Prepayment, Salience, and Welfare *

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Abstract

The use of prepaid electricity meters requires customers to make payments prior to consumption, as opposed to the conventional end-of-the-month bill. If prepayment enhances price salience, we would expect consumers to exhibit greater responsiveness to price changes compared to their postpaid counterparts. This paper investigates this hypothesis by investigating the impact of prepaid electricity metering on consumer responsiveness to price changes compared to traditional postpaid systems in Indonesia, which has over 40 million households using prepaid electricity – the highest number in the world. Using quasi-experimental tariff variations driven by the changes in national regulations, we present compelling evidence that prepaid meter users exhibit at least double the price elasticity compared to their postpaid counterparts. Our incentivized survey on individual willingness to pay indicates positive consumer welfare, underscoring increased consumer surplus from the use of prepayment systems. Our applied welfare analysis quantified the efficiency loss, consumer gains, and pollution externalities. This suggests that salience-improving technologies, such as prepaid electricity meters, have the potential to advance climate policy goals by curbing carbon emissions through energy conservation.

Keywords: electricity, prepayment, elasticity, salience, energy conservation
JEL codes: Q41, Q42, Q53

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1 Introduction

The electricity sector plays a pivotal role in influencing global energy dynamics and substantially contributes to greenhouse gas emissions (International Energy Agency 2023). Acknowledging the limitations of relying solely on supply-driven policies in pursuing climate policy objectives, there is an urgent imperative to integrate demand-driven strategies to bolster energy conservation efforts. One relevant policy question is which interventions can support these efforts. Research in developed countries underscores the impact of interventions such as automatic billing frequency and in-home displays (Gilbert and Zivin 2014, Sexton 2015, Wichman 2017, Jessoe and Rapson 2014) on consumers' consumption behavior, emphasizing the crucial role of salience and responsiveness to pricing. However, developed nations benefit from advanced metering systems and billing infrastructure like Advanced Metering Infrastructure (AMI), enabling real-time monitoring and efficient billings. In contrast, developing economies face challenges due to the absence of such infrastructure, resulting in monitoring gaps, weak enforcement mechanisms for electricity payments, unpaid bills, and low revenue recovery. These difficulties further impede the sustainable implementation of these interventions.

The question persists as to whether salience-enhancing technologies can play a substantive role in energy conservation to promote demand-driven climate policies in developing economies in the long run. One potential technological solution is prepaid metering, increasingly popular in developing countries as an alternative to traditional monthly billing for electricity usage (UNSGSA 2023).[1] Beyond offering consumers greater financial control, prepaid metering reduces billing costs for providers and prevents meter tampering as the meter disconnects when all credit is used. Existing studies note that prepayment users tend to consume less electricity than post-payment users (Qiu, Xing and Wang 2017, Jack and Smith 2020, Debasish Kumar and Stern 2020, Beyene, Jeuland, Sebsibie, Hassen, Mekonnen, Meles, Pattanayak and Klug 2022), however, the reasons for this trend remain unclear. We posit that prepaid systems heighten price salience, leading to more elastic electricity demand compared to post-payment systems. Prepayment obliges customers to make an upfront payment, creating a direct and immediate financial incentive to conserve energy. This prompts customers to respond promptly to changes in electricity prices and adjust their consumption patterns. This paper investigates the differences in demand elasticity between prepaid and postpaid users, testing whether consumers under prepayment exhibit greater price salience than their postpaid counterparts, all else equal.

The price elasticity of electricity demand serves as a crucial policy parameter, providing policymakers with insights into the economy's responses to climate policies. Estimating elas-

[1] This payment system is believed to enhance end consumers' access to power from renewable sources at affordable prices (International Renewable Energy Agency 2020). It has also expanded to other sectors like water utilities, mobile phones, internet access, transportation, entertainment, and education.

ticity, particularly in developing countries with unique characteristics (Khanna and Rao 2009), presents challenges. The retail electricity price, often lower than the marginal cost due in part to subsidies aimed at social protection (Del Granado, Coady and Gillingham 2012), fosters over-consumption, inattention, and habit formation, limiting the responsiveness of demand to price signals. Additionally, in some developing countries, electricity demand is supply-constrained rather than demand-driven, diminishing the role of price in the electricity demand equation (Khanna and Rao 2009). From a methodological perspective, most of the studies use average price changes to identify the elasticity.[2] However, average prices are determined simultaneously with the level of consumption, giving rise to a correlation between price and the error term of the electricity demand equation and leading to well-known endogeneity biases.[3] Finally, existing studies are often limited in micro-data availability and have to rely on highly aggregated nationwide data, forgoing the heterogeneity within the smaller geographical units that are driven by income and economic activity in the location they reside. As a result, several studies have shown a wide range of values, between -0.85 and -0.04 (Khanna and Rao 2009, Burke and Kurniawati 2018, Durmaz, Pommeret and Tastan 2020, Uddin, Hasan, Phoumin, Taghizadeh-Hesary, Ahmed and Troster 2023, Gillingham, Rapson and Wagner 2016).

We estimate price elasticity using proprietary billing data from an Indonesian utility company at the service unit level for the years 2013-2020. During this period, there was a significant increase in prepaid meter conversion, and, on top of that, the government removed price subsidies for some customers. To test our hypothesis that prepayment reduces electricity consumption through price salience, we use two methods: an event study on the same customer group before and after the tariff changes, and a difference-in-difference methodology comparing two similar customer groups facing similar tariffs at the start but experiencing different tariff changes after 2013. In this approach, the control group customers are plausibly a suitable counterfactual to the treated customers in the absence of tariff changes as they live within the same regions, under the same contracted power capacity[4], and a similar share of prepaid penetration rate. But while the treated customers experienced tariff changes, the control did not.

We find that prices increased by 35% after the subsidy removal, faced by both postpaid and prepaid users over seven years. Two years after the price change, the average usage for postpaid users decreased by only 7-8% compared to the 12-23% usage decline by prepaid users. Due to the sustained and sizable price variation in our study, we are also able to estimate the long-run

[2]This includes instrumenting the price in one region with the average price in nearby regions as in Burke and Kurniawati (2018).

[3]Alberini and Filippini (2011) and Deryugina, MacKay and Reif (2020) point out similar issues in estimating short and long-run demand elasticity in developed countries context.

[4]The contracted power capacity is the maximum consumption allowed at any point in time and it determines the electricity tariff. Thus, households have incentives to choose it based on their expected demand as the installation fees and tariffs increase as the capacity increases. As electricity demand is correlated with income, we argue that the contracted capacity is a sufficient proxy for income.

dynamics of electricity demand. Our findings reveal that the elasticity parameters increase over time for prepaid users compared to postpaid users even though they face the same tariffs. In particular, the price elasticity of prepaid users is two to four times higher than that of their postpaid counterparts.

