The Vicious Circle of Blackouts and Revenue Collection in Developing Economies: Evidence from Ghana*

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Abstract

Access to reliable electricity is one of the largest barriers to economic growth in developing economies. Utilities suffer from the twin challenges of quasi-fiscal deficits and the need to implement rolling blackouts during periods with supply shortages. In this paper, we measure a negative feedback loop between bill payment and rolling blackouts that can create a "revenue trap" for electric utilities. Using household-level data on bill payment and power outages before and after a power crisis in Ghana, we estimate the impact of quasi-random exposure to power outages on subsequent bill payment. We exploit a unique feature of the power grid whereby customers in close proximity are exposed to different levels of blackouts because some are served by a feeder with critical infrastructure "down the line" and others are served by feeders that do not service essential infrastructure. We find that households quasi-experimentally exposed to rolling blackouts accumulate larger unpaid balances relative to households on essential feeders. This is consistent with a negative feedback loop in which decreases in power reliability induce households to pay bills at lower rates and, thus, weaken the utility's financial viability.

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1 Introduction

Access to reliable electricity is viewed as a critical ingredient for economic growth in developing countries. Reliable power supply is an important part of a country's infrastructure to promote business formation and modern production processes. In Sub-Saharan Africa, business owners report electricity as being the second biggest obstacle facing the firm ahead of barriers such as corruption, crime, workforce education, and political stability (World Bank Group [2017]).[1] In rural areas with low electrification rates, there have been substantial policy efforts to expand access to power. However, in urban areas of sub-Saharan Africa, the power challenge is quite different. Many homes and businesses are connected to the grid, however their access to power is not consistently reliable. In a study of households satisfaction with electricity, find that an increase in reliability of one standard deviation in hours available is comparable to electricity connection for a non-electrified household. Policymakers are focusing attention on methods to improve the performance of electric utilities so as to promote economic growth.

However, electric utilities in developing countries such as in sub-Saharan Africa face large challenges. Among the two largest challenges are "quasi-fiscal deficits" and "load shedding". First, utilities often face large revenue shortfalls that require the utility to seek financial assistance from the government to maintain the grid and sustain operations. According to a World Bank report that analyzes the fiscal viability of electric utilities, 37 of 39 Sub-Saharan countries do not have fiscally viable electricity sectors (Trimble, Kojima, Arroyo, and Mohammadzadeh [2016]). Moreover, 20 of the 39 countries do not collect enough revenue to cover operating expenditures. The World Bank estimates that quasi-fiscal deficits of the electricity sector in Sub-Saharan Africa are quite large, averaging 1.5% of GDP. Due to

[1] The most commonly reported "biggest obstacle" is Access to Finance with 23% of firms reporting it as the largest barrier. The second most commonly reported obstacle is Electricity at 13.1%. The other categories include Practices of the Informal Sector (11.1%), Political Instability (9.9%), Tax Rates (9.1%), Corruption (7.8%), Access to Land (5.0%), Customs and Trade Regulations (4.7%), Tax Administration (4.5%), Crime, Theft and Disorder (3.4)%), Transportation (2.8%), Inadequately Educated Workforce (2.2%), Business Licensing and Permits (1.8%), Labor Regulations (1.1%), and Courts (0.5%).

these quasi-fiscal deficits, utilities often cannot operate the existing grid and, even more importantly, do not have the financial resources to expand the grid to service the demand growth that is expected to come with economic growth.

These quasi-fiscal deficits are driven by a number of factors including *low rates of revenue collection* because customers do not fully pay for billed electricity. Bill collection rates are notoriously low in some developing countries, and Sub-Saharan Africa is no exception. Some utilities have moved customers to pre-paid meters to reduce tariff under-recovery, but such a system is costly to deploy and is not widespread in many countries with fiscally troubled utilities.

A second challenge facing many utilities in Sub-Saharan Africa is that supply shortages often require the electric utility to routinely implement rolling blackouts. This activity is known as "load shedding" in the electricity sector because real-time power supply shortages require the utility to rotate parts of the grid to have power involuntarily cut off. It is widely believed that the practice of load shedding is a major barrier to economic growth (Eshun and Amoako-Tuffour [2016]).

In this study, we examine a potentially important interaction between these two challenges. We estimate whether there exists a negative feedback loop between bill payment and load shedding. Specifically, non-payment of bills contributes to a revenue shortfall for the utility, and if it is unable to obtain compensating financial assistance from the government, the utility may be unable to procure power and be forced to implement load shedding. This could trigger a feedback loop. When the utility frequently sheds load so that customers do not receive reliable power, customer bill payment may fall. Lower bill payment rates could operate through several channels. Low reliability may reduce household income so that customers are less able to pay their bills. Alternatively, frequent load shedding could reduce customer goodwill towards the utility and erode the social norm of bill payment.

If this feedback loop exists, then utilities could be caught in a "revenue trap" that is difficult to escape from and stands in the way of providing reliable power in the long-run.

We study this feedback loop in the context of Ghana, which suffered from widespread power shortages in 2014-2015. Amid rapid electrification throughout the county, the electric utility is experiencing both increasing rates of nonpayment and decreased reliability. This begs the question: "Are low payment rates exacerbated by load shedding?" The lack of revenue to the utility makes maintaining reliable power a difficult task, however, load shedding that reduces customer bill payment might then induce further nonpayment.

Estimating the magnitude of feedback loops is inherently challenging from an empirical perspective. By their very nature, feedback loops involve a simultaneity that makes it difficult to empirically identify causality. We exploit an institutional feature of the power grid design that allow us to credibly estimate the effect of outages on bill payment. Residential customers are connected to the power grid by individual distribution feeders that weave throughout an urban area. Importantly, load shedding is implemented by cutting power to *all* customers on specified distribution feeders and rotating among different feeders. In Ghana's capital of Accra, specific distribution feeders are categorized as priority for power if the feeders serve critical pieces of infrastructure such as hospitals, government ministries, and military facilities somewhere on the line. We use this feature of the power distribution grid and the presence of priority feeders as variation in a household's power reliability.

Using household-level data on monthly utility payments, we test if households quasi-randomly located on feeders with more outages accumulate unpaid utility bills at higher rates than households that are located on priority feeders that avoid many of the outages. To do so, we use high frequency spatial data on individual power outage events at the feeder level so that we can measure the number of hours of outages for individual feeders that are priority and non-priority. Such detailed outage-level data are quite unique for utilities in developing countries.

Our empirical analysis uses a difference-in-differences strategy to compare the bill payment patterns of households subjected to more outages because they are served by distribution feeders with different priority status. One concern is that the utility designates priority status based upon factors that are related to whether customers are likely to pay their bills when exposed to outages. However, as we show below, this does not appear to be the case. First, feeders are given priority primarily based upon critical pieces of government infrastructure on the line such as a hospital, military camp, prison, or defense ministry, which suggests that residential bill payment is not a direct factor in the assignment decision. Second, we show that trends in bill payment are quite similar on priority and non-priority feeders prior to the period of widescale outages. We find that quasi-random exposure to power outages reduces subsequent bill payment, which is consistent with a negative feedback loop. Households who are not served by priority feeders during the power crisis, and thus receive a significant number of power outages, accumulate higher unpaid balances relative to households on priority feeders. In our primary specification, unpaid balances increase by 48 Ghanian cedis after 15 months of the power crisis, which represents 4.3% of billed charges. These results suggest that electric utilities can become caught in a revenue trap that undermines the future economic viability of the utility.

