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The Impact of Smart Prepaid Metering on Non-Technical Losses in Ghana

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Abstract: The high incidence of electricity theft, meter tampering, meter bypassing, reading errors, and defective and aged meters, among others, increases utility losses, especially non-technical losses (NTL). A utility in Ghana piloted a non-technical loss reduction program in 2019 to replace postpaid meters with anti-tamper, anti-fraud, and anti-theft smart prepaid meters. By using customer-level residential billing panel data from 2018 to 2019 obtained from the utility, we assess the effectiveness of this program using the difference-in-differences fixed-effect approach. On average, the results indicated that the reported amount of customers' monthly electricity consumption increases by 13.2% when any tampered postpaid meter is replaced with a smart prepaid meter, indicating the NTLs by customers. We further employed quantile difference-in-differences regression and observed that reported energy consumption has increased for all households except those at the lower quantile (25th quantile). We conclude that smart prepaid metering could be a remedy to reduce NTLs for the electricity distribution sector in areas where electricity theft is rampant.

Keywords: smart meters; electricity theft; non-technical losses; difference-in-differences; quantile regression

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1. Introduction

Access to a reliable and adequate supply of electricity is central to the achievement of socioeconomic and environmental development in any country [1,2]. The growth of different sectors of an economy is highly dependent on the development of the electricity sector. The quality of life and poverty of the citizenry are all linked to the vibrancy of the electricity sector.

Over the years, the Government of Ghana (GoG) has shown considerable commitment to providing adequate electricity to its citizenry through the National Electrification Scheme (NES), Self-Help Electrification Project (SHEP), Ghana Energy Development and Access Project (GEDAP), and some decentralized renewable power projects [3,4].

Despite the tremendous contribution of electricity to the country's total gross domestic product (GDP), it is evident that Ghana faces some major serious challenges in the electricity sector, such as high losses and power reliability. Not only in Ghana, globally, power utilities are faced with issues of losses, and several efforts are being made to reduce them, as they have serious cost implications [5]. The losses affect the finances of the utilities such that the utilities are unable to raise the needed funds to invest in logistics for their operations, conduct maintenance, or invest in new projects that can help power reliability [6,7]. Losses lead to electricity shortages and unreliable power supply that affect businesses, firms, agricultural enterprises, unemployment, health systems, transportation systems, and the economy [8–10].

The losses are of two types: (1) technical losses and (2) non-technical losses (NTL) or commercial losses. Technical losses are inherent in electrical equipment, and they are associated with heat dissipation as current passes through them to reach the customer. Improvements in equipment and power system design can reduce these losses, although this requires a substantial amount of capital [11]. Electricity theft, meter tampering, incorrect meter reading, defects, and aged meters cause NTLs [12,13].

NTLs have severe effects on generation capacity, as the situation requires generation to meet the growing demand for legitimate and illegal consumers. NTLs overload generating plants and make the planning of supplying reliable power very challenging. To ensure a reliable power supply at all times, NTLs must be taken into account, and studies have shown that NTLs constitute approximately 10–50% of the total generation capacity, especially in developing countries [14–16]. Other authors in their studies have shared similar concerns in many countries, such as India [17], Nepal [18], Nigeria [19], Ghana [20], Uganda [21], Kenya [22], and Tanzania [23].

This study focuses on NTL in the distribution sector, since the economic viability of the whole electricity sector hinges on distribution [24]. The distribution sector, especially in Africa, is bedeviled with high NTL caused mostly by electricity theft, meter bypassing, meter tampering, defective and aged meters, incorrect meter readings, deliberate submission of false meter readings (sometimes by utility meter readers), precise measurement of consumption for flat-rate customers (unmetered customers), and customers connected but not yet receiving bills.

Electricity theft constitutes nearly 80% of non-technical losses [25]. Electricity theft simply means defrauding or stealing electricity from a utility. It can also be defined as when a consumer illegally obtains services without the supplier's required agreement or contract [16,20]. It is an unlawful way of obtaining energy for various uses without being measured for billing, resulting in losses to utility companies. The essence of such theft is to avoid paying for the electricity used, and as long as power is required for essential services, people may indulge in these illegal practices [14,16,26,27].

Rajwanshi [27] asserts that the act necessitates changing the metering of electric energy, which has the potential to alter the metering voltage, current, and power factor. The most common ways of stealing electricity found in the literature are directly tapping electricity from a distribution line, grounding the neutral wire, tampering with meters, and interchanging the input–output connection terminals of the meter. Inserting a disc to stop the meter coil from rotating, injecting foreign materials and drilling holes into electromechanical energy meters, depositing a highly viscous fluid, and inserting film are also methods of perpetrating electricity theft. Other ways include resetting energy meter readings, using strong neodymium magnets, damaging the pressure coil of the meter, and improperly exposing the meter to mechanical shock [14,16,26,27].

Notably, in addition to the development of state-of-the-art technology, electricity theft is a widespread global phenomenon. Studies performed on a sample of 102 countries around the world between 1980 and 2000 suggest that electricity theft is on the rise worldwide [20], with dire consequences for the economy of any country where it is committed. It is estimated that approximately $58.7 billion in revenue is lost because of electricity theft annually by power utilities among the top 50 emerging market countries [28]. Saikiran and Hariharan [29] assert that, globally, $20 billion is lost every day because of electricity theft, and electricity theft causes annual economic losses of approximately $4 to $6 billion in the USA [25,30,31]. Additionally, in the UK, an estimated £173 million is lost annually because of electricity cheating [17,32]. This problem is even worse in developing countries. For example, India loses $12 billion annually through electricity theft [29], and a study conducted by the World Bank indicated that India's GDP has decreased by 1.5% as a consequence of electricity theft [33].

Similarly, Ghana continues to struggle with high reported cases of electricity theft and other illegal activities, leading to approximately 30% loss of electricity supplied by the utilities [34]. Nunoo and Attachie [20] argued that Ghana's utilities lose over $1 billion because of electricity theft. Electricity theft is the fundamental cause of the financial crisis facing distribution companies in Ghana, and the high rate of electricity theft is worrisome and needs to be curbed. It is noted that the high NTL is commonly associated with customers using a postpaid metering system [35].

Detecting electricity theft involves conducting regular on-site visual inspections to identify illegal meter connections. Doing so is a very tedious exercise and is very expensive for utilities. Most residential consumers indulge in unlawful connections at night when utility workers are not working. Another method of checking electricity theft involves studying a consumer's consumption patterns to identify very low or zero energy recordings and then following up at the consumer's premises to ascertain what the cause may be. These approaches and many others used to detect electricity theft are cumbersome, and the expected gains or results are unsatisfactory.

In response, to address this problem, the Northern Electricity Distribution Company (NEDCo) implemented an NTL reduction program in 2019, which sought to replace postpaid meters with anti-tamper, anti-fraud, and anti-theft smart prepaid meters. The purpose of the implementation of smart prepaid meters is to curb electricity theft and retrieve lost energy.