There are several reasons why electricity consumption may be lower for prepaid users than for postpaid users, even within the same contracted power capacity. First, one might think that those who are more aware of their electricity bills self-select to prepaid or a particular customer class. We conduct a battery of robustness checks such as matching, instrumental variable approach, and placebo check and still reach a similar conclusion: prepayment increases price elasticity. Second, prepaid users might lower their consumption due to liquidity constraints associated with prepayment. However, this is not likely the main driver for two reasons: the electricity bill constitutes less than five percent of total monthly spending, and several small purchases can be made.[5] Our placebo analysis shows that the electricity demand trends are similar between postpaid and prepaid users in the absence of any tariff changes, thus providing reassurance that the earlier results are primarily driven by the interaction between the tariff changes and the metering type. Finally, we provide further checks on the remaining identification threats.

A technology that increases price salience should, in theory, improve consumer welfare by reducing distortions from optimal choices. However, this welfare enhancement may not occur if the technology itself generates negative utility that is independent of price effects. For example, if consumers have an aversion to using prepaid meters, and these meters are mandated by the government, their utility could decline for reasons unrelated to the salience effect. In practice, consumer welfare might also be influenced by non-monetary aspects of the meter, such as user convenience, and by consumers' capacity to prepay for electricity. To gain a more comprehensive understanding of the net welfare implications of prepaid metering, we complemented our analysis with an online survey.

Employing an incentivized choice elicitation method commonly utilized in the literature(Allcott and Kessler 2019, Jack, McDermott and Sautmann 2022), we find that the net welfare effect—proxied by the willingness of consumers to forgo a monetary amount to continue using the prepaid meter—is positive. Our analysis further reveals that the households studied are not liquidity-constrained when paying their monthly bills. Lastly, through applied welfare analysis, we quantify the transition to prepaid meters, along with a 35 percent increase in price due to subsidy removal, results in an efficiency loss but a gain in consumer surplus due to improved salience. Importantly, the environmental benefits from avoided pollution significantly outweigh

[5] An increase in transaction costs from purchasing the prepaid tokens may lead customers to consume less total electricity to compensate for incurring this additional cost. However, this amount is very small, around \$0.2 USD or 0.1 percent of the average monthly bill.

these gains and losses, underscoring the substantial ecological advantages of the conversion, particularly given Indonesia's high carbon intensity per unit of electricity generation.

Our findings provide the first evidence that prepaid meter users have a more elastic demand relative to postpaid users. Estimating elasticity requires having exogenous variations in prices in addition to a high rate of take-up of prepaid, which is rare. Previous studies conducted in developing countries have shown that prepayment systems can reduce electricity consumption by up to 14 - 24% in residential settings using methods such as randomized phase-in of the metering, difference-in-difference, and matching techniques (Qiu et al. 2017, Jack and Smith 2020, Debasish Kumar and Stern 2020, Beyene et al. 2022).[6] Our findings are consistent with these results, indicating a similar decline in consumption. By leveraging our variation in the tariffs, we identify the elasticity parameters that might explain the lower consumption of consumers under prepayment. Our incentivized survey confirms that the increased awareness of households regarding their own electricity consumption among prepaid users is one possible explanation.

This paper contributes to the existing literature on the impact of salience on consumption, which has primarily focused on developed countries. For example, previous research shows that in electronic toll collection, consumption becomes less elastic as salience decreases (Finkelstein 2009). In addition, increases in taxes included in posted prices have a greater effect in reducing alcohol consumption compared to taxes applied at the register (Chetty, Looney and Kroft 2009). Another study, a field experiment in the US, finds that price elasticity triples when price changes are combined with information provisions through in-home displays (Jessoe and Rapson 2014). However, in developing countries, where advanced technologies, such as in-home displays, tend to be expensive compared to prepaid meters, research on salience is limited. To our knowledge, our work is among the first to study the impact of salience on electricity demand in developing countries.

A large body of literature have estimated for long-run elasticity demand using dynamic panel models of aggregated state-level data (Alberini and Filippini 2011, Campbell 2018, Burke and Kurniawati 2018). These studies require strong assumptions about the form of serial correlation, except (Deryugina et al. 2020) which uses quasi-experimental variations coming from Illinois policy that generated plausibly exogenous shocks to residential electricity prices in over 250 communities in the US. Our study is among the first in a developing country setting that uses quasi-experimental variations driven by the removal of subsidies that impacted over six million households in Indonesia.

The electricity sector in developing countries plays a pivotal role in shaping climate policies due to the increasing need for energy to support economic growth and the rising demands of a growing population (Wolfram, Shelef and Gertler 2012). The adoption of prepayment systems

[6] In developed countries, the reduction is similar in magnitude 12 percent in Phoenix, USA (Qiu et al. 2017).

can influence consumer behavior, leading to more optimized electricity use that is consistent with the goals of climate policy to reduce carbon emissions through energy conservation. An understanding of the mechanisms of how prepayment can influence consumption is crucial for policymakers and utility companies to create effective electricity pricing and subsidy policies, as well as to facilitate energy conservation. A prepayment system is an example of a policy that can help make electricity demand more elastic by providing households with more immediate feedback on their energy consumption with a relatively low investment cost. This promotes energy efficiency and meets the growing energy demand sustainably. Our estimates will be valuable in helping policymakers predict electricity consumption in response to reforms to electricity tariffs and the increasing penetration of prepayment systems in many developing countries.

The rest of the paper proceeds as follows. In the next section, we provide the institutional details. We then describe the dataset and the empirical analysis in Sections 3 and 4, respectively. Section 5 investigates further threats to the identifications. In Section 6, we perform an applied welfare analysis. Finally, we conclude the paper in Section 7.

2 Institutional Details

Indonesia, the fourth most populous country in the world, has experienced substantial growth in electricity consumption, with household usage exceeding that of the industrial sector (see Figure 1).[7] The total electrical energy sold in 2020 is 243 terawatt-hours (TWh), higher than the total electrical energy sold in 90% of countries in the world. Of these 243 TWh, the sectoral shares of total consumption ranked from largest to smallest is as follows: households (R1) at 46%, industry (I1) at 29%, businesses (B1) at 18%, and others – which include social service sectors, government buildings, and public street lighting – at 7% (PLN 2020).

