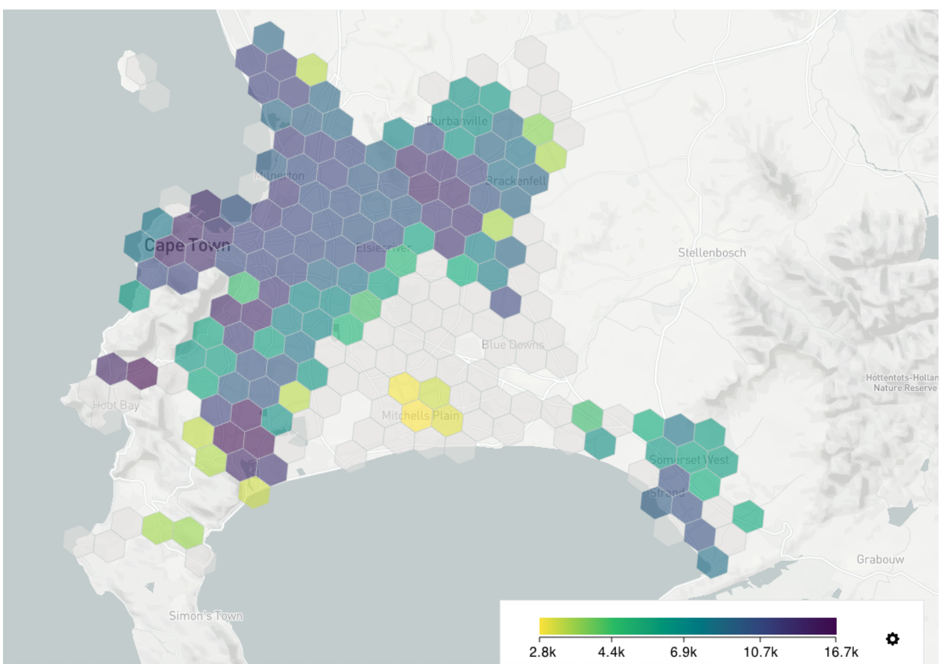


Note: This figure shows the probability that a firm is in the home and repair (top left), leisure and entertainment (top right), personal services (bottom left), and profesional services industries (bottom right) for below-median firms. Across all panels, we plot the day fixed effect residualized outcome. In all cases, the horizontal axis shows the firm's daily maximum normalized rank. A rank of 1 indicates that the firm is located in the last area on the schedule to receive an outage while a rank of -1 indicates that the firm is located in the area would be the next on the schedule to receive an outage should the severity of rationing worsen. The points represent the average residualized outcome by rank. The line plots the linear fit of the residualized outcome on rank separately on either side of the cutoff. The shaded area represent the 95% confidence interval.

FIGURE C.20. 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.

Table C.1. SME Survey Summary Statistics

Variable	Mean	Mean (Above-med.)	Mean (Below-med.)	p-value
Has access to external funding	0.186	0.219	0.105	0.010
Has backup generation	0.797	0.842	0.686	0.006
Has a card machine	0.668	0.740	0.488	0.000
Mostly electronic payments	0.518	0.558	0.419	0.029
Mostly physical payments	0.435	0.395	0.535	0.030
Can anticipate loadshedding events	0.694	0.698	0.686	0.845
Experienced loss of sales due to loadshedding	0.372	0.367	0.384	0.794
Experienced disruptions due to loadshedding	0.306	0.326	0.256	0.224
Customers assume business is closed during loadshedding	0.309	0.340	0.233	0.058
Customers use cash instead of card during loadshedding	0.332	0.344	0.302	0.482
Median Monthly Revenue Range	R30,000-R75,000			
Median Employment Range (Full-time Equivalents)	11-20			
N	301	215	86	

Note: This table reports summary statistics for a survey of Cape Town metropolitan area SME owners conducted in October 2024. All variables are binary except for revenue and employment. Reported *p*-values are for tests of difference in means for firms with reported revenue below the Platform sample median monthly revenue (R10,000 per month). Questions about loadshedding experiences are stated beliefs from firm-owners.