To the best of our knowledge, no research has tested for evidence of this revenue trap or investigated methods to mitigate such feedback effects. In doing so, this paper contributes to two areas of research on growth in developing economies. We build upon a small but growing body of literature on the causes and consequences of power outages in developing countries. There is an emerging literature on the impact of power shortages on firm productivity, revenue, and costs (Allcott, Collard-Wexler, and O'Connell [2016], Fisher-Vanden, Mansur, and Wang [2015]). Recent research has studied productivity in Ghana to show that blackouts during the Ghanian power crisis in 2014-2015 reduced labor expenditures and profits in the garment making industry (Hardy and McCasland [2016]). In light of unreliable power supply, Abeberese, Ackah, and Asuming [2017] study strategies small and medium firms employ to mitigate observed productivity losses including the use of generators, switching production times, and adopting less energy intensive means of production.

This research informs policy decisions about the willingness to pay for grid reliability and the causes of "tariff under-recovery". Policymakers are recognizing the potentially large benefits to increasing bill payment rates, and the literature is beginning to study means to address tariff under-recovery (Burgess, Greenstone, and Ryan [2016]). Twerefou [2014] uses stated preference data to argue that Ghanians are willing to pay more than the current tariff for reliable power supply. Our project is related to the literature on how subsidized power deters investment decisions and creates a "subsidy trap" (McRae [2015]). In contrast to McRae, we do not focus on the role of informal power connections and government subsidies; rather we study underpayment of existing tariffs by metered customers as contributing to lower utility revenues.

An emerging literature is developing on the potential role of prepaid meters as a solution to tariff under-recovery (see, for example, Jack and Smith [2015]). In the case of Ghana, while some customers have prepaid meters, the majority of residential customers - more than 60% - do not use the prepaid system. In this context, it is important to understand whether a negative feedback loops exists among post-pay customers for several reasons. In the short-run, the utility must address tariff under-recovery in a system where the majority of customers use the postpaid system. In the longer-run, the magnitude of the negative feedback loop will factor into a cost-benefit analysis of expanding prepaid meters to the majority of households in Ghana that are not currently on the prepaid system.

2 Background and Empirical Strategy

2.1 "Dumsor" Power Crisis in Ghana

The power sector of Ghana is split into three separate components: generation, transmission, and distribution. The Volta River Authority, owned by the government of Ghana, is responsible for most the generation capacity in Ghana. All generated power is transmitted by GRIDCo through high voltage electrical lines to the Electricity Company of Ghana (ECG), the primary distributor in Ghana. The electricity is then stepped down to lower voltages levels and delivered to customers by ECG. During power supply shortages, GRIDCo calls for widespread rolling blackouts which ECG implements to reduce the demand on the grid.

Ghana, as well as many other developing counties, has had a history of power shortages. Much of Ghana's electricity is generated through hydro-power, namely the Akosombo Dam which was built in 1965. Thus, past reliability issues in 1982-1984, 1998-2000, and 2006-2007 were spurred by a lack of rainfall and ability to generate enough power supply to meet the country's demand. In response to past energy crises, the government diversified its generation capacity including several thermal plants and it invested in the West African Gas Pipeline (WAGP) which transports natural gas from Nigeria to Benin, Togo, and Ghana. However, Ghana again began experiencing supply shortages in late 2012 due to a compilation of growing demand, poor rainfalls, and interrupted gas supply through the WAGP.

While intermittent outages continued through 2013, it was not until 2014 that rolling blackouts were instituted throughout the country. Due to sustained supply shortages, the Electricity Company of Ghana (ECG), announced a schedule in which customers would experience 12 hours without power followed by 48 hours of reliable power. However, as the energy crisis increased in October 2014, ECG announced they were having trouble sticking to the announced schedule [Ghana Web, 2014]. Thus, load shedding was ramped up several times reaching 24 hours without power and only 12 hours of constant power in February 2015. The energy crisis became known as "Dumsor", coming from the words dum meaning 'off' and so meaning 'on' in a dialect of the Akan language.

An important feature of the blackouts in Ghana is that some feeders were exempt from these rolling blackouts. Feeders are designated as priority and thus protected from widespread loadshedding based upon critical pieces of government infrastructure on the line such as a hospital, military camp, prison, or defense ministry. Our variation in household exposure to outages is driven by whether, due to the layout of the power distribution grid, the household is served by one of the priority feeders.

2.2 Empirical Strategy

In order to identify the causal impacts of reliability on bill payment, we exploit plausibly exogenous household exposure to power outages. Households that are served by "protected" feeders were substantially less likely to be subjected to load shedding when supply shortfalls occurred. In our formulation, a household is considered treated with (more) reliable power if it is served by a protected feeder during the Dumsor period.

Formally, we implement a generalized difference-in-differences design with the following regression model:

$$Outcome_{ht} = \alpha_h + \gamma_t + \beta ProtectedFeeder * DumsorPeriod_{ht} + \epsilon_{ht} \quad (1)$$

where $Outcome_{ht}$ represents the outcome of interest for household, h, in quarter, t. Our primary outcome is the household's average unpaid account balance in quarter t, which is our metric of bill payment behavior, as we describe in our data section below. We allow for static differences in account balance across households with household fixed effects, α_h, as well as factors affecting all households in a given quarter with γ_t fixed effects. $ProtectedFeeder$ is an indicator of whether the household is served by a feeder that is prioritized to receive power during load shedding periods. $DumsorPeriod$ is defined as beginning in the second quarter of 2014, as we discuss above. In results below, we confirm that protected status impacted grid operations – protected feeders received substantially less load shedding during Dumsor. β, the coefficient of interest, measures the difference in outcomes for households on protected feeders, and thus exposed to fewer outages, as compared to households on unprotected feeders during the Dumsor period.

The underlying assumption behind this approach is that households on protected feeders would have had similar changes in account balance as households on unprotected feeders, absent protection from the increased blackouts during Dumsor. That is, households on unprotected feeders provide a good counter-factual for what would have happened to households on protected feeders had they been exposed to increased outages as well. A priori this assumption is plausible because we are narrowing our sample to households in similar neighborhoods that happen to be served by different feeders. The illustration in Figure 2 shows an example of the variation in outages in a neighborhood in Makola district. The top panel of the map shows an aerial view of the neighborhood that is served by the two different feeders. The bottom panel shows a map of buildings with electric meters. The teal line running up the middle of the map delineates the boundary between geographic 'rounds' that are served by different feeders. The round on the right side of the map is served by a feeder that also serves the historic Osu Castle (which is not shown on the map but is located to the 'southeast'). Customers on this protected feeder experience an average of 28 hours of load shedding per month during Dumsor. The round on the left is served by a feeder that is not protected and experiences an average of 42 hours of load shedding per month during Dumsor.