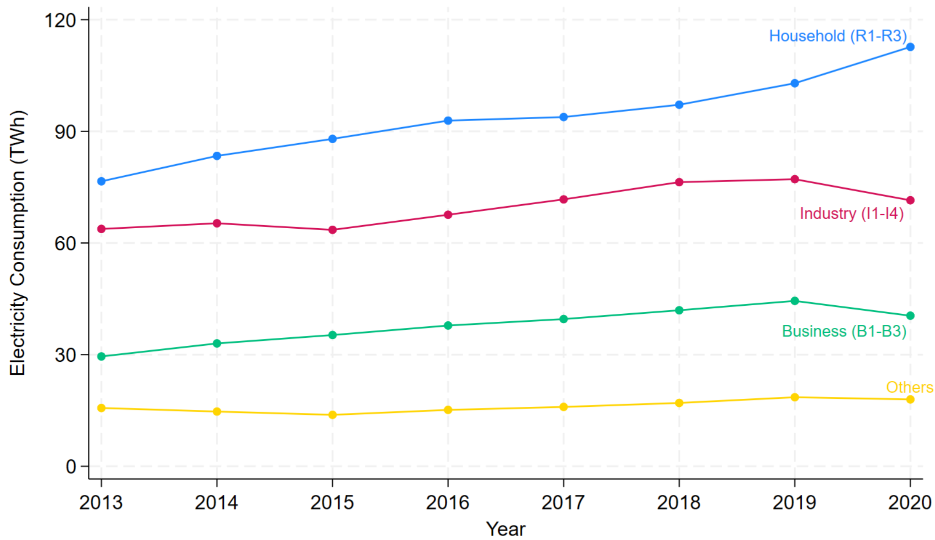
All of the customer classes in Figure 1 are divided into different subclasses of customers based on contracted capacity in voltage ampere (VA).[8] VA ranges from 450 VA for R1, B1, I1 to above 30,000 kVA for I4 customers. The subsidy regulation occurred primarily among 900 and 1300 VA customers, thus our paper focuses on these VAs.[9]Since a customer's VA provides a maximum usage at any given time, comparing households within the same VA is important in ensuring comparability of their electricity consumption patterns. To put things in perspective, a 1 horsepower air conditioner consumes 860 watts of electricity, and as such, can only be used by households with 1300 VA and above. A household with 900 VA will be able to use such an

[7]This increase in consumption is due to the country's expansion in the electricity sector (i.e., construction of more power plants).

[8]Voltage Ampere (VA) is a measure of contracted capacity which indicates the maximum electricity that can be used at one moment in time.

[9]We include customers with 450 VA, and 2200 VA in the robustness checks.

Figure 1: Growth in electricity consumption in Indonesia by customer class



Notes: Electricity consumption by sector using sales quantity (excluding on-site generation). The 'others' sector is the sum of electricity consumption by public services and government offices. Source: PLN (2020).

appliance only when all other appliances are switched off, as exceeding the allocated VA will trip the power.[10] Table S4 in the Appendix shows a list of appliances – and their respective wattage – that can typically be found in households under each VA category. Based on this list of appliances, households with 450 and 900 VA are relatively poorer households compared to households with 1300 or 2200 VA. The largest number of residential customers falls within the 450 and 900 VA categories.

The regulation changes primarily affected customer class R1 (residential customers), which will be the central focus of our analysis. To establish a counterfactual group for R1, we will use the B1 customer class who were not affected by the regulation. Customer class labels are put in place by the electric utility as a means to regulate tariffs. Informal surveys and anecdotal evidence suggest that households generally lack awareness of their classification as either R1 or B1 customers. We argue that these two customer classes are likely to exhibit a similar pattern of electricity usage. We posit that B1 customers are likely to respond to electricity price changes in a manner similar to R1 customers within the same voltage area (VA), based on several considerations. First, although R1 is officially designated for residential homes and B1 for small businesses, the practical distinction between these categories is often blurred. In many cases, small businesses operate out of residential properties, and residential homes may house informal businesses. Consequently, both groups have similar opportunities to engage

[10]It is not possible for households to turn on multiple appliances at the same time with the sum of Watts exceeding their designated VA, as the power will trip.

in business activities and likely exhibit comparable patterns of electricity usage. Secondly, residential properties operating informal businesses often run very small enterprises, such as shops, restaurants, or laundromats, which are constrained by the VA limit. This similarity in the nature and scale of operations between R1 customers with informal businesses and B1 customers further supports our choice of B1 as a counterfactual group.[11]

Postpaid to Prepaid Metering Conversion Program. *Perusahaan Listrik Negara* (hereafter, PLN) is a state-owned electricity company in Indonesia that provides most of the public electricity and electricity infrastructure in Indonesia, including power generation, transmission, distribution, construction of power plants, and retail sales of electricity. They deliver electricity to end users with electricity tariffs determined by the Government. Traditionally, all electricity users have been using postpaid meters (see right photo in Figure 2). However, in 2008, PLN conducted a pilot that converted postpaid users to prepaid users and has, since then, been gradually converting the rest of its meters (see left photo in Figure 2).[12] The main goal of the conversion is to simplify the business process by eliminating steps such as meter recording, billing, payment, and recording of debts. Since prepaid meter customers will need to purchase a token before using the electricity, there will no longer be a need for PLN to record meter readings and bill customers. In many countries, it is a well-known fact that prepaid metering benefits utility companies because the alternative (i.e., traditional postpaid billing) can be challenging to administer and often result in unpaid electricity bills, which can then create financial difficulties for utilities (Jack and Smith 2020). In Cape Town, Jack and Smith (2020) show that a prepayment system can benefit the utility company through improvements in revenue recovery.

In 2010, PLN conducted a unilateral meter replacement initiative for small VA customers (Natalia 2014). This initiative also included prepaid default, where new meters offered were only prepaid meters. According to the decision of the Minister of Energy and Mineral Resources, the use of prepaid electricity was made mandatory for new or upgraded electricity installations, leaving these customers no other choice but to use prepaid electricity (Yuliani and Saputra 2014). These small VA customers were subjected to this rule because they constitute PLN's largest customer base, and therefore the cost of billing them is the highest per kWh sold.

Figure 3 shows the increase in prepaid metering customers since 2013. The prepaid penetration rates between R1 and B1 are similar as the program does not differentiate different

[11] In Section 4, we employ an instrumental variable approach that does not distinguish between an R1 or a B1 customer class, and find that our results do not change. In Section 5, we use an alternative control group that is within the same customer class of R1 and also find similar results. These findings suggest that our findings are robust to our choice of a control group.

[12] https://regional.kompas.com/read/2008/01/17/14361123/pln.luncurkan.listrik.prabayar. PLN calls it *listrik pintar* which means smart electricity. In some countries, it is also called pay-as-you-go electricity.