In recent years, smart metering has gained popularity in the energy sector, especially in electricity and gas, as it eliminates NTLs by inhibiting customers' cheating behaviors that are common with conventional meters. Often, the introduction of smart metering aims to change customers' consumption behavior toward energy saving [36–41]. For example, Qui et al. [42] employed the matching approach and a difference-in-differences method to estimate the impact of a prepaid electricity plan with smart metering on residential electricity consumption in metropolitan Phoenix in the USA. They recorded a 12% reduction in electricity usage upon switching to a prepaid program. Jack and Smith [43] examined the effect of prepaid metering on residential consumption and returns to the electricity utility in South Africa. The study employed the fixed-effect strategy and concluded that electricity usage fell by 13% as a result of the switch from postpaid to prepaid. Similarly, Bager and Mundaca [44] examined the relationship between loss aversion and consumer behavior in a nonprice policy intervention through smart meter technology in Copenhagen, Denmark. The study also used the difference-in-differences strategy. The results suggest that the control group reduced their daily consumption by an average of 7%, while the treatment group reduced their daily consumption by an average of 18%.

Conversely, in developing countries where electricity cheating is common, the introduction of this technology tends to benefit utilities through electricity theft management rather than energy saving management. These suggest that any increase in the reported amount of electricity consumption from smart metering constitutes (the lower bound of) the reduced NTLs. We review some of the literature to elaborate on this point. Several studies have highlighted the use of smart meters or prepaid meters as a major option to curb electricity theft [45–49]. However, such studies failed to use a causal inference approach to estimate the quantity of electricity that could be retrieved or recovered using smart meters. There is a lack of empirical studies that quantitatively estimate the causal impact of smart meter programs on NTLs, of which electricity theft constitutes approximately 80%. Thus, our paper makes the methodological contribution to the existing body of knowledge in the literature by applying the difference-in-differences with fixed effects to evaluate the impact of smart prepaid metering on NTL.

In this paper, we try to investigate the impact of smart prepaid metering on NTL in Ghana. It focuses on 1666 residential customers in NEDCo. We used their monthly electricity consumption reports for 24 months (from 2018 to 2019) for the study. A total of 46.3% of these residential customers were switched to smart prepaid meters in 2019 and were compared with the remaining 53.7% of residential customers who continued using postpaid meters. Compared to the existing research in this area, this study is novel and contributes to two aspects. Firstly, to the best of our knowledge, the paper is the first causal-inference study of smart meters' impact on non-technical losses, controlling both the other macro shocks and unit-intrinsic heterogeneities by using a difference-in-differences approach. Secondly, we employ quantile DID regression to estimate the impact at the various customer categories, such as low-demand and high-demand customers, to give a policy direction for the utility. The study analyzes the heterogeneous effects of electricity theft for various customer categories. It provides policy directions to utilities and the government about customer behavior regarding electricity cheating and measures to adopt to resolve these problems. Finally, it provides vital policy significance for utility companies and energy policies.

However, there are a number of limitations to our research. As the installers installed the smart meters "as if" random, a notable limitation of our research stems from the strong assumption of unconfoundedness of our treatment assignment that is not perfectly random, as indicated by the balance test. In addition, the limitation of this paper is a lack of demographic and other characteristics data on the customers. Unfortunately, the utility did not have this information. We could not control for other variables, and further research is needed to examine its impact on the treatment effect. Finally, further research is needed to verify the validity of our result by comparing it to a direct measure of non-technical losses that are possibly observed through capturing the daily consumption of customers using advance nonintrusive load monitoring (NILM) devices.

The remainder of this paper is organized as follows. Section 2 gives a brief background on the smart prepaid metering program. Section 3 lays out the discussion of our data and identification strategies. Section 4 presents the estimation results and discussion. Finally, Section 5 concludes.

2. Smart Prepaid Metering Program in Berekum

In this study, we intend to evaluate a smart meter program that has been piloted by a power utility to curb NTL. NTL has both economic and environmental implications that need immediate attention [49]. We proposed the flowchart in Figure 1 to arrive at the results. Details of the flowchart are explained in this and the remaining sections.

The study area was Berekum. Berekum is the capital of the Berekum Municipality located in the Bono Region. It is located 32 km and 43 km northwest of Sunyani, the regional capital, and Accra, the national capital, respectively. Its latitude is between 7′15″ S and 8.00′ N, and its longitude is between 2′25″ E and 2′50″ W. Berekum covers approximately 1635 km^2 (i.e., 0.7%) of the 233,588 km^2 total landmass of Ghana (https://web.archive.org/web/20120622101800/, http://berekum.ghanadistricts.gov.gh, accessed on 12 March 2021).

In 2013, Berekum had a population of 62,364 ("World Gazetteer online". World-gazetteer.com, accessed on 12 March 2021). The average household size in the municipality is four (4) persons per household. In the 15–65 age group, 67.3% are economically active, while 32.8% are economically inactive [50]. A small proportion of the economically active population, 7.7%, consists of unemployed or underemployed individuals, students, and homemakers, while 92.3% of the economically active population is employed [50]. Notably, 63.3% of the economically active population is self-employed without employees. The nature of the employment is skilled agricultural forestry and fishery (43.7%), services (22.4%), and craft and related trade (18.8%) [50]. Compared to the regional averages, access to essential services and facilities is encouraging (https://web.archive.org/web/20140303162353/, http://berekum.ghanadistricts.gov.gh/?arrow=atd&_=34&sa=4855, accessed on 12 March 2021).

Power is distributed to the municipality by NEDCo. NEDCo serves the municipality with 34.5 kV (kilovolt) and 11.5 kV, and the majority of the people in the municipality have access to grid-based electricity. Ghana Statistical Services (GSS) [50] asserts that the rate of access to electricity in the municipality is 78.1%, with urban Berekum having an access rate of 84.0%. The utility has a district office in Berekum with staff to handle both technical and commercial activities.

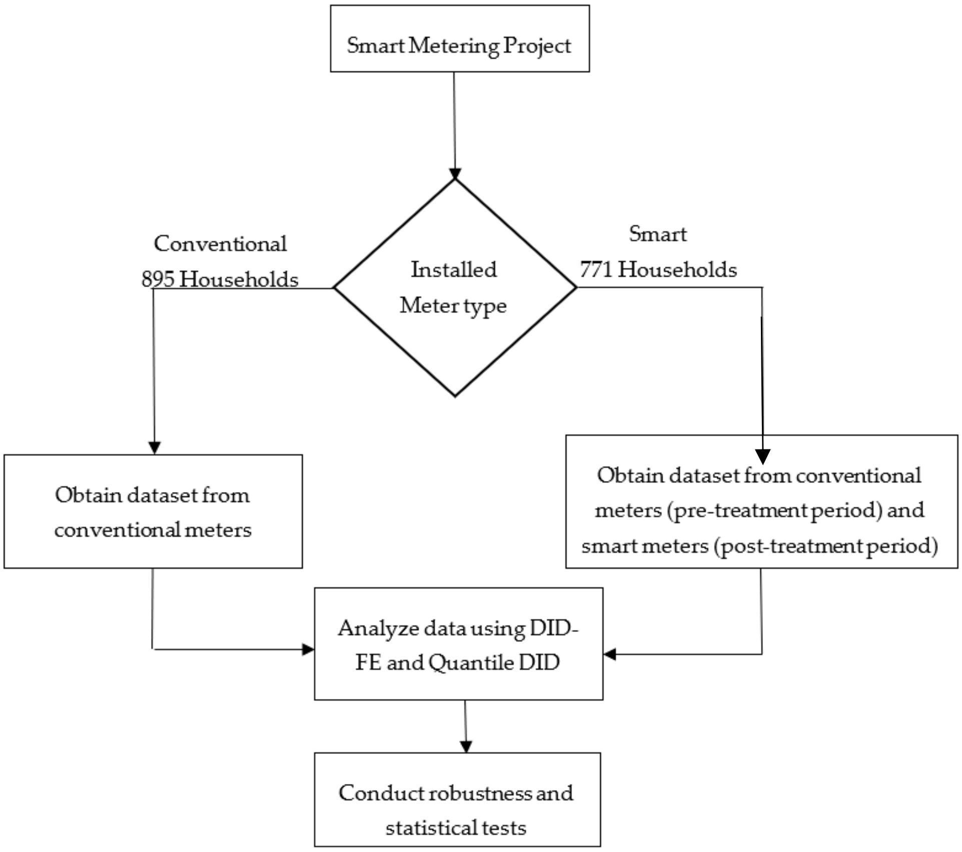

Figure 1. Flowchart diagram.