TABLE C.2. Correlation between covariates and outage

	$\mathbb{1}$(Outage)	
	(1)	(2)
Number of Days on Platform	4.91×10^{-7}*	4.46×10^{-7}
	(2.8×10^{-7})	(3.24×10^{-7})
$\mathbb{1}$(Informal)	0.0002	7.1×10^{-5}
	(0.0024)	(0.0025)
$\mathbb{1}$(Owner is Citizen)	-0.0004	-0.0004
	(0.0010)	(0.0006)
$\mathbb{1}$(Services)	-0.0004	-1.66×10^{-5}
	(0.0006)	(0.0004)
Log Rolling Non-Outage Amount	-3.78×10^{-5}	-2.51×10^{-5}
	(6.05×10^{-5})	(6.81×10^{-5})
Property Value in Suburb (Thousand Rand)	7.68×10^{-7}	6.75×10^{-7}
	(1.05×10^{-6})	(1.09×10^{-6})
Log Rolling Non-Outage Transactions	0.0002	0.0001
	(0.0002)	(0.0002)
Food, drink, and hospitality	-5.72×10^{-5}	1.87×10^{-5}
	(0.0003)	(0.0003)
Healthcare, Beauty, and Fitness	0.0001	-0.0003
	(0.0007)	(0.0003)
Home and Repair	0.0003	-0.0002
	(0.0006)	(0.0004)
Leisure and Entertainment	0.0008	0.0002
	(0.0010)	(0.0007)
Personal Services	-0.0001	-0.0004
	(0.0006)	(0.0004)
Professional Services	0.0002	-0.0002
	(0.0006)	(0.0003)
Transportation	0.0002	-0.0003
	(0.0010)	(0.0006)
Age of Owner		-7.35×10^{-6}
		(1.57×10^{-5})
$\mathbb{1}$(Female-Owned)		-0.0001
		(0.0004)
$\mathbb{1}$(Uses WiFi)		0.0003
		(0.0003)
Travel and Tourism		0.0004
		(0.0007)
Date FE	Yes	Yes
Wald (joint nullity), p-value	0.99972	9.51×10^{-46}
R^2	0.79533	0.79282
Observations	10,682,316	9,182,520

Note: This table presents estimates from regressing various covariates on the probability of a firm experiencing an outage and the resulting p-value on the Wald test. 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.3. Summary Statistics on Card Sample

	N	Mean	SD	Min	P25	P50	P75	Max
Daily Number of Transacted Firms	81051	1.11	0.16	1	1	1.07	1.16	5
Daily Number of Transacted Regular Firms	81051	0.33	0.3	0	0.07	0.25	0.5	2.45
Daily Number of Transacted New Firms	81051	0.78	0.33	0	0.57	0.85	1	5
Number of Identified Regular Firms	81051	4.26	2.03	3	3	4	5	37
Average Daily Transactions	81051	1.11	0.16	1	1	1.07	1.16	5
Average Daily Spending	81051	348.16	460.66	2	156.26	250.54	405.24	27072.5
Average Regular Firm Outage Exposure	81051	0.33	0.23	0	0.15	0.35	0.5	1
Average Daily Spending Share at High-Performing Firms	81051	0.94	0.12	0	0.93	0.99	1	1
Average Daily Spending Share at Low-Performing Firms	81051	0.06	0.12	0	0	0.01	0.07	1
Average Daily Spending Share at New Firms	81051	0.69	0.28	0	0.5	0.76	0.93	1
Average Daily Spending Share at High-Performing New Firms	81051	0.64	0.28	0	0.47	0.7	0.87	1
Average Daily Spending Share at Low-Performing New Firms	81051	0.05	0.1	0	0	0.01	0.06	1

Note: This table shows the summary statistics of the 81,051 cards for whom we can identify more than 2 regular merchants during the year 2021–2022, conditional on any transactions. The table summarizes the average daily behavior of each card in the sample.

TABLE C.4. Effect of outages on firm revenue and transactions: IV Estimates

	Log(Daily Sales)				Log(Daily Transactions)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Outage)	-0.0261*	-0.1176***	-0.1225***	-0.1290***	-0.0017	-0.0375***	-0.0383***	-0.0414***
	(0.0145)	(0.0140)	(0.0137)	(0.0139)	(0.0034)	(0.0034)	(0.0036)	(0.0038)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)		0.1698***		0.0799**		0.0667***		0.0352***
		(0.0220)		(0.0352)		(0.0076)		(0.0096)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)			0.1750***	0.1095***			0.0673***	0.0384***
			(0.0200)	(0.0327)			(0.0080)	(0.0109)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.5193	2.5193	2.5193	2.5193	0.64854	0.64854	0.64854	0.64854
F-test (1st stage), $\mathbb{1}$(Outage)	113,154.6	56,641.9	56,658.6	37,792.9	113,154.6	56,641.9	56,658.6	37,792.9
F-test (1st stage), $\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)		403,746.9		269,184.1		403,746.9		269,184.1
F-test (1st stage), $\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)			403,117.0	268,773.5			403,117.0	268,773.5
Observations	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423

Note: This table presents IV estimates from an augmented Equation 8 on the effect of exposure to an electricity outage on log daily sales (columns 1–4) and log daily transactions (columns 5–8). The instrumental variable that we use is the firm's daily maximum rank interacted with the stage of outage. All logged variables are defined as $\log(1+x)$. The coefficient on $\mathbb{1}$(Outage) represents the effect of an exposure to an electricity outage in column 1 of panels A and B. In columns 2–5, 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. Effect of outages on firm performance: Outage days only

