Effectiveness of a Power Factor Correction Policy in Improving the Energy Efficiency of Large-Scale Electricity Users in Ghana

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Abstract: Confronting an energy crisis, the government of Ghana enacted a power factor correction policy in 1995. The policy imposes a penalty on large-scale electricity users, namely, special load tariff (SLT) customers of the Electricity Company of Ghana (ECG), whose power factor is below 90%. This paper investigates the impact of this policy on these firms' power factor improvement by using panel data from 183 SLT customers from 1994 to 1997 and from 2012. To avoid potential endogeneity, this paper adopts a regression discontinuity design (RDD) with the power factor of the firms in the previous year as a running variable, with its cutoff set at the penalty threshold. The result shows that these large-scale electricity users who face the penalty because their power factor falls just short of the threshold are more likely to improve their power factor in the subsequent year, implying that the power factor correction policy implemented by Ghana's government is effective.

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1. Introduction

The power factor is a relevant measure of the efficiency of electrical energy use. A higher power factor implies efficient energy use and simultaneously ensures the safe, smooth, and efficient operation of electrical utilities. The power factor is the ratio between active power and its vector sum with reactive power, where active power executes actual work such as producing heat, illumination, and moving vehicles and machines. Reactive power is used to maintain the electromagnetic field that ensures the accomplishment of the work of active power. Summing the active and reactive power vectorially produces an amount of apparent power, which defines the total required energy capacity. A high power factor therefore implies an efficient use of the electricity generation capacity, while a low power factor reflects an abysmal use of energy. Facilities with a low power factor use more electricity than actually needed to conduct useful work [1]. A poor power factor should be corrected to reduce waste and the production costs of energy and thereby to help save the environment. There are ways to improve a low power factor to a desirable level of efficiency. The most mature, economical, and simple method is through an investment by energy consumers in capacitor banks [2]. These banks compensate for the inductive load demand of reactive power and thereby minimize the stress or burden on the electricity supply system [3].

Another alternative would be the use of synchronous alternators (or synchronous compensators). By exciting or de-exciting the magnetic fields, these inject reactive power into the network so that the voltage profiles of the system can be improved and the losses can be reduced. However, their

high installation and maintenance costs make them unsuitable for such applications in developing nations. Firms can further improve their power factor by carefully considering the design of processes and load cycles that have a repetitive nature during the design phase. Such a technique typically uses a computer algorithm to determine the ideal compromise in the relevant design parameters for improved energy efficiency and power factors. This approach, however, achieves a higher power factor at the sacrifice of reduced output levels in terms of the firms' production.

A higher power factor results in lower energy-related costs to users. According to the literature, improving power factors in industrial set-ups results in 10% to 30% cost savings. A study [4] estimated the cost savings of an independent power producer that carried out a power factor correction measure of its facility. However, the necessary investment in capacitor banks places a financial burden on users, making them reluctant to improve their power factor. Regardless, given the growing concern about climate change and increasing demand for electricity consumption, power factor correction has the potential to affect long-term economic and environmental gains to society [5]. Many countries, including Ghana, therefore urge electricity users, especially larger ones, to improve their power factor through this policy. Since 1995, the government in Ghana has imposed a policy that penalizes large-scale electricity users, labeled as special load tariff (SLT) customers, of the Electricity Company of Ghana (ECG) whose power factor falls short of 90%. This paper investigates the effectiveness of this power factor correction policy implemented by the Ghana government.

Historically, Ghana has been heavily dependent on hydro power supply, only in 2016 was it exceeded by thermal generation. Prior to that point, hydro power had accounted for the majority of the electricity supply of Ghana over history. As late as 2010, for example, the share of hydro power was approximately 70%, while that of thermal was just approximately 30%. Power from renewable energy (e.g., solar) entered the supply in 2013, but it accounts only for a negligible portion of the entire power supply [6].