Most of the customers in NEDCo, especially at the municipal and district levels, including Berekum, use the postpaid metering system (conventional metering system). With postpaid metering, an energy meter is installed at the customer's premises, and at the end of every month, the customer's meter is read by the utility's meter reader to capture energy consumption. The recorded reading is used to generate an electricity bill for the customer [35].

This kind of metering system has some challenges, such as reading errors, accumulated bills, and delays in bill payments [35]. Additionally, the location of the postpaid meters at the customers' premises allows the customers to tamper with the meter and steal power. In 2018, the rates of electricity theft, meter bypassing and meter tampering were alarming, informing the decision of the utility to switch to the smart prepaid metering system [51].

Smart prepaid metering is convenient for both the utility and the customer. The utility is able to generate revenue in advance, as customers are supposed to purchase units, i.e., kilowatt-hour (kWh), before use. Thus, it eliminates the issues of late electricity bill payment and nonpayment by defaulting customers. The burden of hired meter readers for meter reading and sending customer bills are eliminated with the use of smart prepaid meters [35]. For the customer, it helps in planning electricity consumption, as he receives a daily notification of his energy consumption. Per the meter design, it gives notification of when the units (kWh) will be exhausted to enable the customer to plan ahead [52–54].

The utility introduced the smart prepaid metering program in May 2019 after a customer education process. The utility purchased a limited quantity to pilot because of the cost of the smart prepaid meter. The first batch of approximately 1000 smart prepaid meters was installed in Berekum "as-if" randomly on top of the service pole. The smart prepaid meters were initially loaded with 10 kWh units to ensure supply continuity even if the customers were not at home, but these units (kWh) were deducted at the instant of customer first purchase. The decision to install the meter on the pole top was made to prevent the customer from obtaining access to the meter. The customer only has access to the meter keypad, where he can key his units (kWh) in the event that the meter is not loaded automatically from the vending point.

The meter is the sole property of the utility in Ghana. It is not sold to the customer whenever the customer request for service. The service is in the form of a new service connection, temporal connection, separate meter connection, and meter transfer connection. The utility delivers these services with the type of meter available at the instant of customer service request and within the permitted time stipulated by the Public Utility Regulatory Commission of Ghana (PURC). The cost of the meter replacement is borne by the utility. The intent of the smart prepaid meter pilot program by the utility was to derive the usefulness and the benefit that comes with the smart prepaid meter technology for both the customer and the utility.

The utility further hoped to expand the program if the objectives are met. It is against that background that only a subset of customers were provided with the smart meters, primarily due to their costs. The utility generated a list of customers capturing all the various customer categories in the program area. The list of customers generated for the meter installation was more than the smart prepaid meters available. It was given to meter installers to install the meters "as-if" randomly at the program location provided the customer's information is found in the list.

3. Data and Empirical Strategy

3.1. Data Description

We obtained a panel dataset of customers' monthly electricity consumption from 2018 to 2019 that are reported and recorded by NEDCo. It comprises a 24-month electricity bill for each customer. Control group and pre-treatment treatment group data are only monthly, available from the utility's customer billing management system (CBMS), while the post-treatment treatment group data were obtained from the smart prepaid vending system. A smart prepaid vending system provides daily data; however, since the control group (and pre-treatment treatment group) data are only monthly, our unit of observation is bounded to be monthly.

Our dataset contains a total of 39,982 monthly customer observations followed over 24 months (i.e., 1666 customers for 24 months), consisting of 18,502 observations for 771 customers who have been switched to the smart prepaid metering system (treatment group) and 21,480 observations for 895 customers who are still using the postpaid metering system (control group).

In Ghana, customers fall under three tariff categories, namely, residential, nonresidential and special load tariffs (SLTs). Domestic users are classified as residential customers, while commercial users whose energy consumption falls below 100 KVA (kilovolt-amperes) are classified as nonresidential customers, and commercial users whose energy consumption is equal to or greater than 100 KVA are classified as SLT customers [55–57]. Our study focused on residential customers, so we excluded nonresidential and special load tariff (SLT) customers. Details of the summary statistics of our data are reported in Table 1.

The selection of the municipality was not informed by any major decision by the utility; however, customer education on the introduction of the smart prepaid metering system commenced earlier in that municipality. The households whose meters to be replaced were randomly chosen by the meter installers; however, since it is not purely randomized, we will conduct a series of robustness checks.

Table 1. Summary statistics.

Dependent Variable	N. Obs.	Mean	s.d.	Min	Max
Electricity Consumption (kWh/month)					
Total Sample	39,982	89.576	86.984	0	1674
Control	21,480	88.511	91.331	0	1674
Treated	18,502	90.813	81.634	0	1319
Before	26,654	86.595	87.153	0	1674
After	13,328	95.539	86.342	0	1046

Notes: The data are from a 24-month (2-year) panel consisting of 1666 residential customers. The months January 2018 to April 2019 are before the program (customers on postpaid metering), and the months May 2019 to December 2019 are after the program was introduced (smart prepaid metering). The energy retrieved (consumption) is a dummy variable that takes a value of one for residential customers who had their postpaid meter replaced with a smart prepaid meter and zero otherwise.

3.2. Identification Strategies

Smart prepaid metering is more expensive for the utility to acquire compared to postpaid metering. The utility introduced smart prepaid metering as a pilot in the Berekum municipality to reduce NTL. Our main objective is to evaluate the causal effect of smart prepaid metering on NTL. We used two methods for this study. The first method aims to establish an average treatment effect, and the second method aims to know the exact impact for the various customer categories—namely, low- and high-demand customers.

