Do Reward and Reprimand Policies Work in Reducing Electricity Distribution Losses?

PRELIMINARY — NOT FOR CITATION

Ayesha Ali* Khusrav Gaibulloev† Javed Younas‡

December 23, 2018

Abstract

Electricity distribution losses due to theft and non-repayment of bills are costly burden for the power sector, leading to significant financial losses and poor service delivery. Using monthly electricity feeder level data from July 2012 to December 2015, we study the effect of a unique reward and reprimand policy in curbing losses, implemented by the utility serving the city of Karachi in Pakistan. Under this policy feeders were assigned to very high, high, medium, or low outages, based on average losses in the past twelve months using fixed thresholds to separate the categories. To incentivize loss reduction, the distribution company periodically updated the outage category at the feeder level. We use an instrumental variable and fuzzy regression discontinuity design in which we instrument for actual outages by outages predicted by the policy, to study the effect on future losses and the within feeder change in losses. Our IV estimates imply that an additional hour of outages reduces average monthly losses and within feeder change in losses by 6.6%. The RD estimates of the effect on average monthly losses show heterogeneity across different thresholds. The effect on within feeder change in losses ranges between 3.1% to 4.8%.

Keywords: Electricity, Outages, Distribution Losses, Pakistan

JEL Codes: D04, O12, Q48

*Department of Economics, Lahore University of Management Sciences. ayeshaali@lums.edu.pk
†Department of Economics, American University of Sharjah. kgaibulloev@aus.edu
‡Department of Economics, American University of Sharjah. jyounas@aus.edu

1 Introduction

Extant studies show that electrification is a key to economic development (Andersen and Dalgaard 2013; Atems and Hotaling 2018; Dinkelman 2011; Lipscomb, Mobarak, and Barham 2013). Yet, access to reliable electricity in developing countries remains a major challenge. A prime obstacle to improvement in the quality of energy markets is electricity losses – particularly non-technical losses[1] – because the losses reduce the profitability of utility companies and raise the cost of electricity to paying consumers. Furthermore, Smith (2004), using data for 102 countries, documents that electricity theft problem is worsening in many regions of the world. However, little research has been done on effective methods and strategies for reducing electricity losses (Greenstone 2014). We contribute to the literature by utilizing the proprietary feeder-level data from Karachi Electric (KE) – the sole distributor of electricity in Karachi, Pakistan – to evaluate the effect of a unique reward and reprimand policy on curbing the electricity losses. We are not aware of any study that examined such a policy.

Literature identifies a number of reasons for non-technical electricity losses, such as losses related to theft, inability to collect funds, and inefficient metering practices. Governments in democracies use their power over economic policies to improve their electoral prospects, which results in so called political business cycles. Developing countries, due to limited fiscal capacity and budget shortfall, possess constrained ability to have a meaningful impact on economic outcomes. Therefore, these countries may use an alternative channel strategic allocation of public services that are essential inputs to economic activity to influence economic conditions and attract voters. Baskaran, Min, and Uppal (2015), drawing on state-level data from assembly constituencies in India, show that political leaders manipulate allocation of electricity to influence electoral outcomes. This may lead to inefficient use of electricity and losses. Min and Golden (2014) find a correlation between the changes in electricity losses and the timing of state assembly elections in India. In particular, electricity losses are found to be higher immediately before elections. In addition, high losses raise electricity costs and electricity tariffs, which may further influence marginal consumers incentive to avoid payments, thereby increasing losses. Studies show a positive correlation between electricity theft and the price of electricity (Jamil and Ahmad 2014; Mimmi and Ecer 2010).[2] Other factors associated with electricity losses include the quality of government institutions (particularly, the level of corruption, government effectiveness, political stability), the ability of

[1]Non-technical losses are associated with theft, unbilled accounts, and metering errors among others.

[2]Further, non-paying consumers have less incentive to conserve electricity, which results in inefficiency. The end result is capacity shortfall and load shedding (e.g., Jamil 2013). Load shedding forces consumers to substitute for inefficient alternatives (e.g., small generators). Mimmi and Ecer (2010) examine the determinants of illegal use of electricity at household level and find that low income, running home-based (informal) business, and inefficient/incorrect use of home electric appliances increase the likelihood of illegal behavior.

utility companies to efficiently collect bills, per capita income, education, and poverty (Gaur and Gupta 2016; Jamil and Ahmad 2014; Smith 2004).

Various solutions at the government and firm levels are proposed, but rigorous research on the effect of such policies is limited.[3] Jack and Smith (2015) are the closest to our work. They examine the effect of pre-paid metering on electricity spending based on customer-level panel data from the City of Cape Town, South Africa. Similar to pre-paid cell phone, users purchase the amount of electricity they wish in advance and use their credit amount to consume electricity. The electricity power shuts off when the balance reaches zero until the credit is recharged. Their results suggest that pre-paid metering may help with non-payment issues, particularly, among poor people by providing flexibility to those who face liquidity constraints.

The purpose of our study is to evaluate the effect of a unique electricity loss reduction policy in the city of Karachi, Pakistan. Karachi Electric, which is the only distributor of electricity in Karachi, allocates power outages across feeders based on the past electricity distribution losses measured at the feeder level. Feeders get assigned to progressively higher level of outages as past losses exceed predetermined thresholds. To account for endogeneity of outages due to non-compliance and confounding factors we predict outages using the announced policy which provides exogenous variation in actual outages. We implement a simple instrumental variable and fuzzy regression discontinuity design on monthly feeder-level panel data for 2012-2015 to estimate the impact of the number of outages on future distribution losses. Our IV results show that additional hour of outages reduces average monthly losses across feeders by 1.9 percentage points. The effect of outages on change in losses within feeders is 2 percentage points. These estimates imply a reduction in electricity distribution losses of 6.6% from the mean distribution loss levels. The RD estimates of the effect on average monthly losses show heterogeneity, as feeders near the first threshold experience a reduction in average monthly losses while feeders at higher thresholds actually experience an increase in average monthly losses. The effect on within feeder change in losses is negative and an additional hour of outages reduces within feeder losses by 0.9 to 1.5 percentage points or 3.1% to 4.8% from mean loss levels. Using our estimates we quantify the amount of electricity saved in the K-Electric system due to reduction in losses is between 2.5% to 4.3%. Overall, our findings suggest that the policy had a significant negative effect on future losses at the feeder level.

The rest of the paper is organized as follows. Section 2 describes the electricity sector and

[3] For example, a theoretical piece by Di Bella and Grigoli (2017) emphasizes the importance of government credibility in its promise to reduce electricity theft for development of electricity sector. Depuru, Wang, and Devabhaktuni, (2011) propose a technology design to detect and prevent theft but there is no empirical analysis on the effect of such technology.

distribution issues in Pakistan and Karachi, followed by the discussion of data and empirical strategy in sections 3 and 4, respectively. The results are presented in section 5 and discussed in section 6. Section 7 concludes.

2 Nature of Electricity Crisis in Pakistan

2.1 Electricity Sector in Pakistan

Pakistan has been facing a serious energy crisis due to widening gap between electricity demand and limitation in system generating capacity. Currently, the country's transmission and distribution capacity stall at 22,000 megawatts (MW), while total demand for its residential and industrial consumption stands at 25,000 MW, causing a deficit of 3,000 MW (Rehman 2018).To ration this shortfall, the electricity supply is periodically cut off in certain areas especially during peak periods, which profoundly affects the residential and industrial consumers. Major cities and rural areas have experienced power outage, called load shedding, for an average of 8-10 hours and up to 22 hours, respectively (IMF 2013; Walsh and Masood 2013). Peak demand periods also bring about a hike in electricity theft and excessive technical setbacks in the system, mainly due to frequent tripping of overloaded transformers. Outdated electricity transmission infrastructure from powerhouse to consumers grid stations, primary and secondary transmission lines, transformers and meters further exacerbates the distributional problems. All these technical problems and non-technical (theft) losses adversely affect profitability of power utility companies and, thus, the services they provide.[4]

In order to comprehend the nature and gravity of the energy problem, it is important to understand the network of electricity distribution system in Pakistan. There are nine distribution companies, namely, Islamabad Electricity Supply Company (IESCO), Lahore Electricity Supply Company (LESCO), Gujranwala Electric Power Company (GEPCO), Faisalabad Electricity Supply Company (FESCO), Multan Electric Power Company (MEPCO), Peshawar Electricity Supply Company (PESCO), Quetta Electricity Supply Company (QESCO), and Hyderabad Electricity Supply Company (HESCO) and Karachi Electric (KE). While KE is a private entity, the government of Pakistan owns the other eight energy distribution companies. These companies purchase electricity from the government owned electricity producers such as Water and Power Development Authority (WAPDA), Pakistan Electric Power Company (PEPCO) and other small Independent Power Producers (IPPs).