We also provide evidence in support of this assumption in several ways. First, we graphically show that households on protected and unprotected feeders track each other prior to treatment. Pre-divergence is formally tested by adding an indicator for the treated group one year prior to treatment. Additionally, we allow each district to experience quarter-to-quarter shocks affecting bill payment of all customers within the district. Finally, we allow for customers in each block to trend differently over time by adding linear block trends. In all models, robust standard errors are clustered at the feeder level.

3 Data

3.1 Outage Events

In the face of growing demand for power, ECG faced supply shortages due to factors including powerplants requiring repair and difficulties acquiring natural gas to fuel the plants. As a result, ECG was forced to implement large-scale load shedding beginning in early 2014. Although ECG published schedules for load shedding, customers frequently complained that the schedules were not followed. Typically the distribution feeders originate at a transmission substation, and load shedding is triggered by a substation engineer shutting off power to all customers down the feeder line.[2]

ECG maintained detailed logs of all outage events, noting the start and end time of the outage, the feeder that was impacted, and the reason for the service disruption. The vast majority of outage events during our sample period are load shedding, but there are also outages due to equipment failures. It is quite unusual to have high frequency spatial data on outage events for utilities in developing countries. The outage event logs allow us to study with high geographic granularity the relationship between household-level outages and bill payment.

We use data on all outage events in one of the two regions of the capital – Accra East – from January 2013 to May 2015. We aggregate outage event lengths to calculate the total number and length of load shedding events for each feeder every month.[3] Feeder names are matched to an official list of feeders that were prioritized and thus protected from systematic load shedding. There are 24 protected feeders in total, 18 of which we can identify in the outage data. Only 4 of the protected feeders service residential customers, so those feeders' outages are the ones that create the variation in our data, as we discuss in further detail below.

Summary statistics are shown in the top panel of Table 1. The first three columns summarize outages during our the entire sample period of January 2013 to May 2015, and the last three columns summarize outages during the Dumsor period beginning in April 2014. During the sample period as a whole, unprotected feeders are subjected to substantially more load shedding than the protected feeders. During the Dumsor period, the unprotected feeders in our sample average 5.21 load shedding events per month while the protected feeders average only 0.31 events. In terms of hours of load shedding, the unprotected feeders are subjected

[2]We study 11kV feeders that serve the Accra East region of ECG service territory.

[3]This is likely to be an underestimate of the total number of hours as not all outages are attributable to feeders due to inconsistencies in feeder names. We only aggregate hours that we are sure all belong to the same feeder either by official or colloquial name.

to 48 hours per month while the protected feeders are subjected to only 2.7 hours. When we include outages from all causes, the total rises very little, indicating that the primary driver of outages is load shedding rather than equipment failures. Figure 1 shows the variation in load shedding hours over time. Load shedding has minimal impact on protected feeders over the entire sample period. However, load shedding on unprotected feeders rises significantly beginning in 2014 topping 100 hours in February 2015. The crisis became most severe in early 2014, so we define 'treatment' to begin in the second calendar quarter of 2014 for our empirical analysis below.

3.2 Household Bill Payment

ECG provided account information for all customers from January 2013 to May 2015.[4] For each meter, we observe monthly account snapshots including the amount of electricity consumed, the current charge for new consumption, the amount paid, and the running account balance. Customers receive their bill each month and must go to a bill collection post to make payments on their account. Because of the travel costs associated with paying the bill, many customers make payments every other month. In light of this, we focus our analysis on the running account balance throughout our period as the primary measure of account health.

Our empirical strategy requires us to match households to feeders in order to estimate the relationship between outages and subsequent bill payment. The meter numbers on customer accounts include a 17-digit geographic identifier that pinpoints the neighborhood of the household, specifically a geographic unit called a block that is subdivided into rounds. System engineers from each of the seven districts in Accra East provided us with lists of the block-rounds that are served by each feeder.

This allows us to identify which customers are served by each feeder and to classify whether each household is served by a protected feeder during Dumsor and is thus quasi-

[4] In June 2015, ECG switched bill payment systems and transitioned some customers to pre-pay meters.

randomly experiencing fewer outages. As previously discussed, we focus on the region of Accra East for which we have protected designation for electricity feeders. Only two of the districts in Accra East have both protected and unprotected feeders serving households. Thus, our primary analysis is for these two districts, Makola and Roman Ridge, with 29,070 and 93,580 households, respectively, making up 37% of all residential customers.

We focus our analysis on household rather than business bill payment behavior. ECG imposes different tariffs for residential customers than for commercial and industrial customers. We are able to identify accounts of residential customers based on the type of tariff that is charged to the account. Roughly 80% of all customers are on the residential tariff. However, the bill payment data include a small number of instances where a customer on a residential tariff consumes an implausibly large number of kWh in a month. These large usage quantities are likely business customers who have been put on residential tariffs. We also observe some customer accounts with negative usage in a month. In order to isolate customers who we believe are residential customers, we restrict our sample to residential tariff customers who never consumer more than 1,500 kwh in a month and always have positive usage.[5]

The bottom panel of Table 1 summarizes bill payment behavior. Households average slightly over 200 kWh of consumption a month which averages a charge of 73 GHS. Usage is quite similar for the households on protected and unprotected feeders, however it is important to note that our difference-in-differences strategy does not require balance in *levels*; it require *trends* to match prior to treatment. Households make a bill payment an average of 1.68 times each three month period, suggesting that monthly bill payment is not a regular practice in Ghana. Finally, households typically carry forward unpaid balance rather than fully paying their bills. Households average an unpaid balance of about 200 GHS each month after any payment is processed.

In our empirical results below, we analyze the relationship between outages and bill payment at the household-level for each calendar-quarter. We choose to aggregate time to

[5]We show that our results are robust to this restriction.

the calendar-quarter because, as discussed above, many residential customers appear to be in the practice of skipping payment in some months. Therefore, analyzing bill payment quarterly is likely to smooth over idiosyncratic payment practices.

Some households drop out of the sample over time. Roughly 20% of meters that we observe in January 2013 fall out of the sample by May 2015. One potential driver of this attrition is that ECG was in the process of moving some customers from post-pay to pre-pay meters. We restrict our sample to meters that are observed at least once in every quarter from January 2013 to May 2015. A potential concern is selective attrition. Using our primary specification, we test for differences in attrition correlated with treatment in the results section. Finally, we observe meters entering into the sample as ECG continues its efforts toward 100% access to electricity. We exclude these meters as well because they are only observed during the treatment period.

4 Results

4.1 Protected Feeder Status and Load Shedding

First, we show that protected feeder status impacts household exposure to power outages. A priori we expect the feeders that service critical pieces of infrastructure will be prioritized for service and thus be subjected to less load shedding. ECG's decision to designate some feeders as priority feeders appears to have affected how ECG makes load shedding decisions. Using the feeders that serve customers in our sample and are situated in the same districts, we calculate the average levels of load shedding.

Protected feeders are subjected to fewer hours of load shedding during Dumsor, as shown in Figure 1. Protected feeders do not receive a significant amount of load shedding in the months prior to the second quarter of 2014 (the quarter when we define 'POST' to begin). Beginning in 2014Q2, protected feeders receive several hours of load shedding in the last months of 2014 and early months of 2015, but in general load shedding is minimal.