3.2.1. Difference-in-Differences with Fixed Effects (DID-FE)

First, we employed the difference-in-differences with fixed effect (DID-FE) approach to investigate the potential causal effect of smart prepaid metering on NTL. By doing so, any time-invariant confounders that may have occurred due to the nonrandomness of the program implementation would be captured [58]. Specifically, we define two dummy variables, Policy and Treated. The variable Policy indicates the month-year (post-May 2019) when the program was implemented, and the variable Treated indicates those residential customers whose postpaid meters have been replaced with smart prepaid meters as follows:

$$Policy = \begin{cases} = 0 \; before\ program\ (Jan\ 2018 - Apr\ 2019) \\ = 1 \; after\ program\ (May\ 2019 - Dec\ 2019) \end{cases} \tag{1}$$

$$Treated = \begin{cases} = 0 \; residential\ customers\ on\ postpaid\ meters \\ = 1 \; residential\ customers\ on\ smart\ prepaid\ meters \end{cases}. \tag{2}$$

The standard DID model estimates the pooled ordinary least squares (OLS) [59] as follows:

$$Consumption_{it} = \beta_0 + \beta_1\, Treated_i + \beta_2\, Policy_t + \delta_1\, Treated_i * Policy_t + u_{it} \tag{3}$$

where $Consumption_{it}$ is the outcome that captures the reported energy consumption amount of customer i in month-year t; Treated is the treatment dummy; Policy is the two periods (i.e., month-year) dummy, and u_{it} is the error term. The coefficient β_1 captures the difference in energy consumption between the control and treatment groups in period one (2018), the coefficient β_2 captures the temporal change in energy consumption for the control group, and the coefficient δ_1 is the interaction that captures the effect of the treatment, that is, how the treatment group changed in period two (post-May 2019) compared to the control group.

To accommodate any heterogeneity across units and time, we add unit and time fixed effects to the above standard DID. That is, we include fixed effects a_i and v_t using the within regression estimator. The fixed effect (a_i) captures any omitted variable that is constant or relatively constant over time. Thus, all time-invariant terms in the treatment ($Treated_i$) are dropped by this time-invariant unobserved heterogeneity term [53]. Similarly, $Policy_t$ must be replaced by time-fixed effects. Therefore, our model (Equation (3)) is reduced to the following explanatory variables:

$$Consumption_{it} = \delta_1 \, Treated_i * Policy_t + a_i + v_t + u_{it} \quad (4)$$

where v_t is the time (month-year) fixed effect.

3.2.2. Quantile Difference-in-Differences

The DID-FE approach estimates the average treatment effect across the various customer categories in terms of electricity demand. In this study, we further want to establish which of the various customer categories engage in more profound electricity cheating: would more cheating be found among low electricity-consuming customers (low-demand customers), median electricity-consuming customers (middle-demand customers), or high electricity-consuming customers (high-demand customers)? To answer this question, we employed our second method, which is quantile regression or quantile difference-in-differences. Scholars [60–64] have argued that quantile regression explains the conditional quantiles of the outcome variable in relation to covariates against modeling the mean. In support of this argument, we used quantile difference-in-differences to identify the customer category where energy is lost the most. Consider y to be the outcome of interest and x are vectors of observed covariates. In our case, it becomes as follows:

$$Q_q(y_i) = \beta_0\,(q) + \beta_1\,(q)\; Treated_i + \beta_2\,(q)\; Policy_t + \delta_1\,(q)\; Treated_i * Policy_t + u_{it} \quad (5)$$

where $Q_q(y_i)$ is the q^{th} quantile of the electricity consumption and $\delta_1\,(q)$ is the treatment effect of the customer at the q^{th} quantile, while $\beta_i(q)$ for i = 0, 1, 2 are parameters for the other covariates for the customer at the q^{th} quantile.

4. Results and Discussion

4.1. Results of DID Fixed Effects

The impact of the smart prepaid metering program on monthly energy consumption was estimated using the DID-FE model. Table 2 shows that on average, 12.656 kWh more energy consumption per month is now reported by smart metering, which is significant at a 1% level. Compared with the mean pre-treatment energy usage level of 95.539 kWh for treatment customers, this increase in electricity demand is equivalent to retrieving approximately 13.2% of electricity losses. It is straightforward to interpret this as the recovered NTL, as cheating is now more difficult after smart meters are installed.

Table 2. Average treatment effect on the energy consumption (kWh/month).

Dependent Variable:	**(1)**
Electricity consumption (kWh/month)	DID-FE
Treatment Effect:	12.656 ***
	(2.372)
Household fixed effectsTime fixed effects	YesYes
Observations	39,982
Number of households	1666
R-squared	0.025

Robust standard errors are in parentheses. Statistical significance at 1% is indicated as ***. The model uses the entire sample size of 24 months: January 2018 to December 2019.

Robustness Checks

We conducted the following robustness checks to confirm the superiority of our chosen model. They are as follows:

(a) Statistical tests to confirm common trend assumption

Figure 2 depicts the average electricity consumption pattern i.e., the electricity consumption in kWh/month of the residential customers in Berekum municipality for both the control and treatment groups.

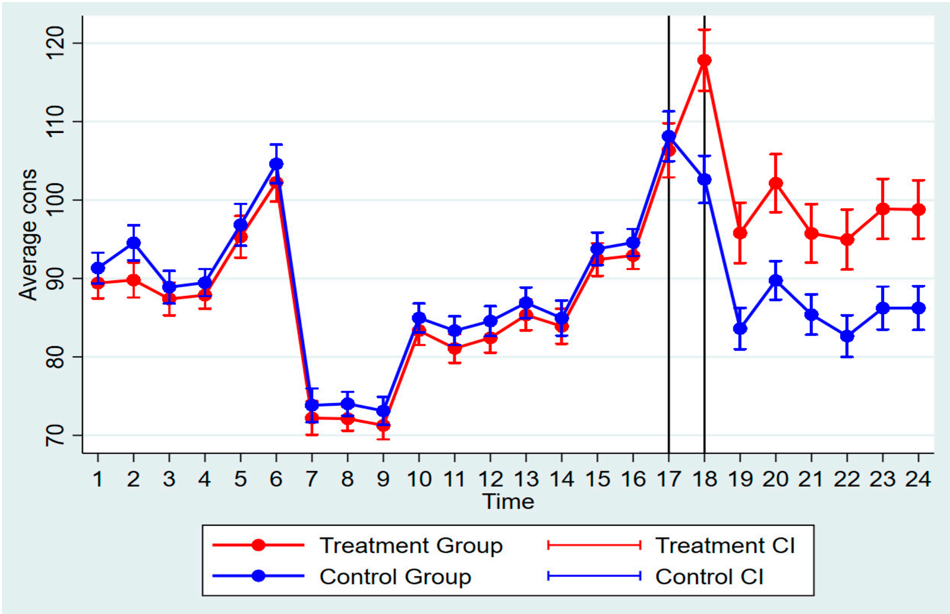

Figure 2. Average consumption pattern (kWh/month) for both the treatment and control groups.

The consumption pattern of the residential customers in Berekum was affected by seasonality and a project that Ghana Grid Company (GRIDCo) and NEDCo were embarking upon during the smart prepaid metering program. There are two main weather seasons in the Berekum municipality: hot and cool. The hot season mainly starts in January and ends in March, while the cool season starts at the end of June and ends in September. During the same period of the program, the major power transmitter (GRIDCo) and the power distributor in the northern part of Ghana (NEDCo) constructed a bulk power supply point (BSP) and 161 kV line from Sunyani to Berekum. The construction of this project resulted in some planned outages and may have affected customers' consumption patterns, as depicted in Figure 2. However, we observed that the planned outages affected the control and treatment groups equally and at the same time, since they are all on the same feeder and in the same community. Indeed, Figure 2 shows that the unobserved factors that have affected the control group have also equally affected the treatment group, since these two groups share a common trend over time before treatment. This presence of the parallel trend in the consumption pattern of residential customers suggests the robustness of DID as the identification strategy.