[4]In Pakistan, many methods of stealing electricity are observed including meter tempering, direct hooking by tapping the wire from the main power line, reverse meter counter, use of magnet to slow the rotation of meter, wire-tapping and meter screw clinging (Hussain et. al. 2016).

The distribution companies then supply electricity to their respective allocated areas.[5] The government, therefore, maintains monopoly in production, supply and policy formation in the countrys power sector.

National Electric Power Regulatory Authority (NEPRA) determines the electricity tariff per unit paid by consumers and the allowable costs of utility companies the difference of the two, called Tariff Differential Subsidy (TDS), is paid by the government to utility companies. This amount of subsidy to electricity consumers, which is based on monthly usage of electricity, is designed in such a way that the unit costs of electricity increases with each higher slab of monthly household consumption. Thus, the amount of per unit subsidy decreases as the consumption of electricity move to a higher slab. A highly concessional lifeline tariff is provided to the poor, whose electricity consumption falls at the lowest slab. However, if a large majority of the poor remains unconnected to the electric grid then such a program provides limited support to vulnerable households.[6]

A downside of an economic activity being under control of the government is that it may use economic policies in such a way that improves their electoral prospects. For example, past studies show that state governments in India have manipulated allocation of electricity around election times to influence economic conditions and attract voters (Baskaran et. al. 2015; Min and Golden 2014). Since electricity tariff rates are set keeping in view the political considerations in Pakistan, the power sector relies heavily on government subsidies to provide electricity (Jamil 2013; Jamil and Ahmad 2014). Aside from technical losses, the revenue of distribution companies also greatly depends on the extent of electricity theft in their respective areas. Jamil (2013) rightly points out that the delay of subsidy payments to the distribution companies results in cash flow failure, causing the mounting issue of circular debts in Pakistan. Until government clears these debts, the electricity distribution companies have to resort to load shedding to control expenses. According to a recent report, circular debts in Pakistans power sector have touched around 1.15 trillion rupees (Bhutta 2018), further aggravating the countrys fiscal constraints.

Electricity shortage can have serious consequences for the economy including lost industrial production and higher unemployment (Pasha et. al. 1989; Siddique et. al 2011). Thus, a viable solution requires regular expansion of cost effective power generation coupled with frequent upgradation of transmission infrastructure to ensure affordable supply of electricity.

---

[5] WAPDA controls mega dams and water projects for producing electricity using hydropower method, while PEPCO and IPPs mainly rely on thermal power process for generating electricity in the country. In addition, the country also produces a small fraction of total electricity employing nuclear power plants by Pakistan Atomic Energy Commission (PAEC).

[6] See Walker et. al. (2014) for an in-depth analysis on the welfare impact of electricity subsidies in Pakistan.

Otherwise, growing demand and high production costs will lead to higher energy prices, and consequently, greater instances of electricity theft. Tirmizi (2013) argues that the cost of providing electricity from generation stage to distribution stage increases almost by 50%. While some the cost is due to the transmission problems, power theft accounts for most of this burden.

2.2 Electricity Distribution in Karachi

Being the most populated and ethnically diverse city, Karachi occupies a unique position in Pakistan. Situated on the Arabian Sea with the two largest seaports handling 95%. of foreign trade, the city is also a financial and industrial hub of the country. It houses headquarters of the most multinational companies operating in Pakistan and contributes about 65% of countrys tax collection (Tariq 2015). Karachi Electric is the only privately owned, vertically integrated power utility company of the county; which engages in generation, transmission and distribution of electricity to all consumers industrial, commercial, agricultural and residential in Karachi. KE's distribution network serves electricity to 2.15 million consumers over an area of 6500 square kilometers. Unfortunately, electricity theft, especially in the densely populated areas, have reached to an alarmingly level in the city. This causes billions of rupees financial losses to the KE and, consequently, it has to resort to load shedding. Frustrated residents vent their anger by engaging in civil disobedience such as non-payment of utility bills, blocking roads and burning tires. In some cases, brawl between angry protesters and police results in damages to properties and lives.

Although responsible authorities announced on several occasions that the government would drastically cut power to the areas where electricity theft was rampant, no firm policy was adopted at the national level (Wasim 2018). In 2010 KE started a unique reward and reprimand policy, under which consumers were subjected to outages based on past losses incurred at the feeder level. Losses were calculated as the difference between the number of units of electricity supplied and billed at the feeder level. Under the announced policy, feeders with average monthly loss of less than 0.25 in the past year were exempted from outages. Feeders with losses between 0.25 and 0.35, received 3 hours of outages per day. Feeders with losses between between 0.35 and 0.50, received 6 hours of outages per day, and once losses cross 0.50 outages were increased to 7.5 hours per day. The outage category was updated every quarter using a rolling average of the past twelve month losses. To incentivize loss reduction, the company periodically updated this classification and also involved communities to build peer pressure to combat this societal menace of power theft. Furthermore, for priming religious and moral values of people, the company also obtained a decree from the well-known Islamic scholars condemning electricity theft (Aziz 2009).

This paper uses monthly data, which we acquired from the KE underwriting a proprietary agreement, at the electricity feeder level from July 2012 to December 2015 to study the effect of this unique policy on curbing electricity distribution losses. We use the exogenous variation in outages created by the the announced policy thresholds to study the effect of outages on future distribution losses using the policy as an instrument for actual outages in simple instrumental variable as well as a fuzzy regression discontinuity framework.

3 Data

We use monthly data from 128 feeders covering the period July 2012 to December 2015. The feeders in our sample are 11 KV feeders supplying electricity from 39 different grid stations to end users, and are representative of a total of 1156 feeders in the KE distribution system. [7] Table 1 shows the characteristics of feeders in the sample. On average there are 2538 consumers (or connections) per feeder with an average consumption per of 1034 Kwh per month. 76% of the consumers connected to the feeders are residential, 22% are commercial and the remaining are industrial consumers.

Our data records the number of units of electricity consumed or supplied into the distribution system and the number of units of electricity billed per month at the feeder level. The difference between electricity consumed and billed units is treated transmission and distribution losses, which includes technical losses, repayment delays, theft and billing irregularities. Theft occurs through illegal and unmetered connections (popularly known as kundas) or through under billing. We restrict our empirical analysis to feeders with past losses between 0.15 and 0.65 which contains 95% of all observations. Using the announced thresholds, we divide the data into the following intervals 0.15-0.25, 0.25-0.35, 0.35-0.5 and 0.5-0.65, where the first two intervals are 0.10 and the last two intervals are 0.15 units wide. We also use a smaller sample in which we restrict our empirical analysis to observations with past losses between 0.20 and 0.575, which creates symmetric intervals around the first and last outage threshold. Figure 1 shows the density of the past losses together with the policy thresholds, showing there are two peaks at the left and right hand side of the distribution. On average, 31% of electricity was lost through transmission and distribution losses. There is a cluster of observations with very high losses giving rise to a second peak near 43%.