Figure 2: Postpaid and Prepaid metering

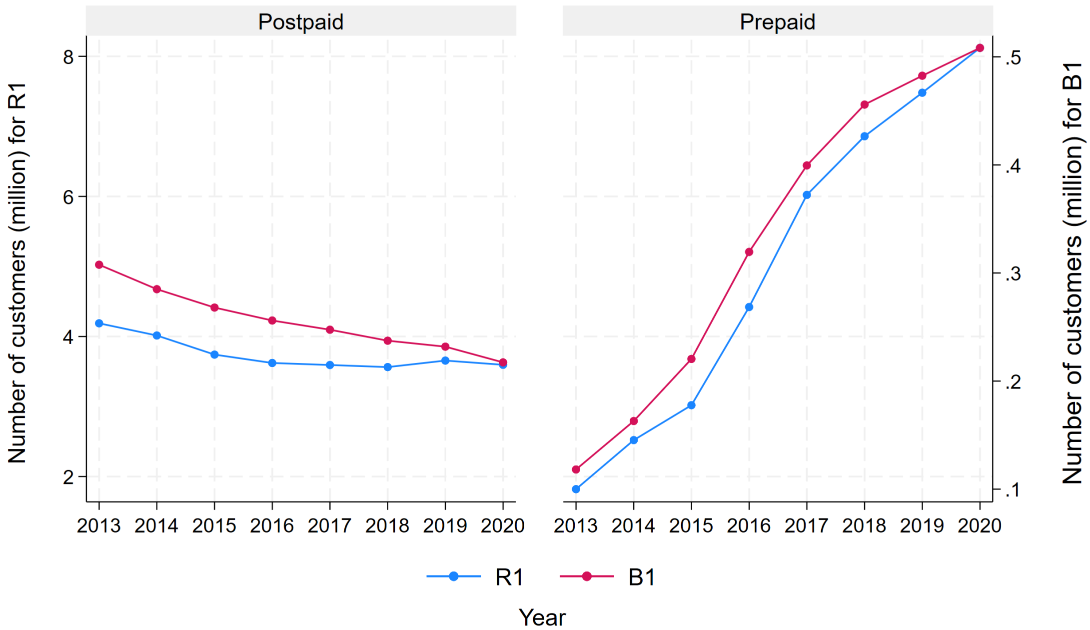
Notes: typical postpaid meter (left) and prepaid meter (right) in Indonesia. A prepaid meter has numbering keys to input the 20-digit tokens for refilling the balance, while a postpaid meter only has numbers that indicate current consumption since the installation of the meter.

classes of customers in this program. This conversion was mandatory and therefore leaves not much room for households to avoid being converted. The share of prepaid customers across the different VA classes also displays similar trends. (see Figure S5 in the Appendix). Figure 4 shows the geographic variation: by 2013, about 20% of customers had used prepaid metering on average, and by 2020, it reached more than 50% in most municipalities.

Price Changes. Prepaid and postpaid users within 1300 VA face the same per-unit price of electricity price. The tariffs are historically politically determined and driven by budgetary considerations (Burke and Kurniawati 2018). The Minister of Energy and Mineral Resources set the electricity tariffs and the level of subsidy for each customer class. The Government of Indonesia has long subsidized electricity prices for low-voltage households (1300 VA and below) as a form of social protection. However, due to the increasing burden of subsidy costs, the Minister of Energy and Mineral Resources has decided to remove price subsidies for the R1 1300 VA customer class. Figure 5 shows the tariff trends for R1 and B1 based on the regulations issued by the Ministry of Energy and Mineral Resources, which were regulated under ESDM No. 30/2012 and continued with Permen ESDM No. 28/2016.[13] Customers under B1 1300 VA

[13]The first major price hikes were from the removal of the subsidy in mid-2014 (announced in 2012) while the second one occurred in 2016. In 2016, tariffs were adjusted monthly based on Permen ESDM No. 28 of

Figure 3: Trends in the number of customers for R1 1300 VA and B1 1300 VA



The figure plots the customers trends for R1 and B1 customer classes, = 1300 VA. Source: PLN.

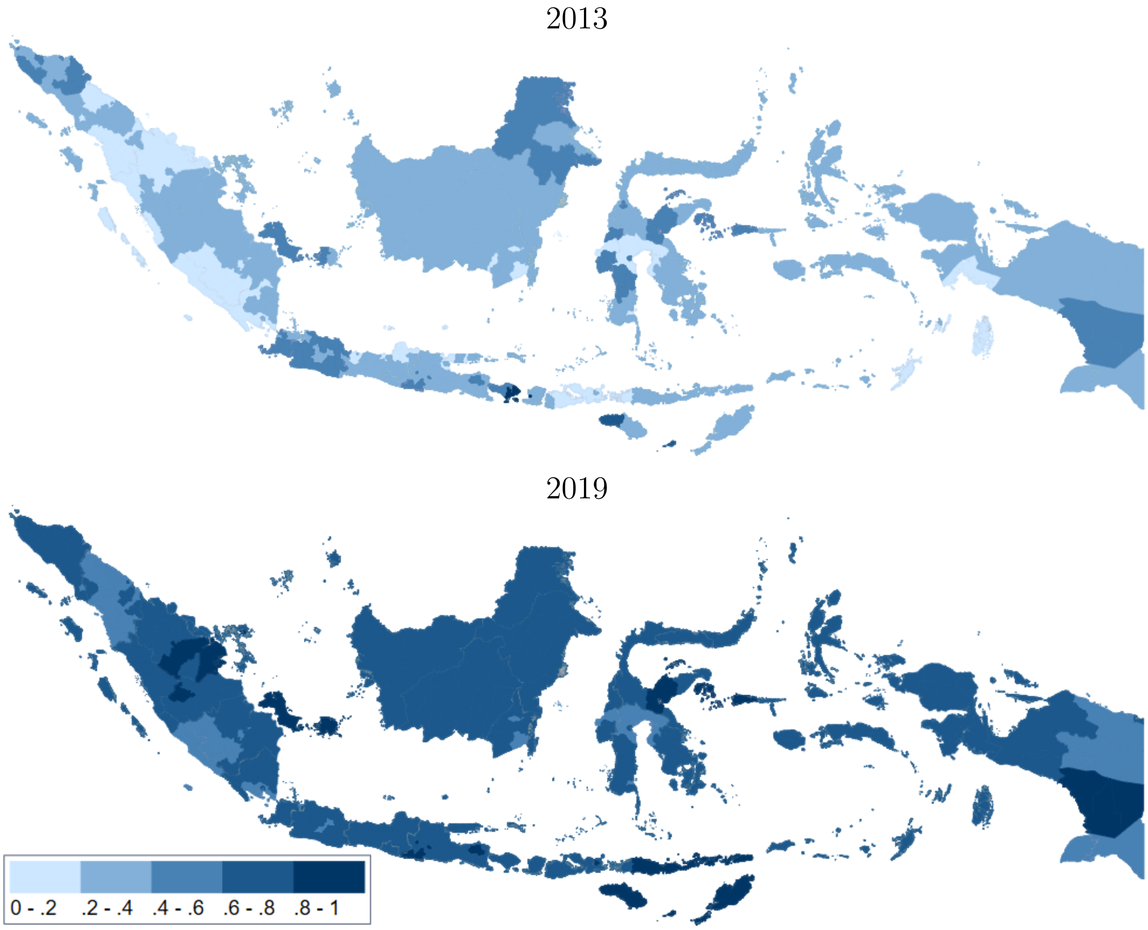
were unaffected by the subsidy removal as the government intended to protect small businesses for economic reasons. The price increase for R1 1300 VA customers was around 40%.

3 Data & Descriptive Statistics

We use proprietary billing data from PLN, aggregated at the service unit-customer class-VA level, covering the entire country from 2013 to 2020. In 2013, there were 138 service units (referred to as *"Unit Pelaksana Pelayanan Pelanggan"*), which increased to 152 in 2020 due to the construction of additional offices. We pair each customer class with monthly electricity tariff data sourced from the published regulations by the Minister of Energy and Mineral Resources for the same period. Since the billing data represents monthly averages for each year, we calculate the weighted average tariff based on the duration of the monthly tariffs. For instance, the 2014 tariff is calculated as half the increased amount since the price increase occurred midway through the year. Using the monthly average for each year comes with the advantage of allowing us to account for seasonality.