In 1983, Ghana was hit by a severe drought that continued into 1984. This situation led the Akosombo Dam to experience a shortfall of water inflows, reaching below 15% of the long-term projected total [6]. This shortfall impacted the electricity supply, as the country's only electricity source was the Akosombo and Kpong hydroelectric power stations. Volta Lake did not fully recover from the 1983 drought before it was hit by another drought in 1993–1994, which again led to a reduction in electricity to consumers. This crisis exposed the country's vulnerability and security issues in terms of hydroelectric power [7].

Previous research has revealed that power factor correction measures by industrial plants, mining establishments, firms, and large commercial buildings can release 20 megawatts of tied-up electricity in a year [7]. At that time, Ghana's electricity capacity was approximately 900 megawatts, with a sizable share exported to the Republics of Togo and Benin. In addition, SLT customers represented only a part of the entire set of electricity users in Ghana. This release of 20 megawatts capacity from SLT customers was therefore considered to be relevant by the government of Ghana in that context. To improve the situation by raising the power factor among its users, in 1994, the government of Ghana announced that it would restructure tariffs to penalize those that do not adopt power factor correction measures, and it enacted this policy in January 1995 [7]. According to the policy, a user whose power factor is below a certain threshold is charged a penalty. The penalty policy is applied to large-scale electricity users, namely, the ECG's SLT customers. Tariff categories in Ghana are classified into three main groups, namely, (i) residential, (ii) nonresidential, and (iii) SLT customers [8]. Residential consumers are domestic users and nonresidential customers use electricity for commercial purposes with a capacity less than 100 kV [6]. SLT customers are defined as those that use energy for industrial purposes with loads greater than or equal to 100 kVA. According to the policy, SLT customers of ECG whose actual power factor falls short of 90% are to be penalized in proportion to the gap and to their size, measured in terms of the maximum electricity demand. For example, if the actual power factor falls short of the threshold by 5%, the penalty is 5% of the electricity bill, determined based on the maximum electricity demand of the users. Users whose power factor is above or equal to 90% are not subject to this penalty.

A relatively large body of literature has investigated the impact of energy efficiency enhancement policies on economic outcomes. For example, Costantini et al. [5] claim that sectoral energy efficiency gains display a negative effect on employment growth. They showed that this negative effect is stronger, in particular, in energy-intensive industries using data from 15 European countries. Lee and Min [9] found a negative correlation between green R&D and the financial performance of Japanese manufacturing firms. A study by Lee and Min [9] is, in the literature, one of a few that analyzes at the firm level to obtain the relationship between policy and firm economic performance.

On the one hand, these studies seem to indicate a negative relationship between energy efficiency improvement and business and economic performance. On the other hand, some of the more theory-based analyses derive opposite results. For example, by using the ASTRA model, or a dynamic, integrated macroeconomic, transport and environmental impact model, Ringel [10] concludes that enhanced green energy policies in Germany trigger tangible economic benefits in terms of GDP growth and new jobs, even in the short term. Hartwig et al. [11] use an input–output analysis-based model to show the positive growth effects and employment of energy efficiency policy in Germany. Henriques and Catarino [12] also use an input–output-based model, called the impact of sector technologies (ImSET) model, to conclude that green investment has the potential to increase employment and wage income. Allan et al. [13] use a computable general equilibrium (CGE) model to measure the impact of energy efficiency improvement in the UK.

In turn, there is a relatively smaller body of literature investigating the impact of policy on improvements in energy efficiency. Tanaka [14] provided an extensive review of energy efficiency policies implemented in the member countries of the International Energy Agency. Cox et al. [15] provided a review of non-energy- related policies. Among these studies, Xiong et al. [16] claim that a policy to restructure the industrial organization would have a large positive impact on provincial industrial energy efficiency in China. They used a slacks-based measure (SBM) that is a sophisticated variation of data-envelopment analysis (DEA), or a linear programing approach, where they allowed the existence of undesirable outputs to address the environmental burden due to inefficiency. They used a Tobit regression to reveal the positive association between industrial organization and energy efficiency as the second-stage regression following the efficiency measurement by SBM. Villca-Pozo & Gonzales-Bustos [17] found, at a provincial level, that tax policies to modernize the energy efficiency of housing in Spain have a nonsignificant impact on energy efficiency. At a more micro level, Anderson & Newell [18] found that manufacturing plants that receive government-sponsored energy audits have improved energy efficiency.