By contrast, the unprotected feeders are subjected to significant load shedding during Dumsor. As shown in Figure 1, outage hours in unprotected feeders are minimal prior to the second quarter of 2014, with the exception of a few months in early 2013. However, beginning around March 2014, the number of outage hours per month begins to significantly rise, averaging over 50 hours per month for six months and over 100 hours in February 2015.[6]

4.2 Effect of Protected Feeder Status during Dumsor on Bill Payment

We are now in a position to assess the magnitude, if any, of a feedback loop between outages and bill payment using the generalized difference-in-differences strategy described in section 2.2. In all specifications, we include household fixed effects to control for unobserved household propensities to pay bills that do not vary over time. In addition, we include calendar quarter fixed effects to control for any factor that the utility changes over time such as efforts to enforce bill payment. Thus we estimate how being served by a protected feeder changes a household's bill payment relative to that household's baseline bill payment behavior.

We first show our results graphically in Figure 3 plotting the estimated divergence between customers on protected and unprotected feeders in each quarter relative to the first quarter in 2013. Importantly, we see customers on protected and unprotected feeders have similar changes in account balance prior to our Dumsor period. This supports our identifying assumption that customers on protected feeders would have changed similarly as customers on unprotected feeders, absent being protected for rolling blackouts. We then see visual evidence of a negative feedback loop as customers that experience fewer outages have relatively lower bill balances than unprotected customers.

In Table 3, we estimate the average treatment effects. In column (1) we find that service

[6]The large drop in reported outages for unprotected feeders in March 2015 is an anomaly in the data in which no load shedding events are reported for any feeder in week 8, 9, 10, or 11 of 2015. Thus, we suspect the decrease to be artificial and a reporting issue.

from a protected feeder reduces the household's unpaid balance over the 15 month period after Dumsor begins by an average of 32 cedis. Put differently, a household without a protected feeder during Dumsor that is subjected to substantial outages increases its unpaid balance. This is consistent with the feedback loop in which decreases in power reliability induces households to pay bills at lower rates.

In column (2), we formally test for pre-divergence. Specifically, we test for whether the increase in unpaid balance could simply reflect other trends in a household's bill payment that are occurring in early 2014. To do so, we add a lead indicator for customers on protected feeders 3 months prior to our Dumsor period. If other underlying trends are present in late 2013 prior to the onset of Dumsor, then this lead variable would be a statistically significant determinants of unpaid bills. However, the lead variable in column (2) is not statistically different from zero (in fact the sign of the point estimate is positive), and the estimate of treatment effect ($Protected * Dumsor$) remains similar.

As robustness tests, we allow for several other unobserved factors to affect bill payment, further testing our design assumption. By conducting each of these robustness tests, we sacrifice statistical power but view the point estimates as an assessment of potential unobservables that could bias our estimates. In column (3), we include fixed effects for each district-quarter to allow for time-varying factors such as neighborhood growth or district-level meter reading and bill collection practices that could impact account balances. Although the estimate is imprecise, the point estimate is consistent with our primary finding that unreliable power increases unpaid balances. In column (4), we allow for linear time trends at the highly granular geographic level of "block". These time trends allow for geographically localized effects in neighborhoods that also could capture patterns in growth, metering, or bill collection practices that are unrelated to Dumsor. As with our robustness test above, in this specification the effect of reliability is imprecisely estimated but the point estimate is similar to that in the primary specification. These two robustness tests, while diminishing our statistical power, suggest that other unobserved factors are not driving our finding that lack of reliability increases unpaid balances.

Finally, we return to our benchmark specification and investigate how the effect of reliability varies over time. One might expect that if a feedback loop exists, that residential customers would accumulate larger unpaid balances as the Dumsor crisis deepened. We do not have access to payment data for enough months after the Dumsor crisis to estimate statistically significant trends over time. However, our results in column (5) of Table 3 are suggestive of unpaid balances growing over time. The largest point estimate of the dynamic treatment effects is that after 15 months, the effect of being exposed to outages via an unprotected feeder causes unpaid balances to increase by 48 GHS. Ideally, we would expand the time period of our outcomes data to study beyond May 2015, however in June 2015, ECG switched bill payment systems, and the transition between payment systems does not allow us to extend our sample period. Thus we cannot estimate the longer-run impacts of outages on the revenue stream of the utility.

It is important to note that this finding is not driven by Dumsor increasing an unprotected household's consumption and thus the size of the monthly bill. The mechanical relationship between treatment and bill size, if anything, would bias *against* this finding. Households on unprotected feeders are likely to *reduce* total electricity consumption and thus bill size. Mechanically, having access to power fewer hours of the day could decrease opportunities to consume (e.g. fewer hours to watch television). However, households may respond by shifting consumption to hours when power is available (e.g. phone charging or electric cooking). As long as any intertemporal substitution is less than one-to-one, consumption and thus bill size will fall. In fact, consumption did not rise for the customers with less reliable power. As shown in Figure 4, trends in consumption were very similar prior to Dumsor, but consumption was larger during Dumsor for households on protected feeders. Therefore, increases in unpaid balances by households facing outages is not driven simply by those households having larger monthly bills. Rather, these households are contributing less to the utility's revenue stream.

We now turn to Table 3 in which we estimate our primary specification from Column 1 of Table 2 under alternative sample restrictions. Recall, the primary sample for our analysis includes residents with reported usage less than 1500 kwh per month in the two districts in which we observe residential customers on both protected and unprotected feeders. Column 1 replicates our main estimate with our primary set of sample restrictions for comparison. In Column 2, we expand our sample to include all districts in Accra East noting that the coefficient, -27.55, is similar to our main estimate of -32.25 and statistically significant at the 1% level. Alternatively, we restrict our primary sample to include only blocks with residents on both protected and unprotected feeders in Column 3. This cuts our sample dramatically and reduces our precision, however, the coefficient is similar in magnitude at -47.2. Next, we show our results are not sensitive to the sample restrictions based on consumption in the remaining columns. In Column 4, we first show our result is robust to including all customers on the residential tariff with a reported coefficient of -42.04 and statistically significant at the 1% level. In Column 5, the estimate is similar in magnitude, -29.94, when including households with negative usage reported. Columns 6 through 9 report estimates for residential customers with positive usage but less than 2500, 2000, 1000, and 750 kwh per month, respectively. Estimates remain stable ranging from -32.12 to -33.68, and statistically significant at conventional levels. This set of robustness tests supports our primary finding that customers unprotected from rolling blackouts are more likely to carry higher account balances than their protected counter-parts, and that this result is not driven by various sample restrictions.

Notably, we include only customers who are observed at least once in every quarter of our sample period from January 2013 to May 2015. A potential concern is that our balanced panel is the result of selective attrition in a way that is correlated with treatment. For example, imagine if customers on protected feeders who were less likely to pay their bill were either disconnected or switched to a pre-paid meter during Dumsor. We would observe similar results in lower account balances for protected feeders, however, it would be due to selective attrition rather than exposure to outages. To test for this, we estimate the likelihood of being observed in each quarter for all households beginning in our sample in the first quarter of 2013. We note that if this were the case, we would see a divergence in the likelihood of being observed on protected and unprotected feeders during Dumsor. However, in Figure 5, we plot the dynamic coefficients from equation (1) and find no evidence that treatment is correlated with the likelihood of being observed. Thus, we conclude our results are consistent with customers either refusing or being unable to pay their utility bill in response to increased blackouts.