Figure 2 shows the distribution of average hours of outages observed at the grid station level across the city of Karachi. There is a cluster of grid stations with outages below two

[7] A feeder is a transmission line that transfers electricity from a substation to a distribution transformer, which supplies electricity to the end user.

hours near the richer areas and the central business district (south-east Karachi). However, grid stations with low levels of outages (and lower losses) are geographically interspersed with grid stations with higher outages (and higher losses). Figure 2 shows how the actual number of hours of outages varied with the past annual losses of the feeder, showing substantial non-compliance with the stated policy. According to KE, some of the lower loss feeders lying adjacent to higher loss feeders may get assigned to higher outage hours due to concerns about theft into the low loss areas. However, we also observe few of the higher loss feeders getting low levels of outages. In the bottom panel, we compute the average outage hours over 1 percentage point wide bins of past losses. Consistent with the policy average outage hours are increasing with the feeder's past annual losses. We also observe a jump in the mean outage hours as losses cross the medium loss threshold. The jump is smaller close to the high and very high loss thresholds.

Using the monthly loss data we construct our outcome variables to measure the levels and the changes in future losses at the feeder level. We use the level of losses in the next month and the average of the monthly loss in the next three months. Averaging over three months reduces the noise in losses that arises due to billing and administrative irregularities unrelated to theft. To calculate the change in losses, we use the difference between losses in the next and the previous month. Similarly, to calculate the change in quarterly losses, we use the difference in the average monthly loss in the next quarter and the average monthly loss in the previous quarter. By looking at within feeder changes in losses we are able to remove any fixed unobserved feeder characteristics such as quality of infrastructure, that may be correlated with outages and future losses.

Table 2 shows the mean of the levels and changes in monthly loss and average monthly losses calculated over the next quarter, by past annual loss categories. We observe that the mean of future losses 0.29 which is 2 percentage points lower than the mean of past losses (0.31). We observe a drop of 1.8 percentage points in the average monthly losses in the next quarter relative to the previous quarter, with higher changes recorded for feeders in the high loss categories. This suggests that feeders with higher losses that faced higher outages also experienced larger drop in distribution losses.

4 Empirical Strategy

The policy assigns outages to feeders through a mechanism that is typical of a regression discontinuity (RD) design with multiple thresholds, however we observe substantial non-compliance with the policy. The number of hours of outages received by feeder (T_i) in a given month depends on the average monthly losses recorded in the past year (L_i) in such a way that the probability of being in the low, medium, high or very high outage regime should have discontinuity at various thresholds of L_i announced by K-Electric. Figure 3 shows that not every feeder receives the number of hours of outages that would be predicted by its past losses. The outage hours increase discontinuously at the first threshold that separates the low and the medium loss feeders. Outage hours increase as past losses increase but the discontinuity is less pronounced at the high and very high loss thresholds. Given that the policy was implemented imperfectly, we use a simple instrumental variable strategy as well as a fuzzy RD design to estimate the effect of outages on future distribution losses.

4.1 Instrumenting for Outages

We can use the announced policy to predict the number of hours of outages ($\hat{T}_i$) that would be received by a feeder, and use the predicted outages as an instrument for actual outages. According to the policy, at each threshold c_j, outages should increase from a lower to a higher level, resulting in a step function of L_i. Predicted outages can be thought of as assignment to treatment, while actual outages are the observed treatment status of different feeders. As long as actual outages increase with predicted outages, and predicted outages do not affect the outcome of interest except through actual outages, we can use predicted outages as an instrument for actual outages. We identify the effect of outages on future losses and change in future losses using the following first stage and second stage equations:

$$T_{it} = \alpha_0 + \alpha_1 L_{it} + \alpha_T \hat{T}_{it} + \alpha_2 X_{it} + \delta_t + \gamma_g + e_{it} \tag{1}$$

$$y_{it} = \beta_0 + \beta_1 L_{it} + \beta_T T_{it} + +\beta_2 X_{it} + \delta_t + \gamma_g + u_{it} \tag{2}$$

where X_{it} are the observed time varying feeder level characteristics, δ_t are month and year fixed effects that account for fixed unobserved seasonal and temporal variations in losses. γ_g are grid fixed effects that control for unobserved characteristics that are common to all feeders belonging to a grid station. We cluster standard errors at the feeder level. The coefficient α_T identifies the effect of predicted outages on actual outages, while the coefficient β_T is the IV estimate of the effect of outages on the outcome.

4.2 Fuzzy Regression Discontinuity (RD) Design

We also estimate the effect of outages using a pooled fuzzy RD design in which we normalize the distance of each feeder's past losses from the nearest threshold c_j. Specifically, for each c_j, we consider observations with past losses such that $c_{j-1} + k_{j-1} < L_i < c_{j+1} - k_{j+1}$, where

k_{j-1} and k_{j+1} are the mid points of the interval between c_{j-1} and c_j, and between c_j and c_{j+1}, respectively. For all observations belonging to a given threshold, we calculate the distance from the threshold ($L_{d,it}$) and use that as our running variable.

$$y_{it} = f(L_{d,it}) + \beta_p^{RD} T_{it} + \beta X_{it} + \delta_t + \gamma_g + v_{it} \quad (3)$$

where $f(L_{d,it})$ can take a flexible polynomial functional form,X_{it} are the observed time varying feeder level characteristics, δ_t are month and year fixed effects, and γ_g are grid fixed effects. As before, standard errors are clustered at the feeder level. In this specification, β_p^{RD} gives the effect of increasing outages on future distribution losses by comparing observations above and below the threshold.

This RD identification strategy is valid as long as the recorded monthly losses which are used to calculate the average loss in the past year at any given month, are not manipulated to sort above and below the announced thresholds. We check this by implementing the McRary test that tests for discontinuity in the density of the running variable (normalized past losses) near the thresholds. Appendix Figure A1 show the running variable does not show any discontinuity near the thresholds. We further check for manipulative sorting by carrying out a balance test of pre-determined feeder characteristics. For each characteristic we test if outages have a significant effect on the characteristic using our IV and RD specification. If there is manipulative sorting near the thresholds, then these pre-determined characteristics will be systematically related to outages. As Appendix Table A1 shows we do not find any evidence that these characteristics are systematically correlated with the outages.

Apart from estimating a pooled RD effect, we also allow the effect of outages to vary by threshold, using the following specification:

$$y_{it} = f(L_{d,it}) + \sum_{j=1}^{3} \beta_j^{RD} (T_{it} * n_j) + \beta X_{it} + \delta_t + \gamma_g + v_{it} \quad (4)$$

where n_j is a dummy variable that is equal to 1 if observation i belongs in the neighborhood around the threshold c_j, as defined above. In this specification, β_j^{RD}, captures the heterogeneous effect of increasing outages near threshold c_j.

5 Results

Table 3 shows the results from estimating the first stage relating the policy to actual outages. Column 1 shows that an additional hour of outages as predicted by the policy increases actual outages by 0.334 hours. We also report the reduced form effect of the policy (intent to treat effect) on future losses in columns 2 to 5. The estimates are not significant when using the monthly loss and change in monthly loss variables. When looking at the average monthly loss in the next quarter and the change in average monthly loss we find that the policy had a significant effect. Specifically, an additional hour of outages predicted by policy reduced average monthly losses recorded over the next quarter by 0.6 percentage points. Using the mean monthly loss of 0.29, this translates into a 2% reduction in future monthly losses. We also find that within feeder change in average losses is -0.7 percentage points which implies that losses in future quarter are lower as compared to losses in the previous quarter of the same feeder, which also translates into a 2% reduction in within feeder losses.

Table 4 reports the results from estimating the effect of outages on future losses using predicted outages as an IV for actual outages. We find that outages reduced future losses and the results are almost three times as large as the reduced form effect. The effect on monthly losses and within feeder change in monthly losses is not significant. However, when we average over the quarter, we find that an additional hour of outages reduced average monthly losses by 1.9 percentage points. The effect on within feeder change in losses is 2 percentage points. These effects imply that an additional hour of outages reduced future monthly losses by 6.6%.