While these papers use a reduced form regression, such as the Tobit, to obtain a relationship between policy and energy efficiency, there are more model-based studies that construct a theoretical model to describe the mechanism between policy and energy use. Ringel [10] investigated the linkage between green energy policies in Germany and the country's primary energy consumption and greenhouse gases using the ASTRA model. Li et al. [19] used the VALDEX index that is a measure of energy efficiency based on value added, to find the impact of policies on eliminating low-efficiency production capacity and improving the energy efficiency of energy-intensive industries in China. Using a bottom-up approach, Fleiter et al. [20] investigated the impact of grants for small and medium enterprises in Germany to carry out energy audits of their facilities on their energy efficiency improvements.

Most of these studies, however, either showed a correlation between policy and energy efficiency or derived the results based on models that are dependent on their assumptions. For example, the Tobit regression conducted by Xiong et al. [16] shows a correlation and does not reveal the causation between policy and energy efficiency. In fact, relatively few studies have used appropriate empirical strategies to determine policy impact on energy efficiency. Yu & Zhang [21] investigated the impact of a "smart city policy" implemented in China on energy efficiency using a difference-in-differences (DID) approach at a city level. However, DID only addresses the time-invariant heterogeneity and is still based on the selections-on-observables assumption. In addition, many of these studies investigated the impacts of

energy efficiency policies at an aggregated level. To our knowledge, no study has investigated the impact of a power factor correction policy on its improvement by applying a reliable identification strategy to more micro-level data.

This paper, therefore, aims to add to the literature by identifying the causal impact of the power factor correction policy on energy efficiency improvement using firm-level data. Specifically, this study applies a regression discontinuity design (RDD), with a cutoff at the 90% penalty threshold stipulated by the policy, to five years of panel data consisting of 183 SLT customers of ECG for the years following the policy announcement in 1994 to 1997 as well as in 2012. The paper shows the effectiveness of the power factor correction policy in Ghana: firms strictly improved their power factor if it fell short of the required threshold. This paper is organized as follows. Section 2 discusses the data and identification strategies. Section 3 presents the estimation results. Finally, Section 4 concludes the paper.

2. Empirical Strategy

2.1. Data

A series of power crises in Ghana, mainly due to low water inflows, were recorded during multiple periods. The first power crisis dates back to the early 1980s, and this was followed by another in 1998. During these periods, many large-scale electricity users did not operate at their full capacity. Hence, we constructed our time-series data set starting from the year just before the policy enforcement up to the year just before the second power crisis took place in 1998.

Due to power crises, some large-scale electricity users ceased operations either temporarily or permanently. We excluded those SLT users from our data and limited it to the companies that sustained their business during our sample period to construct strongly balanced panel data. Thus, we constructed panel data for 183 SLT companies for five years, namely, from 1994 to 1997 and for 2012, which comprised 915 observations. Our data included power factor values of these SLT companies obtained from the ECG. Data collection took place in 2017.

Table 1 shows the summary statistics for these 183 companies. Our outcome was a dummy variable that indicated whether the firm improved its power factor compared to the previous year; it took a value of one if the firm's power factor improvement from the previous year was strictly positive, and zero otherwise. SLT customers are categorized in terms of the voltage with which their electricity is supplied. High-voltage SLT customers are those firms that are supplied electricity at 33,000 volts; medium-voltage customers are supplied at 11,000 volts; and low-voltage SLT customers are supplied at 415 volts. The observed panel data from the ECG provide information for SLT customers in Greater Accra, which consists of Tema, East and West Accra, as well as the Western Region of Ghana. Tema is the industrial hub of Ghana, and most SLT customers are located in these study areas.

Figure 1 provides a box plot of the power factor distribution over the sample period and clearly shows the overall improvement of the power factor among the SLT customers over the years. The policy was first announced in 1994 and enacted in 1995. Table 1 shows that as many as 88.5% of firms improved their power factor between 1994 and 1995, immediately after the policy announcement. The mean and minimum values of the power factor among these firms continuously improved over the period. By 2012, the average was above the penalty threshold of 90% and the minimum value had reached as high as 74%.