5 Conclusions

Our results are consistent with a negative feedback loop between outages and bill payment. We find that unpaid balances increase by 48 GHS 15 months after the beginning of Dumsor for households quasi-experimentally exposed to outages via service by a non-priority feeder. This accumulated balance is significant – it corresponds to 4.3% of an average household's billed charges over a 15 month time horizon. This finding adds an important piece of evidence on the role that unreliable power can play in inhibiting economic growth. Previous research has shown that firms cite reliability as a business obstacle and that outages impact firm productivity. This paper shows another dynamic – a negative feedback loop between reliability and bill payment – that can create a revenue trap for electric utilities.

References

Ama Baafra Abeberese, Charles Ackah, and Patrick Asuming. Productivity losses and firm responses to electricity shortages: Evidence from Ghana. Working paper, 2017.

Michaël Aklin, Chao-yo Cheng, Johannes Urpelainen, Karthik Ganesan, and Abhishek Jain. Factors affecting household satisfaction with electricity supply in rural India. *Nature Energy*, 1(11):16170, 2016.

Hunt Allcott, Allan Collard-Wexler, and Stephen D. O'Connell. How do electricity shortages affect industry? evidence from India. *American Economic Review*, 2016.

Nana Ama Boansi Boakye, Frank BK Twenefour, and Mary McArthur-Floyd. The impact of power outage Dumsor on the hotel industry: Evidence from Ghana. *Journal of Energy Technologies and Policy*, 2016.

Robin Burgess, Michael Greenstone, and Nicholas Ryan. Let them buy light in rural Bihar. working paper, 2016, 2016.

Energy Commission of Ghana. National Energy Statistics 2005-2014. Technical report, 2015.

Maame Eshun and Joe Amoako-Tuffour. A review of the trends in Ghana's power sector. *Energy, Sustainability and Society*, 5, 2016.

Karen Fisher-Vanden, Erin T. Mansur, and Qion Juliana Wang. Electricity shortages and firm productivity: Evidence from China's industrial firms. *Journal of Development Economics*, 2015.

Ghana Web. ECG struggling to follow loadshedding timetable, pro, 2014. Accesed on 23-October-2018 at https://www.ghanaweb.com/GhanaHomePage/NewsArchive/ECG-struggling-to-follow-loadshedding-timetable-PRO-330416.

Morgan Hardy and Jamie McCasland. It takes two: Experimental evidence on the determinants of technology diffusion. 2016.

Abdallah Ibrahim, Genevieve Cecilia Aryeetey, Emmanuel Asampong, Duah Dwomoh, and Justice Nonvignon. Erratic electricity supply (dumsor) and anxiety disorders among university students in ghana: a cross sectional study. *International journal of mental health systems*, 10(1):17, 2016.

Kelsey Jack and Grant Smith. Pay as you go: Prepaid metering and electricity expenditures in South Africa. *American Economic Review*, 2015.

Francis Kemausuor, George Yaw Obeng, Abeeku Brew-Hammond, and Alfred Duker. A review of trends, policies and plans for increasing energy access in ghana. *Renewable and sustainable energy reviews*, 15(9):5143–5154, 2011.

Kenneth Lee, Edward Miguel, and Catherine Wolfram. Appliance ownership and aspirations among electric grid and home solar households in rural Kenya. NBER working paper series, 2016.

Shaun McRae. Infrastructure quality and subsidy trap. *American Economic Review*, 2015.

Chris Trimble, Masami Kojima, Ines Perez Arroyo, and Farah Mohammadzadeh. Financial viability of electricity sectors in Sub-Saharan Africa: Quasi-fiscal deficits and hidden costs. Technical report, World Bank Group, 2016. World Bank Group, August 2016.

Daniel Kwabena Twerefou. Willingness to pay for improved electricity supply in Ghana. *Modern Economy*, 2014.

Frank Wolak. Managing demand-side economic and political constraints on electricity industry re-structuring processes. RSCAS working paper, 2011.

Catherine Wolfram, Orie Shelef, and Paul Gertler. How will energy demand develop in the developing world? *Journal of Economic Perspectives*, 26(1):119–138, 2012.

World Bank Group. Enterprise surveys. Technical report, 2017.