Next we estimate the effect of outages on future losses using the pooled RD specification in which we use normalized past losses, or the distance of each observation from the nearest threshold, as the running variable. Table 5 shows the results. The pooled effect of outages on the level of future losses is positive and implies that future monthly losses increase by 3.9 to 4.3 percentage points in response to an additional hour of outages when crossing the policy thresholds. Separating the effects by threshold, we find that for feeders in the neighborhood of the first threshold dividing the low and medium loss feeders, the effect of an additional hour of outages is -1.1 to -1.5 percentage points. For feeders in the neighborhood of the second and third thresholds, separating medium, high and very high loss neighborhoods, the effect of outages on future loss levels becomes positive. When crossing the high to very high loss threshold, the effect is 2.3 to 2.7 percentage points increase in the level of losses recorded by feeders.

The reason for this positive effect at higher thresholds could just be mechanical, as outages are determined on the basis of past losses which are correlated with future losses. If future losses do not decline fast enough, then the average feeder loss above the threshold will be higher than the average feeder loss below the threshold. Another possibility is that the deterrence effect is actually lower in high loss areas. This may be the case if theft is socially more acceptable, consumers do not fear getting caught, or if it is actually harder to catch theft. Therefore, consumers in high loss areas actually engage in more theft during the non-outage hours.

However, the effect of outages on the within feeder change in monthly loss and the change in average monthly loss in the next quarter is negative. This implies that the feeders that are above the threshold experience a larger reduction in losses as compared to feeders below the threshold. The RD effects imply that losses are 0.9 to 1.4 percentage points lower due to an additional hour of outages, an effect of 3.1% to 4.8% from mean loss levels.If we separate the effects by threshold, we find that individual effects are very similar in magnitude to the pooled effect ranging from -0.9 to -1.5 percentage points.

In order to assess the robustness of the RD estimates, we repeat the pooled regression using square, cubic and quartic terms in normalized losses, and different bandwidths ranging from 0.01 to 0.05 percentage points above and below the threshold. The results are shown in Appendix Figures A.2-A.5. We find that our estimates of outages on the level of losses and within feeder change in losses are robust to changes in polynomial order and changes in bandwidth. The standard errors increase as we reduce the bandwidth but the estimates remain significant.

Overall, our results paint a picture in which the reward and reprimand policy of KE led to a reduction in future losses at the feeder level. Since the policy was implemented imperfectly, the intent to treat effect is smaller than the effect found using IV specifications. We find that an additional hour of outages predicted by the policy led to approximately 2 percentage point decrease in average monthly losses across and within feeders which is 6.6% of mean monthly losses. The RD results reveal heterogeneity in the effect of outages on future losses across feeders. We find that the pooled effect is actually positive and significant and this is driven by feeders lying in the neighbourhood of high and very high loss thresholds. However, the effect on within feeder change in losses is negative and translates into a 3.1%-4.8% reduction in future losses due to an additional hour of outages. To sum up, the RD results imply that if we look across feeders future loss levels were higher, but if we look at within feeder change in losses, we find a significant negative effect of outages on future losses, which is smaller than the IV estimates.

6 Discussion

We can use our results to quantify the savings that would arise due to reduction in feeder losses as a result of implementing this policy. Our estimates imply that an additional hour of outages reduces future average monthly losses within feeders by 3.1% to 6.6%. Using the mean consumption units in our sample of 99,1403 Kwh, we can calculate that the per month per feeder distribution losses will decline by 30,733 to 65,432 Kwh. Extending the savings to a total of 1156 feeders in the system, we can compute that KE can save a total of 426 Gwh to 908 Gwh annually. This is between 2.5 % to 4.3% of total electricity fed into the system in 2015.[8]

While our results imply that on average, the policy led to a significant reduction in within feeder losses in all areas, in order to fully quantify the costs and benefits of such a policy we need to take into account system wide effects. One such effect is the spillover of theft from high loss areas neighboring loss areas. If consumers in high loss areas facing high outages can resort to stealing electricity from low loss areas get fewer outages, the losses of low loss areas will also go up. If KE extends the high level of outages to the low loss areas, this may create perverse incentives for consumers in those areas to steal as well. To the extent this is already happening, our estimates suggest that the net effect at the feeder level is still a reduction in losses.

From the consumers perspective, the policy leads to a re-allocation of electricity across consumers based on past losses (theft) in their area. To understand the effect on consumers, we need to quantify the welfare reduction due to an additional hour of outages on those consumers who are in the higher loss areas and compare it to the welfare improvement of a reduction in additional hour of outages for those consumers who are in the lower loss areas. This would require quantifying the value that consumers in different areas place on an additional unit of electricity.

Furthermore, we need to evaluate the long term effect of implementing such a policy. If KE can improve its profitability and operational performance over a short period of time as a result of this policy, the quality of service could improve and outages could decline with time in all areas. However, it may be the case that the deterrence effect of high outages declines over time. Consumers may resort to even more stealing during non-outage hours if they do not have confidence in the ability of KE to improve service quality,or if they think other users will not be deterred from stealing.

7 Conclusion

Can a reward and reprimand policy that allocates electricity outages on the basis of past distribution losses reduce future losses by deterring theft? We ask this question using monthly feeder level data from Karachi, Pakistan, where the utility company implemented increasing levels of outages as past feeder losses crossed predetermined thresholds.

We use an instrumental variable strategy and a fuzzy regression discontinuity design

[8]According to NEPRA (2015), K-Electric purchased 16,815 Gwh of electricity for distribution in the fiscal year 2014-15.

to estimate the effect of outages on future average monthly losses across feeders and the within feeder change in losses. Our IV estimates show that an additional hour of outages predicted by the policy led to approximately 2 percentage point decrease in average monthly losses across and within feeders. This is a reduction of 6.6% in losses from mean loss levels. The RD results reveal heterogeneity in the effect of outages on future losses across different thresholds. We find that the pooled effect on average monthly loss levels is actually positive and significant and this is driven by feeders lying in the neighbourhood of high and very high loss thresholds. We conjecture that this may be due to the fact that losses do not decline fast enough for average loss levels to fall for feeders above the threshold as compared to feeders below the threshold. However, the effect on within feeder reduction in losses is larger for feeders above the threshold, and translates into a 3.1%-4.8% reduction in future losses due to an additional hour of outages.

To sum up, our results imply that the policy was successful in lowering distribution losses at the feeder level reducing average monthly losses across and within feeders by 3.1% to 6.6%. Exploring the mechanisms behind loss reduction, the system wide and long term effect of the policy remain future areas of work.

References

Andersen, T. B., Dalgaard, C. J. (2013). Power outages and economic growth in Africa. Energy Economics, 38, 19-23.

Atems, B., Hotaling, C. (2018). The effect of renewable and nonrenewable electricity generation on economic growth. Energy Policy, 112, 111-118.

Aziz, F. (2009) Pakistani clerics condemn theft of electricity. Reuters, July 2009: https://www.reuters.com/article/us-pakistan-power-decree-sb-idUSTRE56C2S920090713

Baskaran, T., Min, B., Uppal, Y. (2015). Election cycles and electricity provision: Evidence from a quasi-experiment with Indian special elections. Journal of Public Economics, 126, 64-73.

Bhutta, Z. (2018) Circular debt of Rs1.1tr passed on to new govt. The Express Tribune, August 2018: https://tribune.com.pk/story/1783395/2-circular-debt-rs1-1tr-passed-new-govt/

Depuru, S. S. S. R., Wang, L., Devabhaktuni, V. (2011). Electricity theft: Overview, issues, prevention and a smart meter based approach to control theft. Energy Policy, 39(2), 1007-1015.

Dinkelman, T. (2011). The effects of rural electrification on employment: New evidence from South Africa. American Economic Review, 101(7), 3078-3108.