2016 which specified the formula to compute unsubsidized electricity tariffs from 2016. The tariffs depend on monthly adjustments by the PLN based on changes in the exchange rate of the rupiah, fuel prices, and monthly inflation. We treat these two regulations as the same regulation that exogenously increases tariffs.

Figure 4: Increasing prepaid metering shares between 2013 and 2019

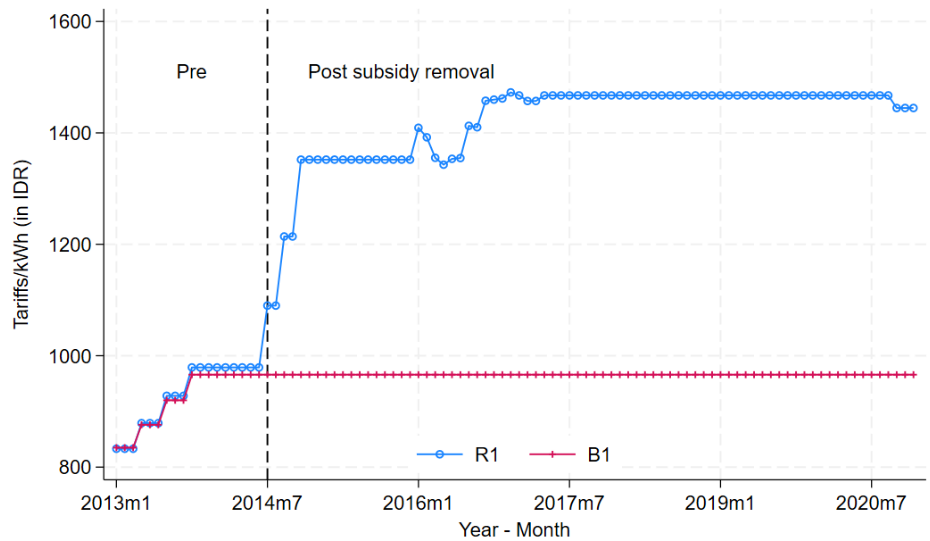


Notes: these figures map prepaid metering penetration for R1 and B1 1300 VA customer class in 2013 and 2019. Source: PLN

Counterfactual group. As discussed in Section 2, our paper focuses on R1 1300 VA and B1 1300 VA customers. Our "treated" group are the R1 customers that were affected by the tariff increases while our "untreated" (or control) group are the B1 customers that were unaffected by the tariff increases. Table 1 shows the mean and standard deviations of key variables for R1 and B1 customers at baseline years, 2013 and 2014. We have two baseline years since R1 customers were exposed to an increase in tariff in mid-July 2014. This makes 2013 our "pure" baseline year.

From Table 1, there are three things that are worth highlighting: (1) the level differences between prepaid vs. postpaid, (2) differences between R1 vs. B1, and (3) the trends between prepaid vs. postpaid and R1 vs. B1. First, prepaid customers consume about 40% less electricity than postpaid customers. This difference in levels of consumption suggests that poorer households may be more inclined to enroll in prepaid metering; thereby explaining the lower level of average consumption even within the same VA. However, as discussed above, how

Figure 5: Electricity price for R1 and B1 customers classes = 1300 VA for both prepaid and postpaid users



Notes: The figure plots the customers trends for R1 and B1 customer classes = 1300 VA. In 2013, there was a small increase for both R1 and B1 due to small tariff adjustments by the government. See footnote 13. Source: PLN.

customers were provided prepaid meters by PLN does not lend credence to the explanation above. [14] To address this level difference, we use a transformed average usage in our analyses below. This transformed variable is indexed by metering type (Equation 1). Second, as result of this transformation, electricity consumption between R1 and B1 becomes more comparable (see Table 2). The difference in electricity consumption between R1 vs. B1 is around 7 kWh or 3% of average usage, with p-values ranging from 0.01 to 0.08. Third, consumption of electricity by prepaid users seems to grow more than that of postpaid, around 15 kWh on average but decreases to 13 kWh in 2014, which could be attributed to the half-year exposure to tariff changes.

[14] Section 4.4 provides evidence that prepaid penetration rates are generally not associated with a broad range of socioeconomic indicators, which is intuitive, as conversion to prepaid metering is primarily initiated by PLN and driven by distance to the PLN service unit and not their electricity consumption within the VA. Table S1 even shows that customers who were assigned prepaid meters were those that were more likely to have new houses, and as such, are likely to not be poorer than their postpaid counterparts.

Table 1: Summary Statistics and Balancing Test at Baseline Years

	2013 (Pre subsidy removal)				2014 (Half-year exposed))			
	R1 1300VA		B1 1300VA		R1 1300VA		B1 1300VA	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Mean and Standard Deviations								
Tariffs (IDR/kWh)	904.8	(0.0)	899.2	(0.0)	1098.8	(0.0)	966.0	(0.0)
Number of customers (000)	521.7	(551.4)	36.9	(30.3)	567.3	(588.6)	38.9	(32.4)
Postpaid	364.0	(394.1)	26.7	(21.4)	349.1	(381.8)	24.8	(20.1)
Prepaid	157.6	(181.2)	10.2	(11.8)	218.2	(228.6)	14.1	(15.3)
Prepaid share (%)	31.9	(12.9)	27.1	(11.0)	41.6	(13.3)	36.2	(12.2)
Monthly bill (000 IDR)	165.7	(32.9)	172.3	(30.3)	195.2	(38.2)	179.3	(30.2)
Postpaid	194.1	(34.3)	199.7	(32.2)	234.9	(40.6)	214.6	(34.4)
Prepaid	105.3	(20.5)	97.2	(21.4)	139.8	(26.6)	116.2	(24.9)
Average usage (kWh)	183.9	(36.7)	192.6	(34.1)	178.9	(34.8)	186.0	(31.4)
Postpaid	216.3	(38.2)	223.9	(36.2)	215.9	(37.0)	222.7	(35.9)
Prepaid	114.8	(22.4)	106.8	(23.3)	127.1	(23.9)	120.5	(25.7)
Observations	276		276		276		276	
Panel B: Within service units differences								
Prepaid vs. Postpaid	-101.51	(3.18)	-117.11	(4.17)	-88.77	(2.91)	-102.22	(4.11)
Postpaid (R1 vs. B1)	-7.65 p-val: 0.07				-6.81 p-val: 0.08			
Prepaid (R1 vs. B1)	7.94 p-val: 0.01				6.64 p-val: 0.03			
(Prepaid vs. Postpaid)X(R1 vs. B1)	15.60 p-val: 0.00				13.45 p-val: 0.00			
Observations	552				552			