Table 1. Summary statistics.

Variable	N. Obs.	Mean	Std. Dev.	Min	Max
Power factor	915	0.821	0.127	0.35	0.98
Year 1994 only	183	0.765	0.127	0.35	0.96
Year 1995 only	183	0.799	0.139	0.36	0.97
Year 1996 only	183	0.810	0.132	0.37	0.98
Year 1997 only	183	0.830	0.124	0.37	0.98
Year 2012 only	183	0.903	0.042	0.74	0.97
High-Voltage SLT Customers only	395	0.818	0.142	0.35	0.98
Medium-Voltage SLT Customers only	340	0.812	0.118	0.49	0.98
Low-Voltage SLT Customers only	180	0.847	0.103	0.59	0.98
SLT Customers in Greater Accra only	520	0.842	0.106	0.44	0.98
SLT Customers in Tema only	275	0.861	0.099	0.44	0.98
SLT Customers in Western Region only	395	0.794	0.145	0.35	0.97
Improvement of power factor (*a dummy variable*)	732	0.701	0.458		
from year 1994 to year 1995	183	0.885	0.320		
from year 1995 to year 1996	183	0.623	0.486		
from year 1996 to year 1997	183	0.634	0.483		
from year 1997 to year 2012	183	0.661	0.475		

Notes: The data includes a balanced five-year panel of 183 firms. The power factor data are provided by Electricity Company of Ghana and measured in the incremental unit of 0.01. Year 1994 is before the policy enforcement and years 1995 to 1997 and 2012 are after policy enforcement. Improvement of power factor is a dummy variable that takes a value of one for the firm whose power factor has strictly improved since the previous year, and zero otherwise.
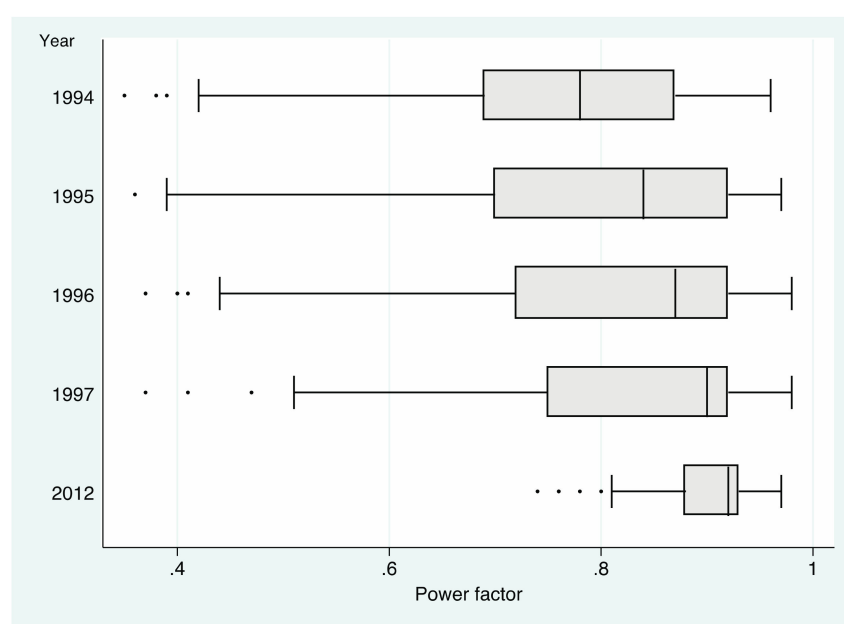

Figure 1. Box plot of power factor distribution over the sample period. A line in the middle of each box indicates the median of the sample in each year. The left and right edges of each box show the first and the third quartiles, respectively. Whiskers show the upper and lower adjacent values. The upper (or lower) adjacent value is the largest (or the smallest) observation that is within 1.5 times the interquartile range from each edge of the box. Dots are the units outside of the adjacent values.