Di Bella, G., Grigoli, F. (2017). Power it up: Strengthening the electricity sector to improve efficiency and support economic activity. Energy Economics, 67, 375-386.

Gaur, V., Gupta, E. (2016). The determinants of electricity theft: An empirical analysis of Indian states. Energy Policy, 93, 127-136.

Greenstone, M. (2014) Energy, Growth and Development. Oxford University LSE, UK: International Growth Centre.

Hussain, Z., Memon, S., Sha, R., Bhutto, Z. A., and Aljawarneh, M., (2016) Methods and techniques of electricity thieving in Pakistan. Journal of Power and Energy Engineering, 4: 1-10

International Monetary Fund (2013) Pakistan: Staff report for the 2013 Article IV consultation and request for an extended arrangement under the extended fund facility. https://www.imf.org/external/pubs/ft/scr/2013/cr13287.pdf

Jack, B. K., Smith, G. (2015). Pay as you go: Prepaid metering and electricity expenditures in South Africa. American Economic Review, 105(5), 237-41.

Jamil, F. (2013). On the electricity shortage, price and electricity theft nexus. Energy policy, 54, 267-272.

Jamil, F., Ahmad, E. (2014). An empirical study of electricity theft from electricity distribution companies in Pakistan. The Pakistan Development Review, 239-254.

Lipscomb, M., Mobarak, A. M., Barham, T. (2013). Development effects of electrification: Evidence from the topographic placement of hydropower plants in Brazil. American Economic Journal: Applied Economics, 5(2), 200-231.

Mimmi, L. M., Ecer, S. (2010). An econometric study of illegal electricity connections in the urban favelas of Belo Horizonte, Brazil. Energy Policy, 38(9), 5081-5097.

Min, B., Golden, M. (2014). Electoral cycles in electricity losses in India. Energy Policy, 65, 619-625.

National Electric Power Regulatory Authority (2016). The State of Industry Report. NEPRA:Islamabad.

Pasha, H.A., Ghaus, A., Malik, S. (1989) The economic cost of power outage in the industrial sector of Pakistan. Energy Economics, 11: 301-318

Rehman, M. (2018) Pakistans electricity generation has increased over time. So why do we still not have uninterrupted supply? Dawn: https://www.dawn.com/news/1430728

Siddiqui, R., Jalil, H.H., Nasir, M., Malik, W.S., Khalid, M. (2011) The cost of unserved energy: Evidence from selected industrial cities of Pakistan. PIDE Working Paper 2011:75, Islamabad. http://pide.org.pk/pdf/Working%20Paper/WorkingPaper-75.pdf

Smith, T. B. (2004). Electricity theft: a comparative analysis. Energy policy, 32(18), 2067-2076.

Tariq, W. (2015) The importance of Karachi. The Express Tribune, October

2015: https://tribune.com.pk/story/971188/the-importance-of-karachi/
Tirmizi, F. (2013) Transmission distribution: Power theft is the mother of all evil. The Express Tribune, June 2013: https://tribune.com.pk/story/557858/transmission-distribution-power-theft-is-the-mother-of-all-evil/
Walker, T., Sahin, S., Saqib, M., and Mayer, K. (2014) Reforming electricity subsidies in Pakistan: Measures to protect the poor. World Bank Policy Paper Series on Pakistan; PK 24/12. Washington, DC: World Bank Group
Walsh, D. and Masood, S. (2013) Pakistan faces struggle to keep its lights on. New York Times, May 2013: http://www.nytimes.com/2013/05/28/world/asia/pakistan-electricity-shortages-reach-crisis-stage.html?ref=todayspaper
Wasim, A. (2018) Outcry in National Assembly over Karachis power crisis. Dawn, April 2018: https://www.dawn.com/news/1401347

Figures

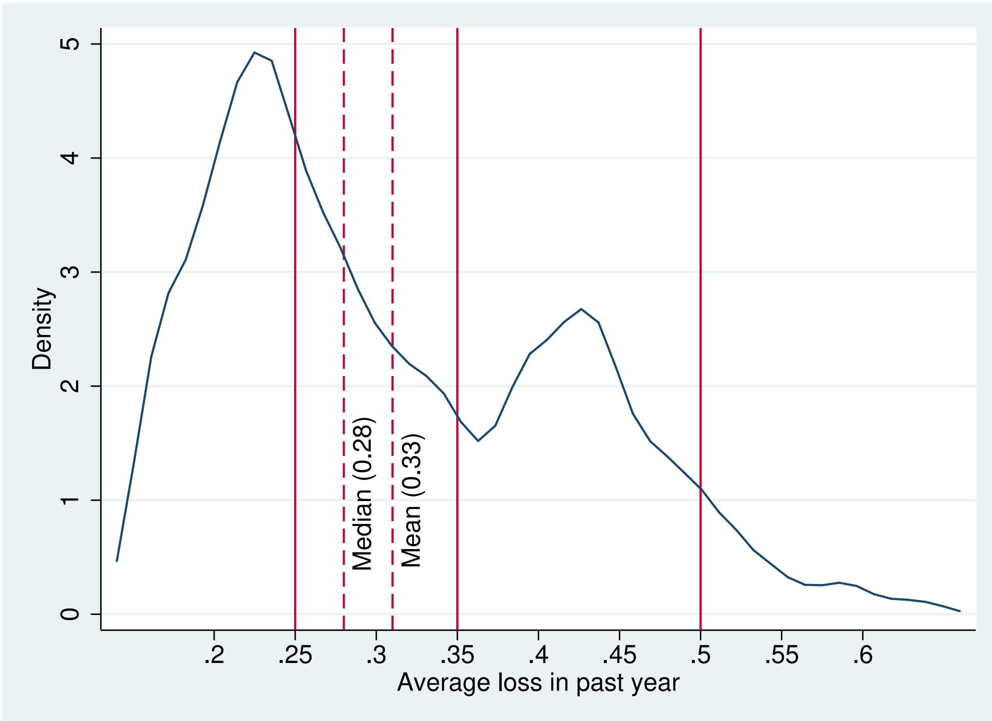


Figure 1: Density of Past Losses

Notes: The figure shows plots the smoothed density of average monthly loss in the past year for observations in the estimation sample. The solid lines mark the thresholds used to separate the Low, Medium, High and Very High Loss feeders. The dashed lines show the sample mean and median loss.