Panel A: Log(Daily Sales)						
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	0.0792***	0.0074	-0.0062	-0.0098	-0.0157**	-0.0138*
	(0.0158)	(0.0143)	(0.0069)	(0.0078)	(0.0071)	(0.0077)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median)				0.0072		-0.0230
				(0.0170)		(0.0182)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block)					0.0186	0.0372***
					(0.0151)	(0.0124)
Date FE	No	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.5074	2.5074	2.5074	2.5074	2.5074	2.5074
R^2	9.05×10^{-5}	0.02448	0.45066	0.45066	0.45066	0.45066
Observations	8,332,174	8,332,174	8,332,174	8,332,095	8,332,095	8,332,095
Panel B: Log(Daily Transactions)						
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	0.0322***	-0.0006	-0.0019	-0.0132***	-0.0146***	-0.0152***
	(0.0063)	(0.0081)	(0.0015)	(0.0026)	(0.0026)	(0.0028)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median)				0.0227***		0.0077
				(0.0058)		(0.0050)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block)					0.0247***	0.0185***
					(0.0056)	(0.0043)
Date FE	No	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.64813	0.64813	0.64813	0.64812	0.64812	0.64812
R^2	0.00016	0.01492	0.57488	0.57490	0.57491	0.57491
Observations	8,332,174	8,332,174	8,332,174	8,332,095	8,332,095	8,332,095

Note: This table presents estimates from Equations 1 and 2 on the average treatment effect of exposure to an electricity outage on log daily sales (panel A) and log daily transactions (panel B), restricting to only days with an electricity outage. All logged variables are defined as $\log(1+x)$. 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 × 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.6. Alternative outage definitions

	Log(Daily Sales)				Log(Daily Transactions)	
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Outages	-2.28×10^{-5}	-0.0306***	-0.0311***	-0.0339***	6.7×10^{-5}	-0.0121***
	(0.0036)	(0.0049)	(0.0046)	(0.0049)	(0.0009)	(0.0013)
Number of Outages $\times$ $\mathbb{1}$(Above Median)		0.0594***		0.0303***		0.0237***
		(0.0071)		(0.0097)		(0.0025)
Number of Outages $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)			0.0604***	0.0355***		
			(0.0069)	(0.0096)		
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.5193	2.5193	2.5193	2.5193	0.64854	0.64854
R^2	0.42918	0.42929	0.42929	0.42930	0.55561	0.55579
Observations	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423

	Log(Daily Sales)				Log(Daily Transactions)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outage Duration	-0.0029	-0.0511***	-0.0520***	-0.0563***	-0.0008	-0.0198***	-0.0199***	-0.0217***
	(0.0055)	(0.0074)	(0.0070)	(0.0074)	(0.0013)	(0.0020)	(0.0021)	(0.0022)
Outage Duration $\times$ $\mathbb{1}$(Above Median)		0.0939***		0.0477***		0.0370***		0.0203***
		(0.0110)		(0.0149)		(0.0039)		(0.0041)
Outage Duration $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)			0.0954***	0.0563***			0.0370***	0.0204***
			(0.0108)	(0.0150)			(0.0041)	(0.0049)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.5193	2.5193	2.5193	2.5193	0.64854	0.64854	0.64854	0.64854
R^2	0.42918	0.42930	0.42930	0.42932	0.55561	0.55581	0.55581	0.55583
Observations	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423	11,995,423

Note: This table presents estimates from Equations 1 and 2 on the average treatment effect of exposure to an electricity outage on log daily sales (columns 1–4) and log daily transactions (columns 5–8) using alternative outage definitions. Panel A considers the number of outages in a given day and panel B considers log total outage duration. All logged variables are defined as $\log(1+x)$. The coefficient on $\mathbb{1}$(Outage) represents the effect of an exposure to an electricity outage in columns 1 and 5 of panels A and B. In columns 2–4 and 6–8, 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.7. Effect of outages on firm performance: Cash-reporting firms

Panel A: Log(Daily Sales)

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Outage)	0.0341	0.0066	-0.1022***	-0.1009***	-0.1115***
	(0.0233)	(0.0127)	(0.0210)	(0.0201)	(0.0215)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)			0.1918***		0.1203**
			(0.0298)		(0.0477)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)				0.1862***	0.0865*
				(0.0275)	(0.0443)
Date FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.8736	2.8736	2.8735	2.8735	2.8735
R^2	0.02838	0.44582	0.44597	0.44596	0.44598
Observations	5,233,221	5,233,221	5,233,175	5,233,175	5,233,175

Panel B: Log(Cash Daily Sales)

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Outage)	0.0215	-0.0007	0.0079	0.0077	0.0086
	(0.0159)	(0.0026)	(0.0076)	(0.0067)	(0.0073)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)			-0.0151		-0.0098
			(0.0114)		(0.0240)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)				-0.0146	-0.0065
				(0.0103)	(0.0224)
Date FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.55610	0.55610	0.55611	0.55611	0.55611
R^2	0.00453	0.49411	0.49411	0.49411	0.49411
Observations	5,233,221	5,233,221	5,233,175	5,233,175	5,233,175

Note: This table presents estimates from Equations 1 and 2 on the average treatment effect of exposure to an electricity outage on log daily sales (panel A) and log daily cash sales (panel B), restricting to firms who report any cash transactions. All logged variables are defined as log(1+x). 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 3–5, 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.