We further conducted a robustness test on pre-trends to ascertain the validity of our identification [65–67]. Using the DID-FE model, we checked whether the coefficients were statistically significant when we perturb the treatment timing to other time points. The coefficients of these falsification tests for the placebo treatment timing starting from February 2018 up to May 2019 were not statistically significant, indicating that there were no heterogeneous trends in the pre-treatment period and that the parallel trend assumption was satisfied. However, the coefficients of the post-trends for the interaction terms from June 2019 to December 2019 were statistically significant, indicating the causal effect of the smart prepaid metering program. This is shown in an event study plot of the average treatment effects of the coefficient estimates and their confidence intervals for the interaction terms in Figure A1 of Appendix A.

(b) Simple comparison of post-treatment values between treatment and control groups

Based on the “as if” randomness of the smart meter installations performed by the installers, we conducted a naive comparison between treatment and control, i.e., those installed with smart meters and those who stay with the conventional meters. We first conduct a two-sample test to evaluate whether there are statistically significant differences between the control and treatment groups in their post-test electricity consumption. Table 3 presents the results that show that the p-value is significant at the 1% level, and this is an indication that the treatment and control customers had statistically significant differences in their electricity usage after the treatment customers switched to smart meters.

Table 3. After treatment comparison between the groups.

	Treatment		Control					
Dependent Variable	**Obs.**	**Mean**	**Obs.**	**Mean**	**Diff**	**S.E**	**t_Value**	**p_Value**
Electricity consumption (kWh/month)	6168	101.305	7160	90.571	10.734	1.497	−7.15	0.000 ***

Robust standard errors in parentheses *** $p < 0.01$.

(c) Balance Test

To ascertain the validity of the above results, a simple comparison of the electricity consumption values for customers in the control and treatment groups before implementing the program is conducted, and the results are presented in Table 4. The result indicates possible unbalancing with weak (10%) statistical significance, implying that the smart meter installations were not perfectly random, which therefore justifies the use of DID to eliminate potential time-invariant confounders.

Table 4. Baseline comparison between the groups.

	Treatment		Control					
Dependent Variable	**Obs.**	**Mean**	**Obs.**	**Mean**	**Diff**	**S.E**	**t_Value**	**p_Value**
Electricity consumption (kWh/month)	12,334	85.567	14,320	87.481	−1.914	1.071	1.8	0.074 *

Robust standard errors in parentheses * $p < 0.1$.

4.2. Results of the Quantile DID Regression

This study further aims to understand the conditional quantiles of the recovered NTLs for different customer categories rather than only obtaining the average impact of smart metering. Figure 3 shows the density distribution of the monthly electricity consumption of the households treated by the smart prepaid metering program. We separated the treatment group data into two time periods: before and after the implementation of the smart prepaid program. Figure 3 shows that the number of customers with zero (or very small) electricity consumption (the bar on the far left in each panel) sharply dropped after the smart prepaid metering program was implemented. This also indicates that cheating, such as meter bypassing, is now difficult after the smart meter is installed, at least for these low-demand customers. Thus, we give a closer look at the heterogeneous impact of smart metering on the households with different demand intensity in this section.

To this end, the results from the quantile DID regression are presented in Table 5. As a referencing benchmark, column 1 shows the average treatment effect (ATE) estimated by using the entire sample, which tells that the recovered energy is 12.648 kWh/month at 1% significance.

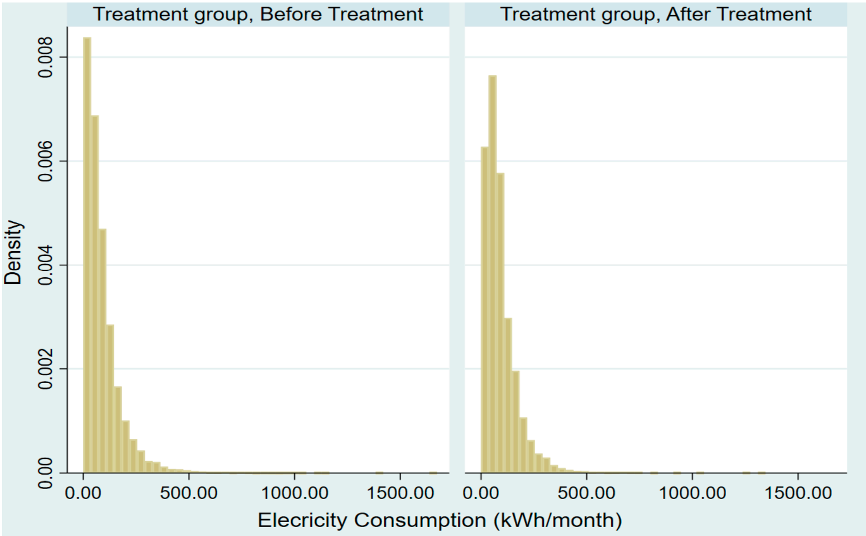

Figure 3. Histogram of electricity consumption by month of the treatment, before and after the treatment.

Table 5. Quantile difference-in-differences (DID) regression results.

Dependent Variable: Electricity Consumption	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(kWh/month)	ATE	q10	q25	q50	q75	q90
Treatment Effect	12.648 ***	4.370 ***	−1.810	6.650 ***	20.600 ***	27.900 ***
	(2.372)	(1.075)	(1.601)	(1.675)	(2.804)	(5.385)
Observations	39,982	39,982	39,982	39,982	39,982	39,982
R-squared	0.004	0.002	0.006	0.006	0.004	0.003

ATE stands for the average treatment effect. Robust standard errors in parentheses; *** $p < 0.01$.

For instance, the quantile DID result in column 3 shows that at the 25th quantile, the treatment effect is −1.810 kWh/month and not significant. Therefore, one would make a poor decision if it is based on the overall estimation only. The results of the coefficients for the 10th quantile (column 2) and 50th quantile (column 4) are 4.37 kWh/month and 6.65 kWh/month, respectively, at 1% significance; however, a comparison with the overall result (column 1) shows that the latter is overestimated for these categories of customers. Similarly, comparing the results of the coefficient for the recovered energy in the overall ATE (column 1) indicates that the ATE is underestimating for residential customers at the 75th quantile (column 5) and 90th quantile (column 6): 20.60 kWh/month and 27.90 kWh/month, respectively.

Figure 4 provides the treatment effect of smart metering by the demand intensity of the consumers. Horizontal dotted lines are the average treatment effect and its confidence intervals. From the figure, it is clear that the recovered NTL is different across the quantiles. Additionally, in the quantile DID, it was observed that the treatment effect decreases from the lowest to lower quantiles (10th to 25th quantiles) and increases at higher quantiles (toward the 90th quantile) with opposite signs across the quantile. This indicates that only those households around the 25th quantile (i.e., the 1st quartile) did not conduct the cheating, or they are the only honest customers. That is, electricity theft was rampant in most of the customer categories in Ghana.