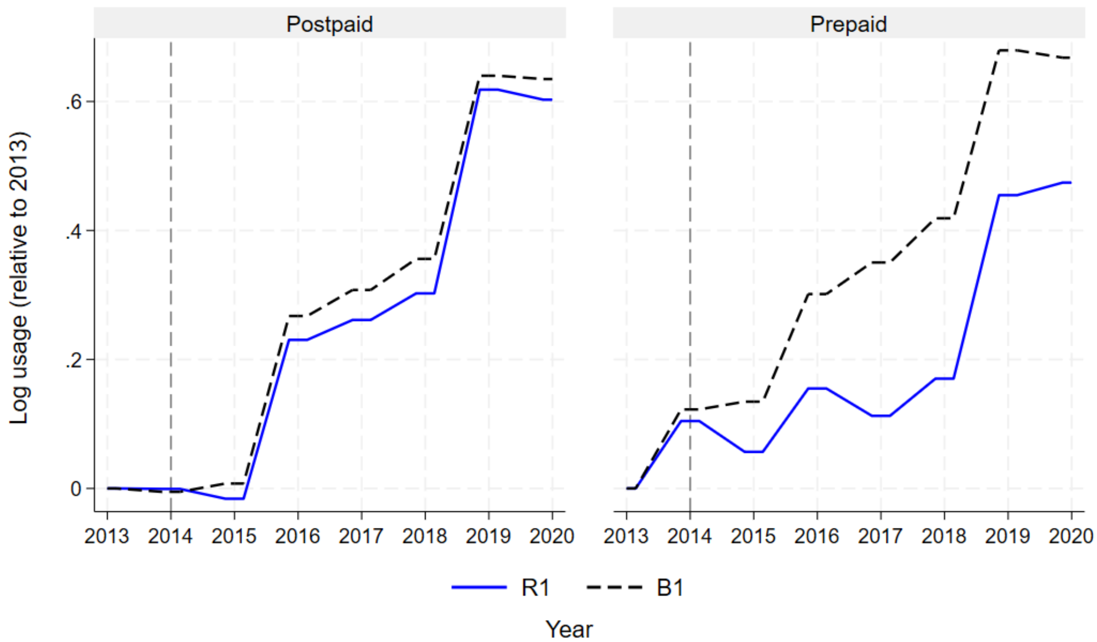
Notes: Panel A reports the mean and standard deviations of each variable at the service unit level for 1300 VA customers. The year 2013 is the pure baseline year while 2014 was affected by the tariff changes that started in July. The number of customers is per thousand people, monthly bills are the monthly average for the year in thousand IDR, and average usage is in kWh, for three categories (1) both meter types, (2) postpaid meter, and (3) prepaid meter users. We dropped outliers around 1% from the total observations. Panel B, first row, shows the conditional mean of average usage within service units. Standard errors of the mean difference of average usage for prepaid and postpaid for R1 and B1 are in the parenthesis. The second row shows mean differences in average usage between R1 and B1 among postpaid users, between R1 and B1 among prepaid users, and the difference between the second and third rows, along with the p-values of the difference.

Outcome Variable. As noted in Table 1, there is a level difference in the average usage of prepaid and postpaid users. The difference can be explained by the technical aspect of the metering along with users' behavior in response to the metering. One example of a distinct technical aspect is that a prepaid meter can only be consumed up to the filled balance, while a postpaid meter can be consumed without limit. To remove some of the meter-specific effects that are constant, we use changes in log usage relative to the baseline year (2013). As such, for each service unit i and consumer class c, our main variable of interest is the difference between the log monthly electricity usage at year t and the base year, 2013. That is:

$$\triangle log(usage)_{ipct} = log\Big(\frac{usage_{ipct}}{N_{ipct}}\Big) - log\Big(\frac{usage_{ipc2013}}{N_{ipc2013}}\Big), \qquad (1)$$

where $\triangle log(usage)_{ipct}$ is the change in log monthly average usage for service unit i with metering type p (i.e., prepaid or postpaid) in customer class c at year t relative to the base year of 2013. N is the number of customers at the service units, metering type, and the customer group. Figure 6 shows that, visually, the indexed log usage (computed from Equation 1) between prepaid and postpaid are much more comparable. The graphical evidence suggests that consumers gradually increase their electricity consumption. Generally, as economies grow, consumers tend to use more electricity over time. However, the growth in average monthly consumption is slower for R1 prepaid users. Recall that those in R1 are exposed to tariff changes. The B1 prepaid users (i.e., those who were not exposed to tariff changes) seem to behave similarly to their postpaid counterparts. This serves as graphical evidence for parallel pre-trends: the "treated" group (R1) and "untreated" group (B1) behave similarly prior to any major tariff changes.

Figure 6: Trends in the usage of prepaid and postpaid users before and after tariff changes



Notes: The solid (dashed) line represents locally smoothed polynomials of year dummies on the indexed log usage – $\triangle log(usage)_{ict}$ – for R1 1300 VA users (B1 1300 VA). The year when the tariffs first increased is depicted by a vertical dashed line. Visually, we see that the prepaid users' consumption growth in R1 is much slower than that of their postpaid counterparts, even though both groups experience an increase in tariffs. We also see that prepaid users in B1 behave similarly to their postpaid counterparts. This is because B1 users are not exposed to tariff changes.

4 Empirical Analysis

This section is composed of five parts. First, we argue that the variations in our main independent variable are indeed exogenous, allowing us to identify causal effects. Second, we use these exogenous variables to establish our identification strategy and estimate the elasticity parameters for each metering type. Third, we re-estimate the price elasticity with a matched sample based on pre-treatment average usage. Fourth, we estimate the impact of the prepayment system on average electricity consumption. And finally, we conduct placebo checks.

4.1 Identification

There are two sources of variation that we rely on for identification: (1) changes in tariffs and (2) prepaid take-ups. In terms of the changes in tariffs, we utilize the exogenous subsidy removal (i.e., tariff increases) set by government regulations. Since we employ tariffs set by government regulation, as opposed to using the average price observed from billing data, our changes in tariffs are plausibly exogenous to demand if changes in demand do not contemporaneously affect changes in prices. Suppose that tariffs are based on revenue recovery which, in turn, correlate with the total demand and influence tariffs. Under this case, if demand follows a random walk, then as long as the government price-setting process takes at least one year to respond to demand, current changes in prices will be uncorrelated with current changes in demand. Moreover, since the customer groups' total demand is too small (8 percent of total demand in kWh) to influence the total anticipated cost of electricity, it is plausible that they are exogenous.

In terms of prepaid take-ups, we use several alternative measures: (1) aggregated bills at the level of the service unit, VA, customer class, and metering type; (2) prepaid penetration share within the level of the service unit, VA, and customer class (in a different specification, we also instrument the within group prepaid penetration share with the surrounding prepaid penetration share). It is important to understand how much conversion to prepaid meters occurred due to household choice, as this will give rise to an endogeneity bias.[15] As discussed in Section 2, we argue that the conversion to a prepaid meter is primarily driven by PLN regulation. However, one might think that due to the inherent nature of the program, prepaid meters would tend to be used by newer households recently acquiring a new house. This will lead to omitted variable bias as there could be unobservable determinants of prepaid meters that are not captured in the regression. Even though we cannot explicitly test this, we provide some supporting evidence of whether prepaid penetration shares are correlated with observable household characteristics in Section 4.4, and we do not find strong evidence of targeted conversion based on specific household characteristics.