2.2. Identification Strategies

The summary statistics above seem to indicate the effectiveness of the power factor correction policy introduced by the government of Ghana. However, the unobserved heterogeneity between the efficient and inefficient units may well confound our outcome in terms of whether they improved their power factor when facing the penalty set forth by the policy. That is, we cannot simply compare the

outcomes of inefficient firms to those of more efficient firms above the threshold when investigating the impact of the power factor correction policy on the improvement exhibited by these firms.

We bypassed this issue of potential endogeneity by conducting an RDD with a cutoff at the penalty threshold set by the policy. RDD is a quasi-experimental method used to identify the average treatment effect of those units around the threshold called a cutoff (please see Appendix A for more details). In the context of RDD, treatment assignment is performed according to whether the observation units are below or above the cutoff. RDD enables a local average treatment effect (LATE) to be identified for those units around the cutoff, even under a situation like ours where conducting a pure randomized experiment or randomized controlled trial (RCT) is not possible (see, for example, Moscoe et al. [22] for details.) When the treatment assignment is unambiguously determined by whether the unit is above or below the cutoff, it is called the sharp RDD. In our case, units will face a penalty if the power factor is below the threshold but not if the power factor is above or equal, without exceptions. Therefore, we must utilize the sharp RDD strategy. In turn, if the treatment assignment depends, but not solely, on whether the unit lies below or above the cutoff, one must use the fuzzy RDD. That is, if by the research design, noncompliers exist, fuzzy RDD is the appropriate identification strategy.

According to the policy, firms whose power factor is below 90% are charged a penalty. Note that firms cannot independently observe their power factor precisely, which suggests that it would be difficult for firms to precisely manipulate their power factor values. Instead, the power factor is measured periodically by the electricity company. In the case of Ghana, the ECG reports their power factor to the firms along with the amount of the penalty, if any. At the end of each month, ECG delivers the electricity bills along with the amount of penalty and the power factor to the customers. The firm then decides whether to invest in power factor improvement. Our data only contain the annual average of the power factor reported to the customers in our sample. To allow for this time lag in decision making by the firms, we used the power factor in the previous year as a running variable that indicated whether the firm faced the penalty in the previous year. Although the penalty scheme designed by the policy in Ghana exhibits a kink at the threshold because our outcome is a binary variable, we still adopt an ordinary discontinuity design, rather than a kink RDD. Because our outcome variable is an indicator capturing whether the firm has improved its own power factor from the previous year, the same company should be tracked to enable our identification. As mentioned earlier, our outcome was a binary variable that took a value of one if a firm strictly improved its power factor independently from the previous year, and zero otherwise. This empirical strategy with lagged and differenced variables made our working sample a four-year panel from 1995 to 1997 plus 2012 for 183 firms, consisting of 732 observations.

ECG measures the power factor of SLT customers in the incremental unit of 1%. Thus, any firm whose power factor is equal to or less than 89% faces the penalty, while those at 90% or above do not. We, therefore, set the cutoff of the running variable at 89.5% in our RDD to determine whether this policy implemented by Ghana's government indeed induced SLT customers of the ECG to improve their power factor.

3. Results

Table 2 presents the RDD estimation results. Column (1) shows the impact of the penalty policy, measured as a gap in the power factor improvement probability between those two types of firms, namely, those whose power factor in the previous year was just above and those whose power factor was below the threshold, estimated using the full sample. Column (2) shows the same impact estimated using only the subsample from 1995 to 1997. We refer to them as Models 1 and 2, respectively.

The coefficients were significantly negative in both models, which indicated that, relative to those immediately below the cutoff, those firms whose power factor was immediately above the cutoff in the previous year exhibited a strictly smaller probability of improving their power factor in the current year. In other words, the firms that were penalized were more likely to improve their power factor in the following year.

Table 2. Sharp regression discontinuity design (RDD) estimation results.