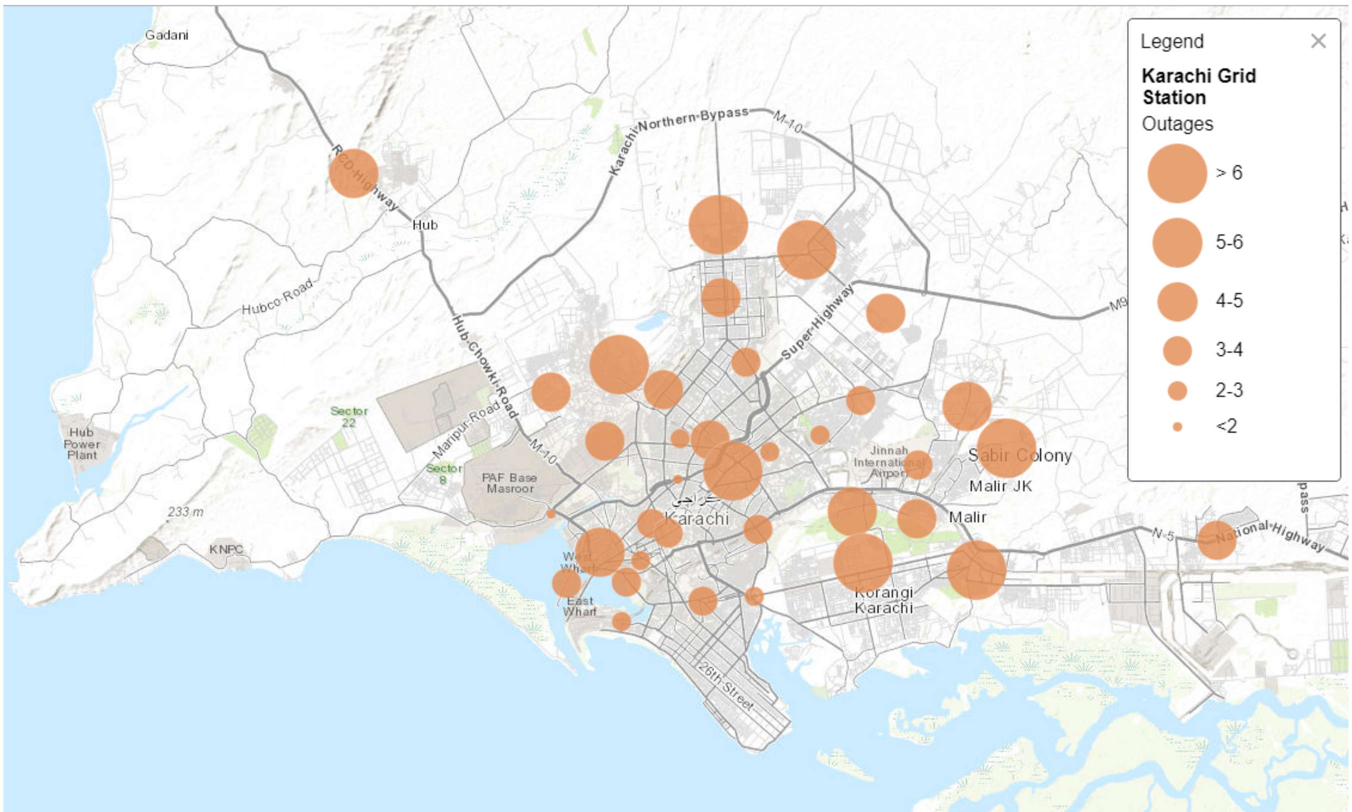
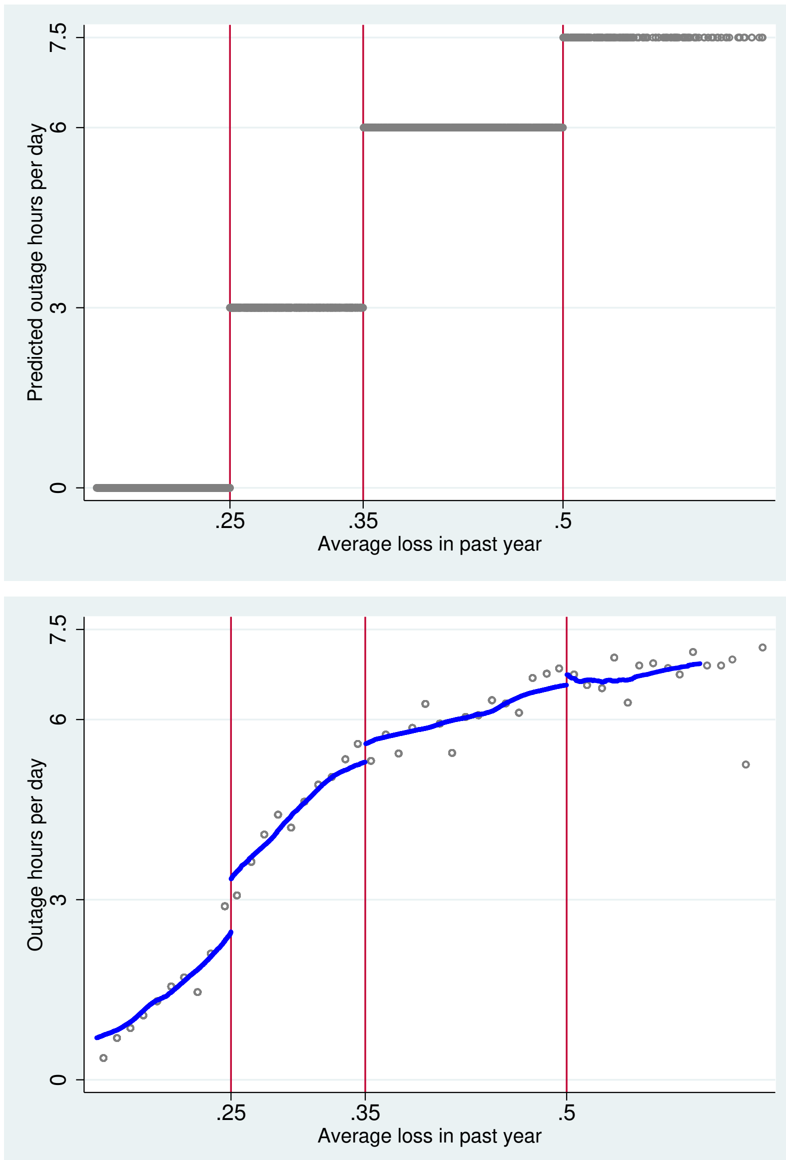


Figure 2: Distribution of Outages Across Karachi (2012-2015)

Notes: The map shows the average hours of outages recorded at feeders connected to each of the 39 grid stations in the sample from July 2012-Dec 2015.

Figure 3: Past Losses, Predicted and Actual Outages



Notes: The first panel shows the number of hours of outages per day as predicted by the policy. The second panel shows the mean of actual outages in 0.01 wide bins of past losses as well as the smoothed mean of actual outages.

Tables

Table 1: Summary Statistics - Feeder Characteristics

	Main Sample	RD Sample
Number of consumers	2,538	2,558
	(1,651)	(1,699)
Consumption units (Kwh)	99,1403	98,7233
	(452,095)	(444,463)
Consumption per consumer	1,034	907
	(4,530)	(3,927)
Average loss in past year	0.311	0.330
	(0.109)	(0.0958)
Fraction residential	0.768	0.775
	(0.272)	(0.262)
Fraction commercial	0.224	0.216
	(0.269)	(0.256)
Fraction industrial	0.008	0.009
	(0.032)	(0.034)
Number of grid stations	39	39
Number of feeders	128	124
Observations	3646	3055

Notes: Mean of the variable with standard deviation reported below it.

Table 2: Summary Statistics - Outages and Future Losses

Loss Category	Outages	Predicted outages	Loss in next month	Change in monthly loss	Average loss in next quarter	Change in quarterly loss
Low	1.539	0	0.205	-0.001	0.206	0.001
	(2.015)		(0.109)	(0.128)	(0.086)	(0.109)
Medium	4.338	3	0.262	-0.018	0.257	-0.024
	(2.180)		(0.127)	(0.143)	(0.102)	(0.128)
High	6.05	6	0.396	-0.018	0.385	-0.029
	(1.649)		(0.138)	(0.154)	(0.118)	(0.133)
Very High	6.698	7.5	0.498	-0.040	0.483	-0.053
	(1.198)		(0.151)	(0.160)	(0.127)	(0.135)
Total	3.881	2.958	0.294	-0.013	0.289	-0.018
	(2.772)	(2.684)	(0.157)	(0.143)	(0.136)	(0.124)
Observations	3646	3646	3361	3243	3304	3293

Notes: Mean of the variable with standard deviation reported below it. Low loss, medium loss, high loss and very high loss feeders have average losses between 0.15-0.25, 0.25-0.35, 0.35-0.50 and above 0.50 respectively. Fraction of feeders in each category is 0.29, 0.39, 0.27 and 0.05 respectively.

Table 3: First Stage and Reduced Form Effect of Policy

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Outages	Loss in next month	Change in monthly loss	Average Loss in next quarter	Change in quarterly loss
Predicted Outages	0.334***	-0.003	-0.004	-0.006**	-0.007**
	(0.072)	(0.003)	(0.002)	(0.003)	(0.003)
Observations	3,646	3,361	3,243	3,304	3,293
R-squared	0.593	0.530	0.240	0.604	0.391

Notes: * p<0.10, ** p<0.05, *** p<0.01 and standard errors clustered by feeder reported in parentheses. All regressions include control for average loss in past year, number of consumers, consumption per consumer, fraction residential and fraction commercial consumers, month, year and grid fixed effects.