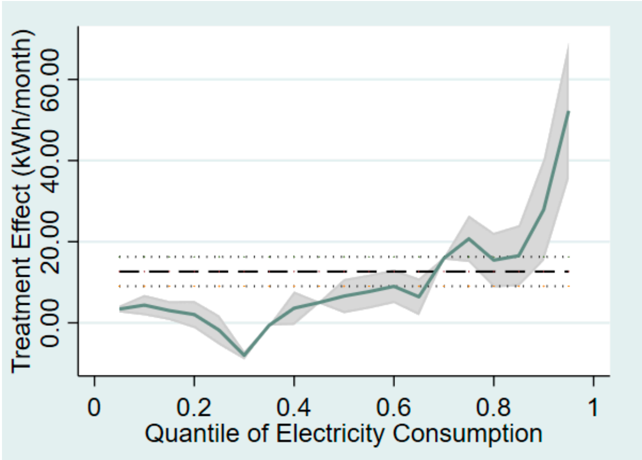

Figure 4. Treatment effect by the quantile of the monthly electricity consumption measured in kWh/month.

5. Conclusions

To address the utility losses arising from electricity theft, meter tampering, and other cheating behaviors of the customers, Northern Electricity Distribution Company (NEDCo), a utility in Ghana, piloted a non-technical loss (NTL) reduction program in 2019 to replace postpaid meters with anti-tamper, anti-fraud, and anti-theft smart prepaid meters. This paper assessed the effectiveness of this program using the difference-in-differences fixed-effect (DID-FE) approach. Through the DID-FE, we obtained an average causal impact across all residential customer categories of 12.656 kWh/month. This concludes that smart prepaid metering could be a remedy to reduce NTL for the electricity distribution sector in Ghana.

Policymakers need to be aware of the heterogeneity of customer consumption behavior to formulate policies. Consequently, to fully establish where cheating or energy recovery is more profound in the residential customer categories and to propose a policy direction, we also conducted a quantile regression coupled with DID. The results of our study showed that the energy loss is more profound with very low-demand customers and medium- and high-demand customers. These results provide insightful policy implications for utilities. The smart prepaid metering policy for NTL reduction should focus on those high-demand customers (75th quantile and 90th quantile) from whom it can retrieve the most lost energy before installing for other customers. On the other hand, the very low-demand customers (10th quantile) are prone to cheating, suggesting that they are unable to afford the little electricity they consume. The government of Ghana should consider tariff reforms other than life-line customer subsidies (set by the Public Utility Regulatory Commission of Ghana at 50 kWh/month) to address their needs.

However, there are a number of limitations to our research. As the installers installed the smart meters only "as if" randomly, a notable limitation of our research stems from the strong assumption of unconfoundedness of our treatment assignment that is not necessarily perfectly done as indicated by the balance test. In addition, the limitation of this paper is the lack of demographic and other characteristics data on the customers. Unfortunately, the utility did not have this information. We could not control for other variables, and further research is needed to examine its heterogeneity on the treatment effect. Finally, further research is needed to verify the validity of our result by comparing it to direct measure of non-technical losses, which are possibly observed through capturing the daily consumption of customer using advance nonintrusive load monitoring (NILM) devices (see [68–70] for example).

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Data Availability Statement: Due to the sensitive nature of this study, we assured the utility that data provided would remain confidential and would not be shared.

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Abbreviations

ATE	Average Treatment Effect
BSP	Bulk Supply Point
CBMS	Customer Billing Management System
DID	Difference-in-Differences
DID-FE	Difference-in-Differences with Fixed Effects
FE	Fixed Effects
GEDAP	Ghana Energy Development and Access Project
GoG	Government of Ghana
GRIDCo	Ghana Grid Company
kV	kilovolt
KVA	kilovolt-amperes
kWh	kilowatt-hour
kWh/month	Electricity Consumption
NES	National Electrification Scheme
NILM	Non-Intrusive Load Monitoring
$NTL_{(s)}$	Non-Technical Losses
OLS	Ordinary Least Squares
PURC	Public Utility Regulatory Commission of Ghana
SHEP	Self Help Electrification Project
SLTs	Special Load Tariffs

Appendix A

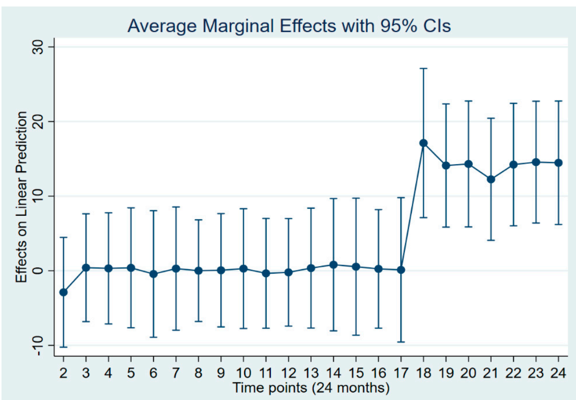

Figure A1. Average effects with 95% confidence intervals for the coefficients of placebo falsification tests, where the horizontal axis represents the time of placebo treatment, except for the 18th month which is the true treatment timing.