Dependent Variable	(1) Full Sample Power Factor Improvement	(2) Subsample of Years from 1995 to 1997 Power Factor Improvement
Treatment	−0.455 *** (0.104)	−0.598 *** (0.127)
N. obs.	732	549
N. obs. above the cutoff	278	183
N. obs. below the cutoff	454	366
Effective N. obs. above the cutoff	116	76
Effective N. obs. below the cutoff	52	44
Bandwidth	0.020	0.020

Notes: Standard errors are in parentheses. Statistical significance at 1% is indicated as ***. The dependent variable is a dummy variable that takes the value of one if a firm strictly improved its power factor since the previous year, and zero otherwise. The running variable is the power factor in the previous year with a cutoff at 0.895. The model in column (1) uses the entire sample of four years, namely, three years from 1995 to 1997 as well as 2012. The model in column (2) uses the subsample of three years from 1995 to 1997 only. Bandwidths in both models are selected by a mean-squared error optimal bandwidth selector. Kernel type of a triangular function is used in both models.

This result is also clearly shown in Figure 2, where the probability of power factor improvement is shown on the vertical axis over the level of the power factor in the previous year on the horizontal axis. Panel (a) shows the figure for Model 1, while panel (b) does the same for Model 2. In both figures, there is a clear discontinuity at the penalty threshold, which is shown as a vertical line. The results show that firms slightly below (i.e., on the left of the cutoff) were much more likely to improve their power factor than firms that were slightly above the threshold line (or on the right of the vertical line). Indeed, the probability of power factor improvement was approximately 90% for firms immediately below the threshold, while only approximately half of the firms immediately above the threshold exhibited an improvement (the gray dot shows the local average within each bin).

A closer look at the result reveals that the effect is stronger in Model 2 than in Model 1. The estimate of the gap in the probability of power factor improvement between firms immediately below and those immediately above the cutoff is as large as 59.8% in Model 2. Figure 2 also shows that the gap is larger in Model 2. The plot of the probability of power factor improvement in Model 2 depicted in panel (b) of Figure 2 shows that firms that were slightly above the threshold were less likely to improve their power factor than the firms in Model 1 depicted in panel (a). In Model 2, we have only three consecutive years; therefore, the resulting greater impact in Model 2 suggests a strong short-term effect of the policy. These results imply that the policy was effective in giving a strong incentive to firms, particularly those that fell slightly below the penalty threshold, to improve their power factor, even in the short term.
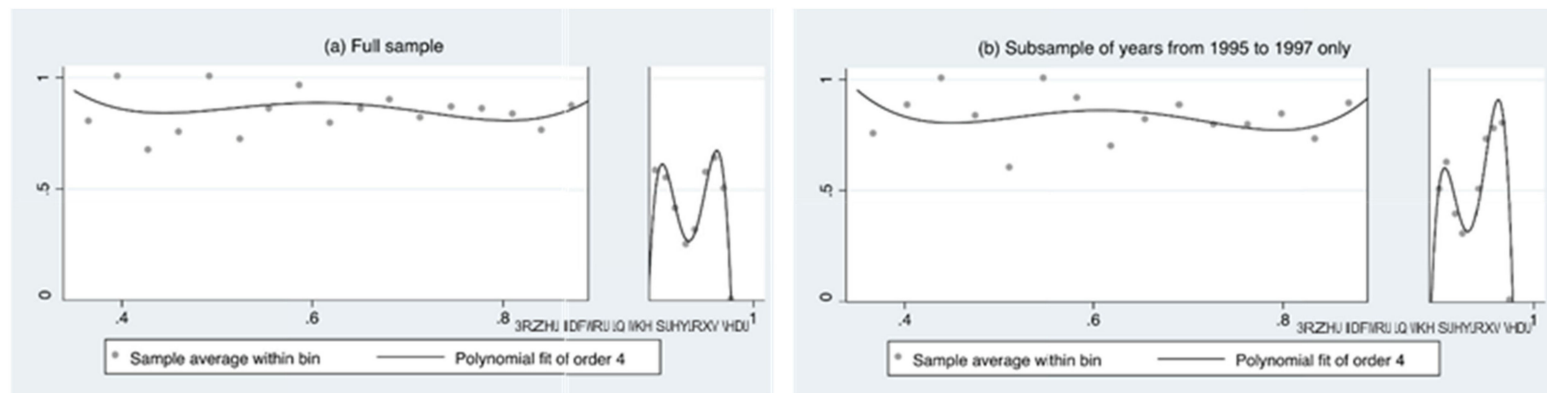
Figure 2. Probability of power factor improvement and its discontinuity at the penalty threshold. The probability of power factor improvement is on the vertical axis, and the level of the power factor in the previous year is on the horizontal axis. The cutoff is shown as a vertical line at 0.895 of the horizontal axis. The number of observations used in panel (**a**) is 732, of which 454 are on the left and 278 are on the right of the cutoff. The number of observations used in panel (**b**) is 549, of which 366 are on the left and 183 are on the right of the cutoff.