Table 4: IV Estimates of the Effect of Outages on Future Losses

	(1)	(2)	(3)	(4)
Dependent variable	Loss in next month	Change in monthly loss	Average Loss in next quarter	Change in quarterly loss
Outages	-0.010	-0.010	-0.019*	-0.020**
	(0.008)	(0.006)	(0.010)	(0.010)
Observations	3,361	3,243	3,304	3,293
First-stage F-stat	24.68	27.68	20.85	21.08

Notes: * p<0.10, ** p<0.05, *** p<0.01 and standard errors clustered by feeder reported in parentheses. Predicted outages are used as an instrument for actual outages. All regressions include control for average loss in past year, number of consumers, consumption per consumer, fraction residential and fraction commercial consumers, month, year and grid fixed effects.

Table 5: Fuzzy RD Estimates of the Effect of Outages on Future Losses

Panel A - Pooled RD Estimates				
	(1)	(2)	(3)	(4)
Dependent variable	Loss in next month	Change in monthly loss	Average loss in next quarter	Change in quarterly loss
Pooled Effect	0.043***	-0.009***	0.039***	-0.014***
	(0.003)	(0.002)	(0.003)	(0.003)
Observations	2,846	2,760	2,785	2,777
First-stage F-stat	196.2	207.5	176.1	175.6
Panel B - Heterogeneous RD Estimates				
Threshold 1	-0.011*	-0.010*	-0.015*	-0.014*
	(0.006)	(0.005)	(0.008)	(0.008)
Threshold 2	0.008**	-0.009***	0.004	-0.013***
	(0.004)	(0.003)	(0.005)	(0.005)
Threshold 3	0.027***	-0.010***	0.023***	-0.015***
	(0.003)	(0.002)	(0.004)	(0.004)
Observations	2,846	2,760	2,785	2,777
First-stage F-stat	9.702	10.55	8.328	8.341

Notes: * p<0.10, ** p<0.05, *** p<0.01 and standard errors clustered by feeder reported in parentheses. Predicted outages are used as an instrument for actual outages, and predicted outages interacted with neighborhood dummies are used as instruments for outages interacted with neighborhood dummies. All regressions include standard controls

Appendix A. Tables and Figures

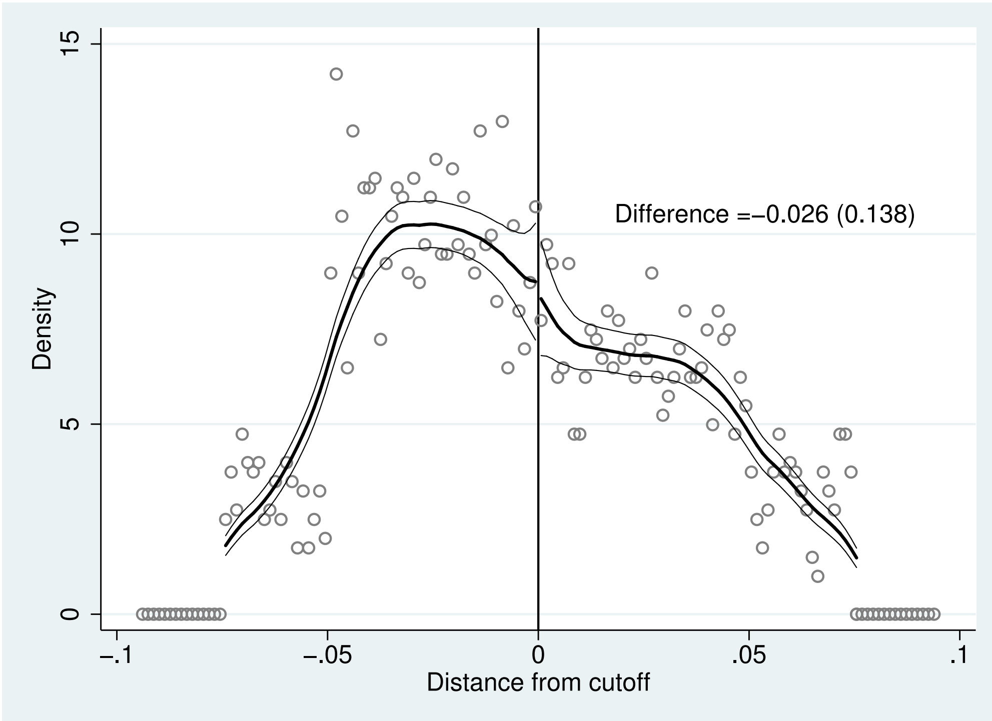


Figure A1: McRary Test for Discontinuity in Past Losses

Notes: The figure shows the results of the McRary density test with past losses normalized using distance from the threshold. Since the density of the normalized losses is not significantly different above and below the threshold, there is no evidence of manipulative sorting near the threshold.

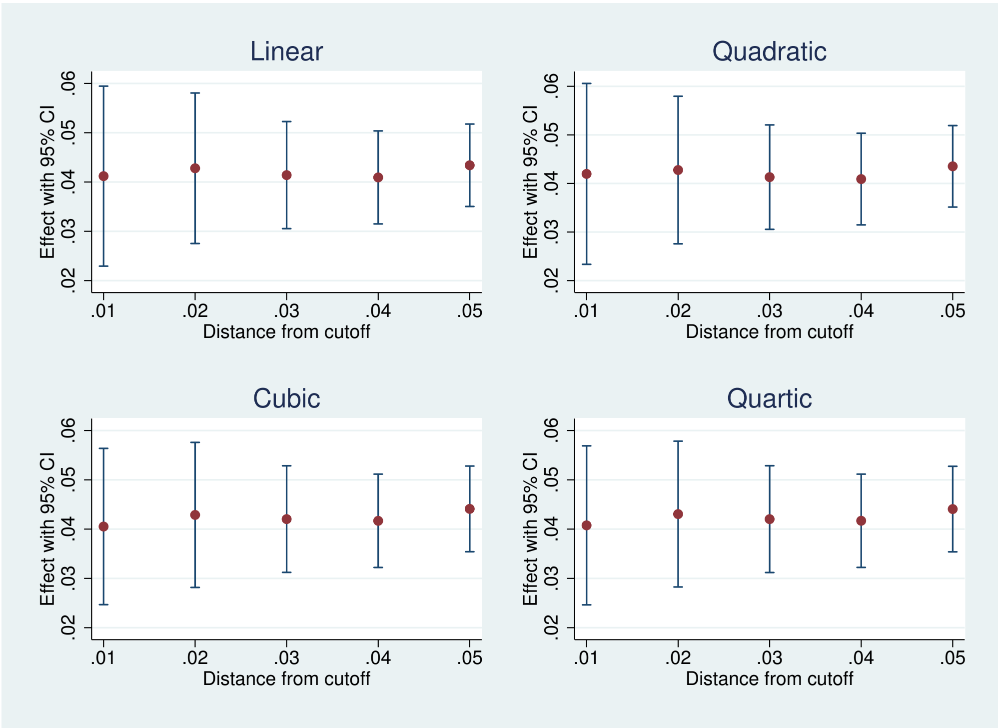


Figure A2: Monthly loss in next month

Notes: The figures plot estimated effect with 95% confidence interval using different bandwidths and polynomials in normalized past losses.