References

1. Otchere-Appiah, G.; Hagan, E.B. Potential for electricity generation from maize residues in rural Ghana: A case study of Brong Ahafo Region. *Int. J. Renew. Energy Technol. Res.* **2014**, *3*, 1–10. Available online: http://ijretr.org (accessed on 2 February 2021).
2. Balezentis, T.; Streimikiene, D.; Mikalauskas, I.; Shen, Z. Towards carbon free economy and electricity: The puzzle of energy costs, sustainability and security based on willingness to pay. *Energy* **2021**, *214*, 119081. [CrossRef]
3. Otchere-Appiah, G.; Hagan, E.B. Decentralized bioenergy generation: An option to extend access to electricity in remote areas and curb perennial power outages in Ghana. *Int. J. Dev. Sustain.* **2013**, *2*, 1513–1522.
4. Kumi, E.N. *The Electricity Situation in Ghana: Challenges and Opportunities*; CGD Policy Paper; Center for Global Development: Washington, DC, USA, 2017. Available online: https://www.cgdev.org/publication/electricity-situation-ghana-challenges-and-opportunities (accessed on 2 February 2021).
5. Siddharth, N.K.; Dhananjay, B.M. Commercial Loss Reduction Techniques in Distribution Sector—An Initiative by MSEDCL. International Journal of Advanced Research in Electrical. *Electron. Instrum. Eng.* **2014**, *3*, 1.
6. Amadi, H.N.; Okafor, E.N. The Effects of Technical and Non-Technical Losses on Power Outages in Nigeria. *Int. J. Sci. Eng. Res.* **2015**, *6*, 9.
7. Nguyen, T.C.; Bridle, R.; Wooders, P. A Financially Sustainable Power Sector: Developing Assessment Methodologies. *Int. Inst. Sustain. Dev.* **2014**. Available online: https://www.iisd.org/system/files/publications/financially_sustainable_power_sector.pdf (accessed on 4 February 2021).
8. Singh, T. Analysis of Non-Technical Losses and Its Economic Consequences of Power System—A Case Study of Punjab State. Master's Thesis, Thapar University, Patiala, India, 2009.
9. Jamil, F. On the electricity shortage, price and electricity theft nexus. *Energy Policy* **2013**, *54*, 267–272. [CrossRef]
10. World Bank, Electric Power Transmission and Distribution Losses (% of Output), 2018. Available online: https://data.worldbank.org/indicator/EG.ELC.LOSS.ZS?end=2014&start=2009 (accessed on 4 September 2020).
11. World Bank. *Reducing Technical and Non-Technical Losses in the Power Sector. Background Paper for the World Bank Group Energy Sector Strategy*; World Bank: Washington, DC, USA, 2009.
12. Pless, J.; Bazilian, M.; Fell, H. Bribes, Bureaucra-cies, and Blackouts: Towards Understanding How Corruption Impacts the Quality of Electricity Supply to End-Users in Transition and Developing Economies. In Proceedings of the Energy & the Economy, 37th IAEE International Conference, New York, NY, USA, 15–18 June 2014.
13. Tallapragada, P.; Shkaratan, M.; Izaguirre, A.K.; Helleranta, J.; Rahman, S.; Bergman, S. *Monitoring Performance of Electric Utilities: Indicators and Benchmarking in Sub-Saharan Africa*; The World Bank: Washington, DC, USA, 2009.
14. Smith, T.B. Electricity theft: A comparative analysis. *Energy Policy* **2004**, *32*, 2067–2076. Available online: http://www.provedor.nuca.ie.ufrj.br/eletrobras/estudos/smith1.pdf (accessed on 2 February 2021). [CrossRef]
15. Antmann, P. Background Paper for the World Bank Group Energy Sector Strategy-Reducing Technical and Non-Technical Losses in the Power Sector, 2009. Available online: https://openknowledge.worldbank.org/bitstream/handle/10986/20786/926390WP0Box3800in0the0power0sector.pdf?sequence=1&isAllowed=y (accessed on 28 February 2021).
16. Depuru, S.S.S.; Wang, L.; Devabhaktuni, V. Electricity theft: Overview, issues, prevention and a smart meter based approach to control theft. *Energy Policy* **2011**, *39*, 1007–1015. [CrossRef]
17. Sharma, T.; Pandey, K.; Punia, D.; Rao, J. Of pilferers and poachers: Combating electricity theft in India. *Energy Res. Soc. Sci.* **2016**, *11*, 40–52. [CrossRef]
18. Sovacool, B.K.; Bambawale, M.J.; Gippner, O.; Dhakal, S. Electrification in the Mountain Kingdom: The implications of the Nepal Power Development Project (NPDP). *Energy Sustain. Dev.* **2011**, *15*, 254–265. [CrossRef]
19. Dike, D.O.; Obiora, U.A.; Nwokorie, E.C.; Dike, B.C. Minimizing household electricity theft in Nigeria using GSM based prepaid meter. *Am. J. Eng. Res.* **2015**, *4*, 59–69.
20. Nunoo, S.; Attachie, J. A methodology for the design of an electricity theft monitoring system. *J. Theor. Appl. Inf. Technol.* **2011**, *26*, 2. Available online: http://www.jatit.org/volumes/research-papers/Vol26No2/7Vol26No2.pdf (accessed on 26 February 2021).
21. Never, B. Behave and save? Behaviour, energy efficiency and performance of micro and small enterprises in Uganda. *Energy Res. Soc. Sci.* **2016**, *15*, 34–44. [CrossRef]
22. Enslev, L.; Mirsal, L.; Winthereik, B.R. Anticipatory infrastructural practices: The coming of electricity in rural Kenya. *Energy Res. Soc. Sci.* **2018**, *44*, 130–137. [CrossRef]
23. Winther, T. Electricity theft as a relational issue: A comparative look at Zanzibar, Tanzania, and the Sunderban Islands, India. *Energy Sustain. Dev.* **2012**, *16*, 111–119. [CrossRef]
24. Sabha, L. *Measures to Check Commercial Losses, a Twelfth Report on Standing Committee on Energy Presented to the Ministry of Power*; Ministry of Power: New Delhi, India, 2015.
25. McDaniel, P.; McLaughlin, S. Security and privacy challenges in the smart grid. *IEEE Secur. Priv.* **2009**, *7*, 75–77. [CrossRef]
26. Anas, M.; Javaid, N.; Mahmood, A.; Raza, S.M.; Qasim, U.; Khan, Z.A. Minimizing Electricity Theft Using Smart Meters in AMI. 2012. Available online: https://arxiv.org/pdf/1208.2321.pdf (accessed on 26 February 2021).
27. Rajwanshi, H. Power Theft Management. PL (EL) 77 November 2019. Available online: https://www.scconline.com/blog/post/2019/11/13/power-theft-management/ (accessed on 2 March 2021).
28. Northeast Group. *Emerging Markets Smart Grid: Outlook 2015*; LLC Northeast Group: Washington, DC, USA, 2014.
29. Saikiran, B.; Hariharan, R. Review of methods of power theft in Power System. *Int. J. Sci. Eng. Res.* **2014**, *5*, 276–280.