4. Concluding Remarks

In confronting its energy crisis, the government of Ghana enacted a power factor correction policy in 1995. The policy imposes a penalty on large-scale electricity users, labeled as SLT customers of the ECG, when their power factor falls below the threshold of 90%. This paper investigated the policy-induced improvement in these firms' power factor by applying RDD to panel data for 183 SLT customers. Our sample period ranged from 1994, when the policy was first announced, to 1997 and also included data for 2012. Specifically, we defined our running variable as the value of the power factor in the previous year, with the cutoff being the penalty threshold. Our outcome was a binary variable indicating whether the firm strictly improved its power factor since the previous year. The results show that the SLT customers whose power factor fell slightly below the threshold in the previous year were indeed more likely to improve their power factor, and the effect was stronger when we limited our sample period to a shorter term. This finding suggests that the power factor correction policy implemented by Ghana's government had an immediate impact on energy efficiency improvement by the country's large-scale electricity users.

Over the last few decades, the total power generation capacity has been constantly increasing in Ghana, and the majority of such change is attributable to the growth of thermal power generation. As a result, the installed capacity of hydro power is now 1584 megawatts and that of thermal is 3456 megawatts, while renewable energy is only approximately 42 megawatts [23]. With the thermal share of the generation mix now being at 68% and hydro set to reduce further, electricity prices will largely depend on international fuel prices; Ghana will thus be more vulnerable to global energy shocks. Energy efficiency has become even more relevant, and power factor improvement is one of the most important, simplest, and inexpensive strategies for achieving efficiency. For Ghana, like other new emerging economies with low energy efficiency, an efficient and stable electricity supply is a prerequisite for achieving its goal of consolidating its middle-income status via industrialization.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

A.1. Regression Discontinuity Design

Let *Ti* be the treatment variable for firm *i* such that

$$T_i = \begin{cases} 0, & if \ z_i \geq \bar{z} \\ 1, & if \ z_i < \bar{z} \end{cases}$$

where *zi* is a running variable for firm *i*, and $\bar{z}$ is the cutoff of the running variable. In our context, *Ti* is an indicator that firm *i* faces the penalty, and *zi* is the power factor of firm *i* in the previous year.

We then describe the outcome *Yi* as

$$Y_i = \beta_0 + \alpha T_i + \sum_{k=1}^{K} \beta_k (z_i - \bar{z})^k + \sum_{k=1}^{K} \gamma_k (z_i - \bar{z})^k T_i + u_i$$

where α gives the causal effect of the treatment.

In estimating the causal effect α, we weight observations according to the distance to the cutoff on the domain of the running variable. The weight is computed automatically by optimizing the mean-squared error of the estimation.

A.2. Estimation Code

We conducted the actual estimation using STATA 15. The actual code is as follows:

rdrobust dpfpositive pf_1, c(0.895).

Here, rdrobust is the command to conduct an RDD estimation. The variable dapfpositive is an indicator that takes a value of one if the change in power factor is strictly positive, while pf_1 is the power factor in the previous year. The last term, c(0.895), indicates that the cutoff $\bar{z}$ in our case is 0.895, implying that the firms with a power factor of 89% or below face the penalty, while the firms with 90% power factor and above do not.

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