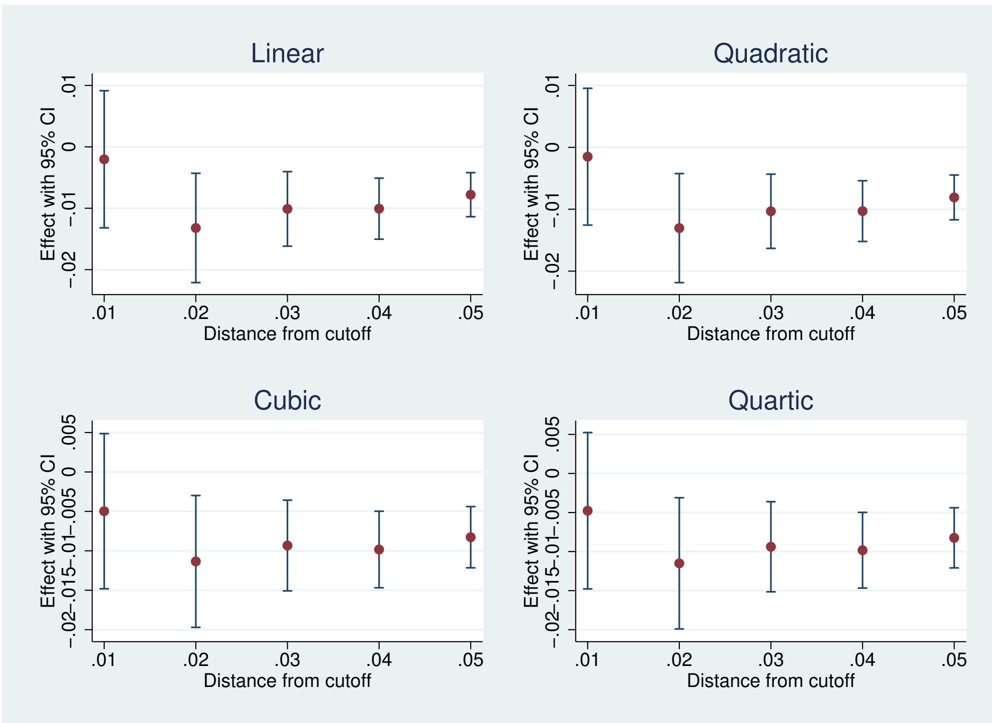


Figure A3: Change in monthly loss

Notes: The figures plot estimated effect with 95% confidence interval using different bandwidths and polynomials in normalized past losses.

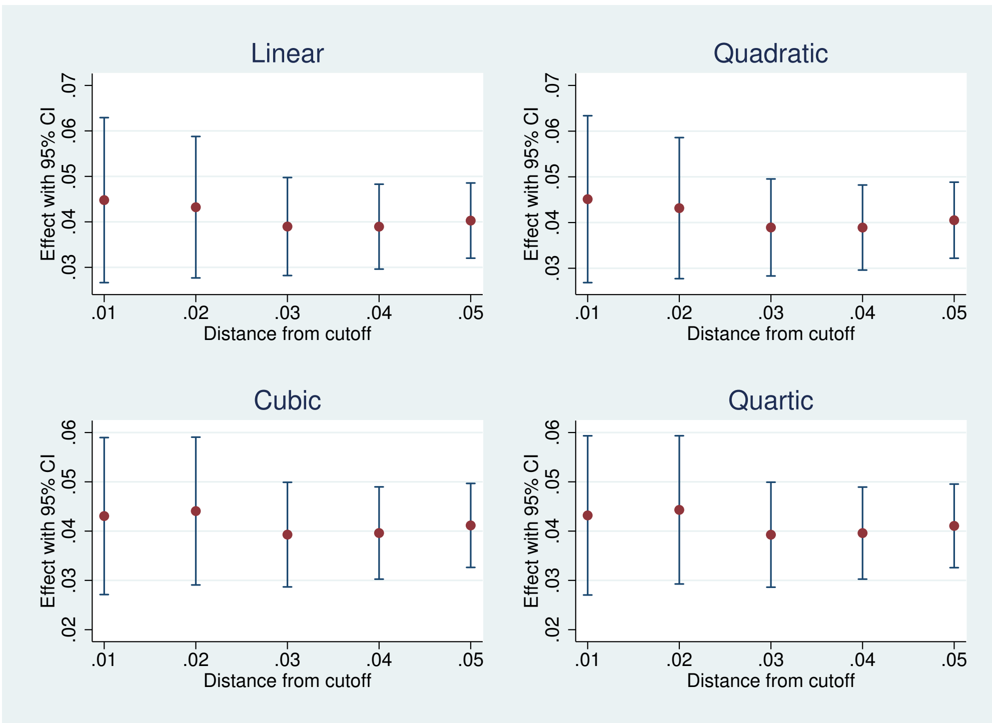


Figure A4: Average monthly loss in next quarter

Notes: The figures plot estimated effect with 95% confidence interval using different bandwidths and polynomials in normalized past losses.

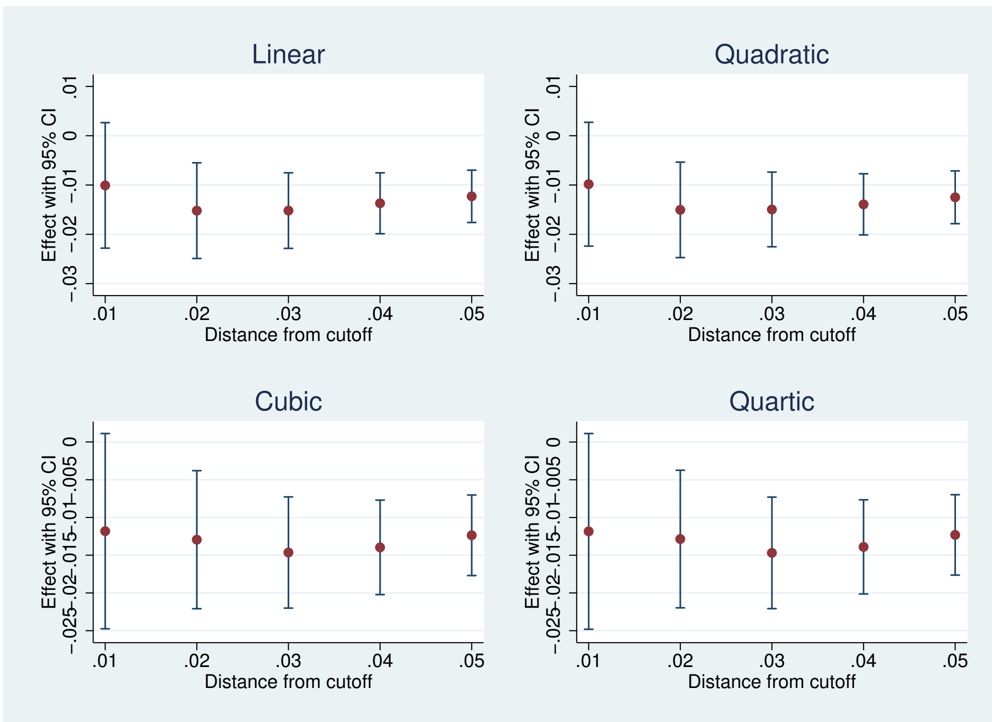


Figure A5: Change in loss in next quarter

Notes: The figures plot estimated effect with 95% confidence interval using different bandwidths and polynomials in normalized past losses.

Table A1: Balance Table - IV and RD specifications

	Effect	p-value	Effect	p-value
Consumption units (Kwh)	-9784	0.806	-19034	0.234
Number of consumers	-63.6	0.598	-216	0.035
Consumption per connection (Kwh)	-922	0.230	325	0.166
Fraction Residential	0.038	0.123	0.010	0.434
Fraction Commercial	0.036	0.130	-0.010	0.432
Fraction Industrial	-0.002	0.340	-0.000	0.909

Notes: The table presents the results of a regression in which the dependent variable is the feeder characteristic and the independent variable is outages. Regressions are estimated using the IV (column 1 and 2) and pooled RD (column 3 and 4)specifications with grid, year and month fixed effects. Standard errors are clustered at the feeder level. The effect of outages and the p-values are reported for each characteristic.