We perform several robustness checks. In Section 4.3, to further improve the comparability between prepaid and postpaid metering types, we match service units based on baseline average usage (2013). Here, we include observations under different VAs that had comparable average kWh usage in 2013 to those of R1 1300 VA. Our conclusion remains similar: prepayment leads to at least double the price elasticity parameter. In Section 4.4, we aim to address the possibility of selection into a prepaid meter even further. Thus, we utilize the share of prepaid meters as the channel through which changes in the tariff may impact overall electricity demand (regardless of metering type). We find that prepayment leads to a threefold increase in the price elasticity parameter. Finally, in Section 4.5, we use other VA classes that also experienced an increase in prepaid metering share but were not exposed to any tariff changes as our placebo check. The results suggest that in the absence of tariff changes, usage between prepaid and postpaid users has similar trends. This reassures us that our earlier findings are primarily driven by tariff

[15]For instance, households that are more aware of their electricity consumption not only opt-in to use prepaid meters but also consume less in general.

changes that interacted with the prepaid system. We discuss our empirical strategies in more detail in the subsections below along with the results.

4.2 Price elasticity of electricity demand by metering type

We begin by estimating the elasticity parameters for each metering separately. For each metering type, we use the difference-in-differences (DiD) approach, comparing R1 customers vs. B1 customers.[16] In Section 5, we use an alternative counterfactual group, and our conclusion remains the same.

We run two ordinary least squares (OLS) regression equations in a sample that combines postpaid and prepaid users. First, following the standard difference-in-differences setup, we interact the treatment dummy with a dummy that is equal to 1 if the year is after the first tariff increase. As such, we have:

$$\triangle log(usage)_{ipct} = c + \alpha_i + \beta_p T_c * Post_t + \gamma_t + \epsilon_{ipct}, \tag{2}$$

where $\triangle log(usage)_{ipct}$ is the change in log usage of service unit i using metering type p in customer class c at year t relative to the base year of 2013, T_c is a dummy indicator for the R1 customer class, $Post_t$ is a dummy indicator that takes on the value of 1 if the observation is for the year 2014 and 0 otherwise. We have two fixed effects. First, we have α_i that captures heterogeneity at the service unit level, and second, we have γ_t which captures time-invariant effects common to all service units and customer class in period t. The constant is c and the error term is ϵ_{ict}. The error term is clustered at the service unit level to allow for correlation within the service unit. The causal effect of removing electricity subsidies on electricity usage is thus represented by the coefficient β.

Table 2 reports within-service-unit differences similar to Panel B in Table 1, but using the indexed log usage as in Equation 1. In the first four columns, we only use the 2014 sample; starting from the fifth column, we use samples from 2015-2020. We consider using the 2014 sample as our best effort to mimic the parallel trend test, considering that the subsidy removal was exposed to R1 customers for half of the year. The first row indicates that in 2014, we find very similar trends between R1 and B1 within service units. This holds among R1 and B1 postpaid users (see second row). Prepaid users in R1 consumed 1 percent less than B1 at the 0.05 significance level (see third row). This is possible as R1 was already exposed to tariff changes for six months. In columns 5-8, we find that for all types of metering, R1 reduced their consumption relative to B1. This suggests that these customers responded to the tariff changes. From this table, we can infer that a 40% increase in tariffs leads to about a 15% decrease in electricity usage, without conditioning on any other fixed effects apart from service unit fixed

[16] As discussed in 2, B1 1300 VA is plausibly a valid counterfactual of R1 1300 VA.

effects. We explore other specifications under this DID framework (in Table 3 columns 1 and 4) to show that our conclusion remains robust to changes in specification – that is: after a major tariff increase, the average consumption among postpaid users changed very little, while prepaid users, consumed much less.

Table 2: Changes in the usage by metering type

	2014				2015-2020			
	R1 1300VA		B1 1300VA		R1 1300VA		B1 1300VA	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within service units differences								
Prepaid-Postpaid	0.05	(0.00)	0.06	(0.01)	-0.10	(0.01)	0.05	(0.02)
Postpaid R1-B1	0.00 p-val: 0.358				-0.04 p-val: 0.000			
Prepaid R1-B1	-0.01 p-val: 0.049				-0.19 p-val: 0.000			
Prepaid-Postpaid R1-B1	-0.01 p-val: 0.020				-0.15 p-val: 0.000			
Observations	1,104				3,486			

Notes: The table reports the mean difference similar to Panel B in Table 1, but using the indexed log usage as in Equation 1.

In addition to using the interaction of dummy variables, we also estimate the elasticity parameter by replacing the interaction terms of $T_c * Post_t$ with the log of price. As such, our OLS regression is as follows:

$$\triangle log(usage)_{ipct} = c + \alpha_i + \delta_p log(price)_{ict} + \gamma_t + \epsilon_{ipct} \tag{3}$$

where we replace $T_c * Post_t$ with $log(price)_{ict}$. We also interact $log(price)_{ict}$ with the year dummies to obtain the elasticity parameter for each year. The β coefficient in Equation 2 and the δ coefficient in Equation 3 are equivalent. We show this equivalence using the following example: when we run a regression of $T_c * Post_t$ on $log(price)_{ict}$, the coefficient of the interaction term is 0.35 (SD = 0.005), suggesting that the tariff changes are 35% on average. As such, $\beta/0.35 \approx \delta$. The δ_p coefficient is interpreted as the elasticity of demand under each metering type.

Table 3 reports β from Equation 2 (columns 1 and 4) and δ from Equation 3 on for postpaid users (columns 2-3) and prepaid users (columns 5-6). Columns 2 and 5 show a 7-year price elasticity while columns 3 and 6 show annual elasticities as we interact the log of price with dummies for each year to capture the long-run dynamics of electricity demand. Column 3 of Table 3 suggests that the price elasticity is zero for postpaid users given the half year of exposure to price changes. However, for prepaid users, the price elasticity is -0.14 which grows to -0.47 after seven years, in contrast to postpaid which only grows to -0.08 after seven years.