Figure 1: Average Monthly Hours of Load Shedding by Feeder Status

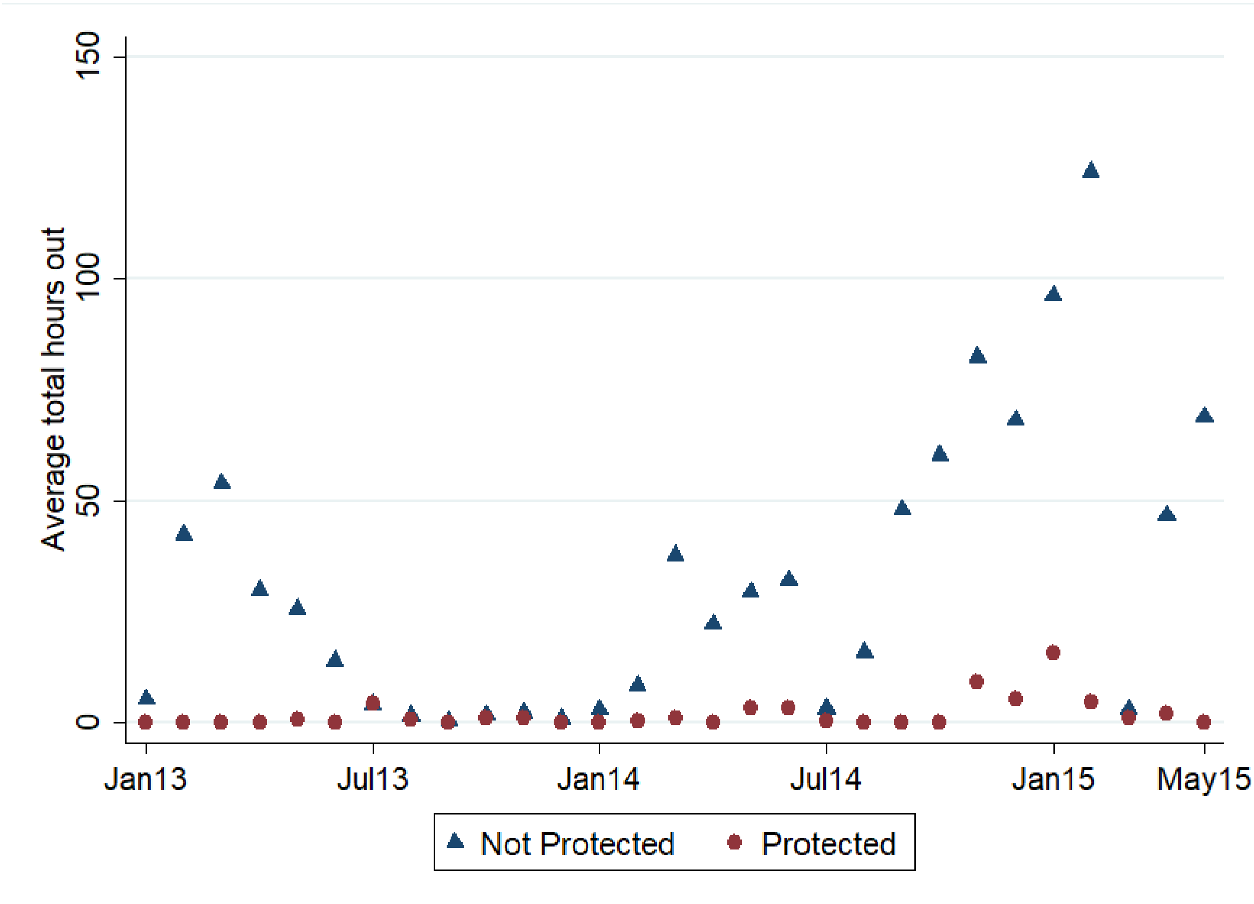
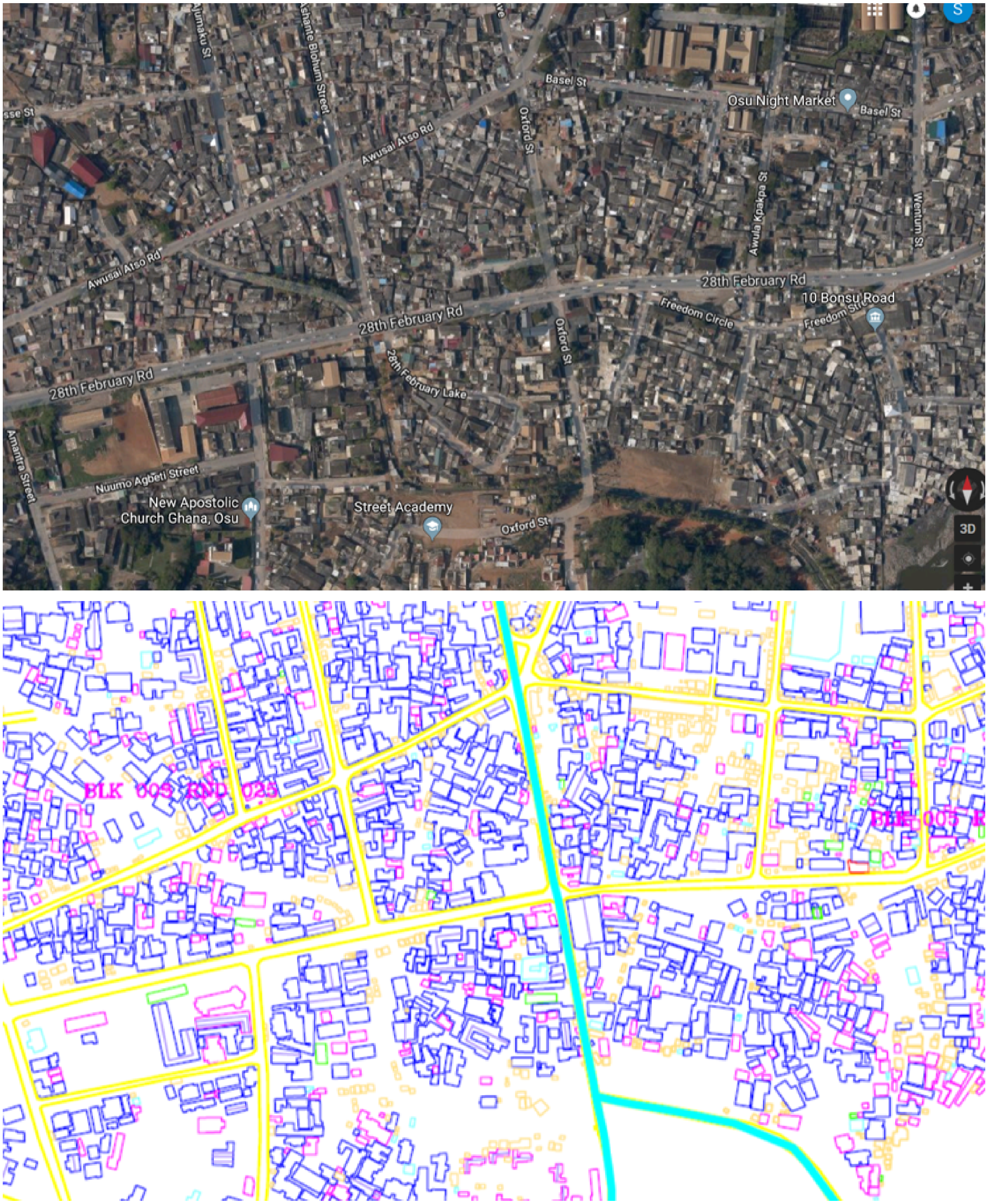
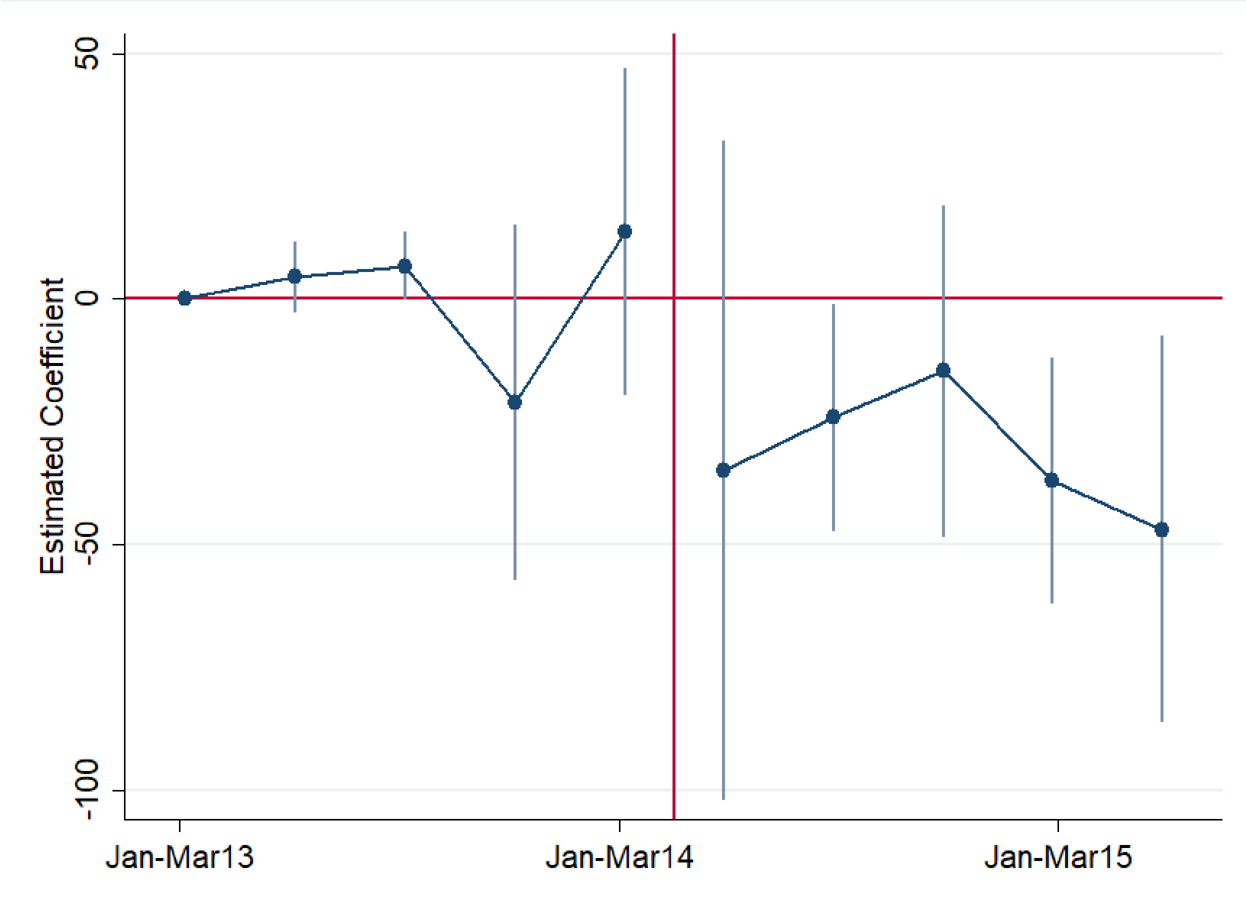