30. Yan, S.; Liu, X.; Jiang, Y.; Ma, L.; Wang, X.; Li, Z.; Lei, J.; Wang, C.; Dong, L.; Han, W. Analysis of Electricity Stealing and Research of Anti-stealing Measures. In Proceedings of the 3rd International Conference on Machinery, Materials and Information Technology Applications (ICMMITA, 2015), Qingdao, China, 28–29 November 2015.
31. Razavi, R.; Fleury, M. Socio-economic predictors of electricity theft in developing countries: An Indian case study. *Energy Sustain. Dev.* **2019**, *49*, 1–10. [CrossRef]
32. Siddall, W.; Bentley, J.; Spring, P. *Energy Theft: Incentives to Change*; IBM: London, UK, 2012.
33. Bhatia, B.; Gulati, M. *Reforming the Power Sector: Controlling Electricity Theft and Improving Revenue*; Public Policy for the Private Sector Note; World Bank: Washington, DC, USA, 2004; pp. 1–4. Available online: https://www.esmap.org/sites/esmap.org/files/DocumentLibrary/VP332-Electricity-Reforms.pdf (accessed on 26 February 2021).
34. Yakubu, O.; Babu, N.C.; Adjei, O. Electricity theft: Analysis of the underlying contributory factors in Ghana. *Energy Policy* **2018**, *123*, 611–618. [CrossRef]
35. Vanmore, S.V.; Avalekar, P.; Patil, I. Prepaid and Postpaid Energy Meter for Billing System Using Microcontroller and GSM. *Int. Res. J. Eng. Technol.* **2016**, *3*. Available online: https://www.irjet.net/archives/V3/i2/IRJET-V3I2213.pdf (accessed on 16 February 2021).
36. Sønderlund, A.L.; Smith, J.R.; Hutton, C.; Kapelan, Z. Using Smart Meters for Household Water Consumption Feedback: Knowns and Unknowns. In Proceedings of the 16th Conference on Water Distribution System Analysis, WDSA 2014, Bari, Italy, 14–17 July 2014; pp. 990–997.
37. Rausser, G.; Strielkowski, W.; Štreimikienė, D. Smart meters and household electricity consumption: A case study in Ireland. *Energy Environ.* **2018**, *29*, 131–146. [CrossRef]
38. Cook, B.; Gazzano, J.; Gunay, Z.; Hiller, L.; Mahajan, S.; Taskan, A.; Vilogorac, S. The smart meter and a smarter consumer: Quantifying the benefits of smart meter implementation in the United States. *Chem. Cent. J.* **2012**, *6*, S5. Available online: http://journal.chemistrycentral.com/content/6/S1/S5 (accessed on 20 February 2021). [CrossRef]
39. Martiskainen, M.; Ellis, J. *The Role of Smart Meters in Encouraging Behavioural Change—Prospects for the UK*; University of Sussex: Brighton, UK, 2009. Available online: http://sro.sussex.ac.uk/id/eprint/59518/1/smart_meters_-_martiskainen_and_ellis.pdf (accessed on 20 February 2021).
40. Department of Energy and Climate Change. *Smart Metering Early Learning Project: Consumer Survey and Qualitative Research*; 2015 DECC Technical Report; DECC: London, UK, 2015.
41. Arif, A.; Al-Hussain, M.; Al-Mutairi, N.; Al-Ammar, E.; Khan, Y.; Malik, N. Experimental study and design of smart energy meter for the smart grid. In Proceedings of the Renewable and Sustainable Energy Conference (IRSEC), Ouarzazate, Morocco, 7–9 March 2013; pp. 515–520.
42. Qiu, Y.; Xing, B.; Wang, Y.D. Prepaid electricity plan and electricity consumption behavior. *Contemp. Econ. Policy* **2016**, *35*, 125–142. [CrossRef]
43. Jack, B.K.; Smith, G. *Charging ahead Prepaid Electricity Metering in South Africa*; Working Paper, Reference Number: E-89201-ZAF-2; NBER: Cambridge, MA, USA, 2017.
44. Bager, S.; Mundaca, L. Making 'Smart Meters' smarter? Insights from a behavioural economics pilot field experiment in Copenhagen, Denmark. *Energy Res. Soc. Sci.* **2017**, *28*, 68–76. [CrossRef]
45. Mwaura, M.F. Adopting electricity prepayment billing system to reduce non-technical energy losses in Uganda: Lesson from Rwanda. *Util. Policy* **2012**, *23*, 72–79. [CrossRef]
46. Viegas, J.L.; Esteves, P.R.; Melício, R.; Mendes, V.; Vieira, S.M. Solutions for detection of non-technical losses in the electricity grid: A review. *Renew. Sustain. Energy Rev.* **2017**, *80*, 1256–1268. [CrossRef]
47. Rodríguez, R.G.; Mares, J.J.; Quintero, M.C.G. Computational Intelligent Approaches for Non-Technical Losses Management of Electricity. *Energies* **2020**, *13*, 2393. [CrossRef]
48. Gul, H.; Javaid, N.; Ullah, I.; Qamar, A.; Afzal, M.K.; Joshi, G.P. Detection of Non-Technical Losses Using SOSTLink and Bidirectional Gated Recurrent Unit to Secure Smart Meters. *Appl. Sci.* **2020**, *10*, 3151. [CrossRef]
49. Ghana Statistical Service GSS. 2010 Population and Housing Census. Berekum District Analytical Report (2014). Available online: https://new-ndpc-static1.s3.amazonaws.com/CACHES/PUBLICATIONS/2016/06/06/Berekum+Municipal+2010PHC.pdf (accessed on 28 February 2021).
50. Northern Electricity Distribution Company. *Northern Electricity Distribution Company Annual Report*; NEDCo: Tamale, Ghana, 2018; Unpublished.
51. Darby, S. Energy feedback in buildings: Improving the infrastructure for demand reduction. *Build. Res. Inf.* **2008**, *36*, 499–508. [CrossRef]
52. Carroll, J.; Lyons, S.; Denny, E. Reducing household electricity demand through smart metering: The role of improved information about energy saving. *Energy Econ.* **2014**, *45*, 234–243. [CrossRef]
53. Liu, A.; Giurco, D.; Mukheibir, P.; White, S. Detailed water-use feedback: A review and proposed framework for program implementation. *Util. Policy* **2016**, *43*, 140–150. [CrossRef]
54. Cook, B.L.; Manning, W.G. Thinking beyond the mean: A practical guide for using quantile regression methods for health services research. *Shanghai Arch. Psychiatry* **2013**, *25*, 55–59.
55. Yu, K.; Lu, Z.; Stander, J. Quantile regression: Applications and current research areas. *J. R. Stat. Soc. Ser. D* **2003**, *52*, 331–350. [CrossRef]

56. Lee, C.Y.; Lotsu, S.; Islam, M.; Yoshida, Y.; Kaneko, S. The Impact of an Energy Efficiency Improvement Policy on the Economic Performance of Electricity-Intensive Firms in Ghana. *Energies* **2019**, *12*, 3684. [CrossRef]
57. Torres-Reyna, O. *Panel Data Analysis Fixed and Random Effects Using Stata (v.4.2)*; Princeton University: Princeton, NJ, USA, 2007. Available online: http://dss.princeton.edu/training/ (accessed on 4 February 2021).
58. Wooldridge, J.M. *Econometric Analysis of Cross Section and Panel Data*; MIT Press: Cambridge, UK, 2010.
59. Wing, C.; Simon, K.; Bello-Gomez, R.A. Designing Difference in Difference Studies: Best Practices for Public Health Policy Research. *Annu. Rev. Public Health* **2018**, *39*, 453–469. [CrossRef]
60. Koenker, R.; Bassett, G. Regression Quantiles. *Econometrica* **1978**, *46*, 33. [CrossRef]
61. Koenker, R.; Hallock, K.F. Quantile Regression. *J. Econ. Perspect.* **2001**, *15*, 143–156. [CrossRef]
62. Fenske, N.; Kneib, T.; Hothorn, T. Identifying Risk Factors for Severe Childhood Malnutrition by Boosting Additive Quantile Regression. *J. Am. Stat. Assoc.* **2011**, *106*, 494–510. [CrossRef]
63. Ajodhia, V.; Mulder, W.; Slot, T. *Tariff Structures for Sustainable Electrification in Africa*; European Copper Institute (ECI): Arnhem, The Netherlands, 2012; pp. 1–56.
64. Koenker, R. Quantile Treatment Effects. In *International Encyclopedia of the Social & Behavioral Sciences*, 2nd ed.; Elsevier: Amsterdam, The Netherlands, 2015.
65. Anders, F.; de Oliveira, G.M. Impact evaluation using Difference-in-Differences. Center for Organization Studies (CORS), School of Economics, Business and Accounting (FEA), University of São Paulo (USP), São Paulo, Brazil. *RAUSP Manag. J.* **2019**, *54*, 519–532.
66. Schnabl, P. The International Transmission of Bank Liquidity Shocks: Evidence from an Emerging Market. *J. Financ.* **2012**, *67*, 897–932. [CrossRef]
67. Courtemanche, C.; Zapata, D. Does Universal Coverage Improve Health? The Massachusetts Experience. *SSRN Electron. J.* **2012**, *33*, 36–69.
68. Saha, D.; Bhattacharjee, A.; Chowdhury, D.; Hossain, E.; Islam, M. Comprehensive NILM Framework: Device Type Classification and Device Activity Status Monitoring Using Capsule Network. *IEEE Access* **2020**, *8*, 179995–180009. [CrossRef]
69. Hasan, M.; Chowdhury, D.; Khan, Z.R. Non-Intrusive Load Monitoring Using Current Shapelets. *Appl. Sci.* **2019**, *9*, 5363. [CrossRef]
70. Hasan, M.; Chowdhury, D.; Shahir, A.; Hasan, K. Statistical Features Extraction and Performance Analysis of Supervised Classifiers for Non-Intrusive Load Monitoring. *Eng. Lett.* **2019**, *27*, 776–782.