Figure 2: Example of Neighborhood Served by Different Feeders



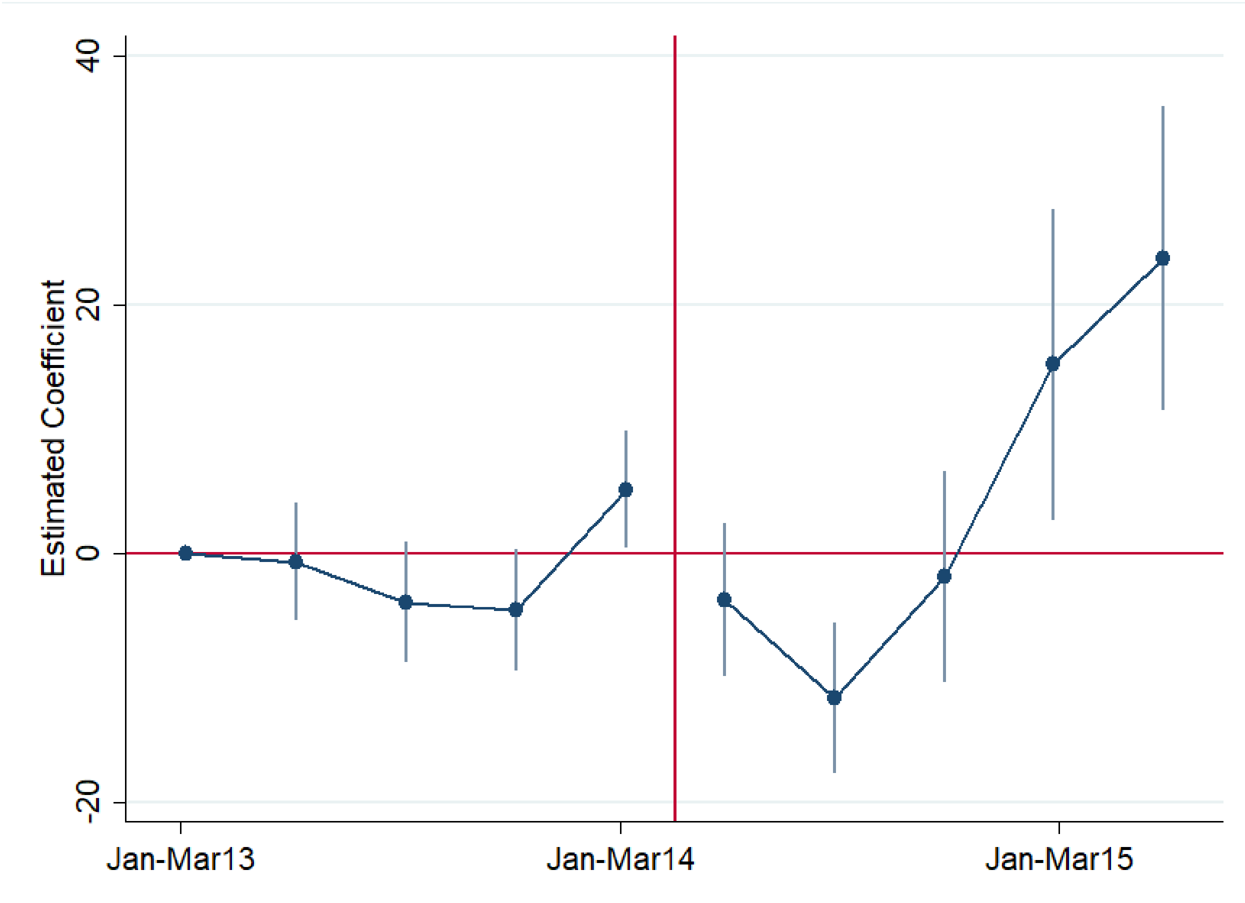
This map depicts a neighborhood in the district of Makola. In the bottom diagram, the thick teal line separates areas served by different feeders. The area to the right of the teal line is served by an 11kV feeder that is designated as potected; that feeder serves a historic fortress Osu Castle which is located south and east of this neighborhood. The area to the left of the teal line is served by a feeder that does not have protected status. Yellow lines depict roads and the blue figures depict structures with electric meters.

Figure 3: Unpaid Balance: Estimated Effect of Protected Feeder



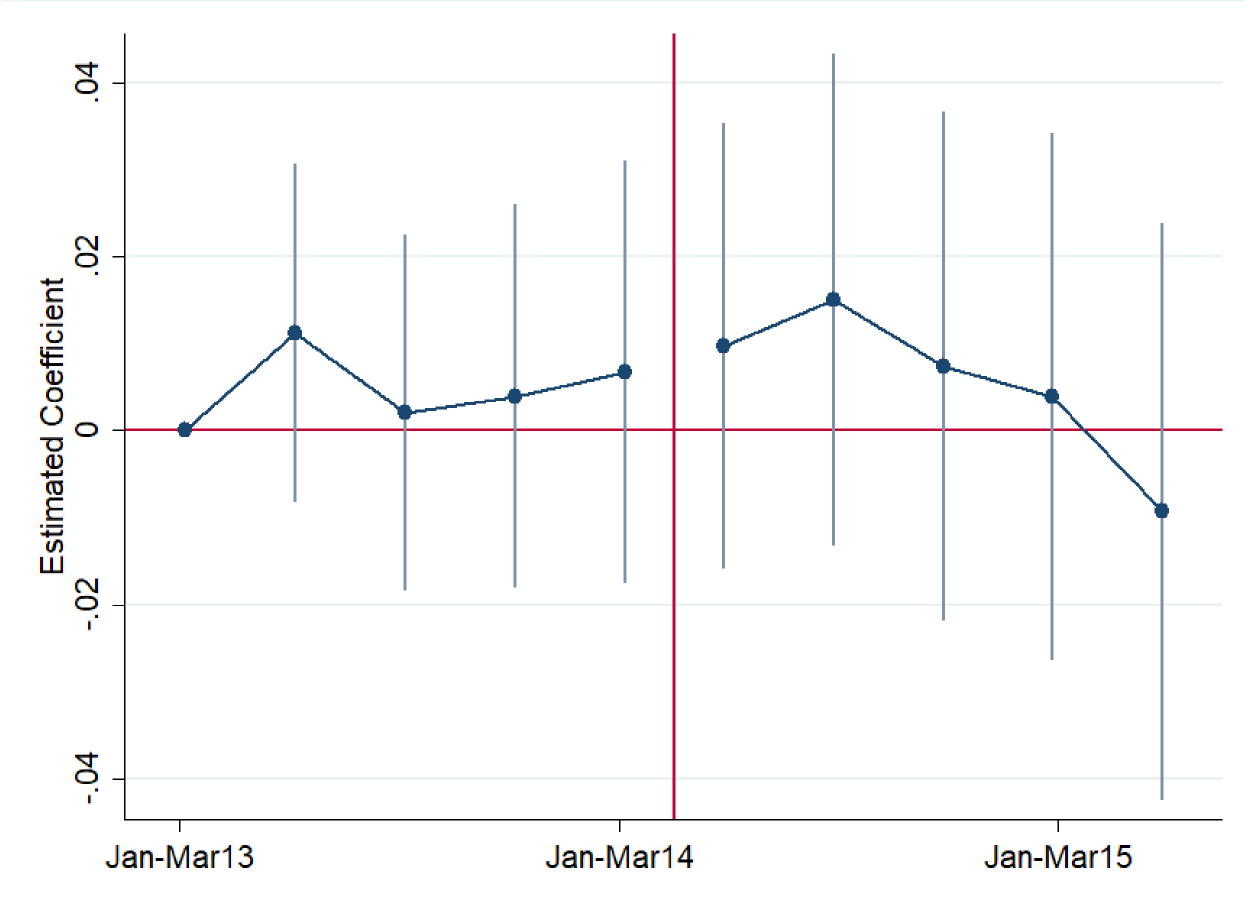
Notes: Dynamic estimates from equation 1 are plotted for unpaid balance (in GHS). Standard errors are clustered at the feeder-level and 95% confidence levels are shown.

Figure 4: Consumption: Estimated Effect of Protected Feeder



Notes: Dynamic estimates from equation 1 are plotted for usage. Standard errors are clustered at the feeder-level and 95% confidence levels are shown.

FIGURE 5: Account Data Observed: Estimated Effect of Protected Feeder



Notes: Dynamic estimates from equation 1 are plotted where the outcome is an indicator for whether or not the meter is observed in a particular feeder-quarter. Standard errors are clustered at the feeder-level and 95% confidence levels are shown.

Table 1: **Summary Statistics**

	All Periods			Post Dumsor		
	(1)	(2)	(3)	(4)	(5)	(6)
	All Feeders	Unprotected Feeders	Protected Feeders	All Feeders	Unprotected Feeders	Protected Feeders
Panel A: Outages						
# of loadshedding events	2.95	3.49	0.15	4.43	5.21	0.30
	(4.73)	(4.97)	(0.78)	(5.65)	(5.83)	(1.11)
Total hours shed	25.87	30.55	1.30	40.95	48.23	2.70
	(45.48)	(48.13)	(7.06)	(56.07)	(58.26)	(10.01)
Total hours out	27.15	31.98	1.83	42.43	49.91	3.15
	(46.44)	(49.12)	(7.25)	(56.97)	(59.12)	(10.14)
Feeder-Month Obs	725	609	116	350	294	56
Panel B: Bill Payment						
Usage (kWh)	216.86	216.80	205.97	216.86	195.85	187.58
	(169.28)	(170.04)	(154.82)	(169.28)	(155.17)	(142.82)
Monthly Charge (GHS)	73.36	73.33	69.43	73.36	83.61	79.77
	(67.41)	(67.64)	(61.89)	(67.41)	(72.38)	(66.53)
Times Paid	1.68	1.66	1.83	1.68	1.58	1.76
	(0.99)	(0.99)	(0.98)	(0.99)	(1.00)	(0.99)
Account Balance (GHS)	196.02	201.50	147.27	196.02	249.60	178.44
	(1522.88)	(1612.24)	(182.33)	(1522.88)	(1970.89)	(211.35)
Household-Quarter Obs	122,650	109,240	8,900	122,650	54,620	4,450

Notes: Summary statistics are reported for the feeders and households used in our main analysis. Outages reported are for feeders serving Makola and Roman Ridge serving residential customers. Account information is for residential customers in Makola and Roman Ridge that are observed once in each quarter during our period and consume only positive units never more than 1500 kwh.

Table 2: **Effect of Dumsor on Unpaid Balance**

Dependent Variable: Household Account Balance					
	(1)	(2)	(3)	(4)	(5)
Protected X Dumsor	-32.25**	-29.02***	-63.77	-45.44	
	(12.40)	(9.081)	(68.63)	(49.05)	
Lead		16.13			
		(19.23)			
Protected X Dynamic Dumsor, 0-3 mths					-35.56
					(33.61)
Protected X Dynamic Dumsor, 3-6 mths					-24.84**
					(11.45)
Protected X Dynamic Dumsor, 6-9 mths					-15.43
					(15.59)
Protected X Dynamic Dumsor, 9-12 mths					-37.77***
					(12.65)
Protected X Dynamic Dumsor, 12-15 mths					-47.64**
					(19.80)
Observations	122650	122650	122650	122650	122650
Meter and Quarter FE	Y	Y	Y	Y	Y
Lead, 3 months	N	Y	N	N	N
Distict X Quarter FE	N	N	Y	N	N
Block Linear Time Trends	N	N	N	Y	N

Standard errors are in parentheses and are clustered at the feeder level.
*p<0.10, **p<0.05, ***p<0.01

Table 3: **Effect of Dumsor on Unpaid Balance, Robustness to Sample**

Dependent Variable: Household Account Balance									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Protected X Dumsor	-32.25**	-27.55***	-47.20	-42.04***	-29.94***	-32.12***	-32.70***	-32.82**	-33.68**
	(12.40)	(6.163)	(21.68)	(8.429)	(9.31)	(10.35)	(10.38)	(12.90)	(13.15)
Observations	122,650	335,670	46,940	198,890	164,050	126,340	125,010	117,520	110,550
Meter & Quarter FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
All Districts	N	Y	N	N	N	N	N	N	N
Restricted Districts	Y	N	Y	Y	Y	Y	Y	Y	Y
Restricted Blocks	N	N	Y	N	N	N	N	N	N
kWh Less Than	1500	1500	1500	ALL	1500	2500	2000	1000	750
Negative kWh Incl	N	N	N	Y	Y	N	N	N	N

Standard errors are in parentheses and are clustered at the feeder level.
*p<0.10, **p<0.05, ***p<0.01