Table 3: The impact of tariff change on electricity demand by metering type

	Postpaid			Prepaid		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat=1 × Post=1	-0.037			-0.17		
	(0.0058)			(0.013)		
Log(price)		-0.11			-0.48	
		(0.016)			(0.036)	
Year=2014 × Log(price)			0.035			-0.14
			(0.034)			(0.064)
Year=2015 × Log(price)			-0.070			-0.23
			(0.014)			(0.041)
Year=2016 × Log(price)			-0.099			-0.39
			(0.016)			(0.040)
Year=2017 × Log(price)			-0.11			-0.57
			(0.019)			(0.038)
Year=2018 × Log(price)			-0.13			-0.60
			(0.020)			(0.040)
Year=2019 × Log(price)			-0.15			-0.54
			(0.021)			(0.040)
Year=2020 × Log(price)			-0.077			-0.47
			(0.031)			(0.042)
Service Unit FE	Y	Y	Y	Y	Y	Y
Service Unit	138	138	138	138	138	138
Mean usage	220.1	220.1	220.1	110.8	110.8	110.8
Observations	2,284	2,284	2,284	2,306	2,306	2,306

Notes: We do the regression on subsamples of prepaid and postpaid users. Columns 1 and 4 report β from Equation 2 and columns 2-3 and 5-6 report δ from Equation 3. Columns 2 and 5 show a 7-year price elasticity. Columns 3 and 6 show price elasticity for each year where we interact the log of price with year dummies. Mean usage in kWh in 2013 (baseline year) is reported.

Compared to the existing literature, Table 3 column 2 shows a price elasticity that is similar in magnitude (Ito 2014) while column 5 shows an elasticity that is larger than those in existing studies. The average between columns 2 and 5 falls within the range of magnitude in Burke and Kurniawati (2018), which is approximately -0.32. This paper also studies Indonesia but utilizes aggregate data without distinguishing between metering types. These initial results show that there is a significant difference between how postpaid users and prepaid users respond to prices. Our conjecture is that prepaid meter users have a higher elasticity of demand compared to postpaid metering systems due to greater price salience.

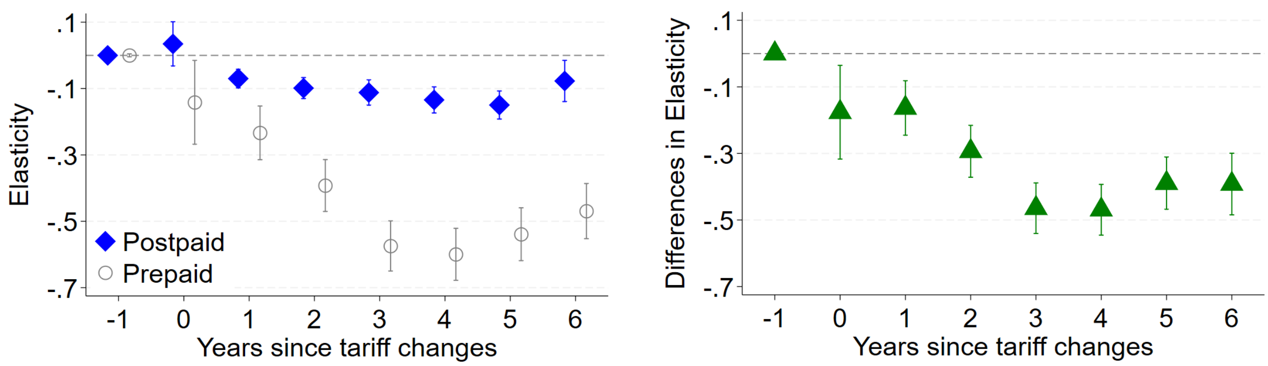
We then take the differences between these two metering types when considering the possibility that customers may have self-selected into a metering type. To quantify the difference in the elasticity parameters between prepaid and postpaid, we include a prepaid dummy (Pre) to Equation 3 and hence, have the following:

$$\triangle log(usage)_{ict} = \alpha_i + \delta log(price)_{ict} * Pre + \delta_0 log(price)_{ict} + \delta_1 Pre + \gamma_t + \epsilon_{ict} \quad (4)$$

Under the tariff changes, we compare how affected prepaid and postpaid consumers respond to these price changes. The left panel of Figure 7 plots columns 3 and 6 of Table 3 while the right panel plots δ_p coefficients from Equation 4. These δ_p coefficients are the elasticity of demand of prepaid metering relative to postpaid.[17] The right panel of Figure 7 shows that prepayment leads to a more elastic demand by about 14 percent six months after the tariff changes, consistent with several existing studies that point out that the short-term reduction in electricity usage is associated with the adoption of prepaid metering by about 14 percent in South Africa (Jack and Smith 2020) and 17 percent in Dhaka, Bangladesh (Debasish Kumar and Stern 2020).

Figure 7: Elasticity Parameters for Postpaid and Prepaid

A. Price elasticity: δ_p from Equation 3. B. δ Prepaid vs. δ Postpaid.



Notes: Figure A plots the price elasticity (δ_p from Equation 3). Figure B compares δ Prepaid vs. δ Postpaid from Figure A. The sample is R1 1300 VA as the treated group and B1 1300 VA as the control group (not exposed to subsidy removal). The whiskers indicate a 95% confidence level. Table S5 in the Appendix reports the results of Figure B in more detail.

We find that prepayment leads to up to four times greater price elasticity than the postpaid counterparts. Figure 7 also shows the dynamics in the long-run price responsiveness. Starting from the year 0 since the tariff changes, the responsiveness starts at -0.14 and gradually increases to about -0.5 in 2017. There is a slight elasticity decline in 2020, which is possibly due to the COVID-19 pandemic. If we omit the year 2020, our estimates remain within a very similar range. Note that after 2017, there were no significant tariff hikes anymore, and therefore we do not think there are significant variations in the prices to cause a continuous increase in the

[17] Table S5 in the Appendix shows the δ_p coefficients from Equation 4.

price elasticity as in the prior years. Nonetheless, the difference in elasticities persists over time, highlighting the long-run dynamics of behavioral responses to prices under different technologies that are long-lasting.

4.3 Matching based on baseline level consumption

Suppose there were some unobservable characteristics that jointly determined a household's choice of metering type and a household's electricity demand pattern, then it might be these unobservable characteristics that drive the differences that we see across metering types. Table 1 shows that this might be a possibility, as prepaid and postpaid users have different levels of baseline average electricity demand. We respond to this possibility by matching prepaid and postpaid users with similar baseline average usage (i.e., level of average consumption in 2013). That is, if we are able to match baseline average usage between prepaid and postpaid, we can also plausibly minimize the differences in unobservable characteristics. To do this matching, we expand our sample to include users with 450, 900, and 2200 VA. We then divide the average usage of all VAs into five groups based on percentiles for each type of metering. We select the 50th percentile where the common support for 1300 VA is the highest. The idea behind this is that prepaid users with 1300 VA consume less than postpaid users with 1300 VA, but their average usage level is likely more comparable to postpaid users with 900 VA at the level.

The results using our matched sample (see Table 4) show similar results to the results using the unmatched sample (see Table 3). In Table 4, we see more comparable mean electricity usage results between our prepaid and postpaid users. The average usage of postpaid users remains higher than prepaid users, but given the standard deviation, the difference in the means is not statistically significant (p-values of 0.624). The results show that the average usage under prepaid meters is at least twice as elastic as the of prepaid users. The price elasticity for the postpaid users is not much different compared to the main results in Table 3. Figure 8 plots the coefficients from Table 4. From the figure, we can infer that prepayment leads to at least double the price elasticity over six years after taking into account similarity in usage across service units and metering types.

4.4 Addressing Omitted Variables

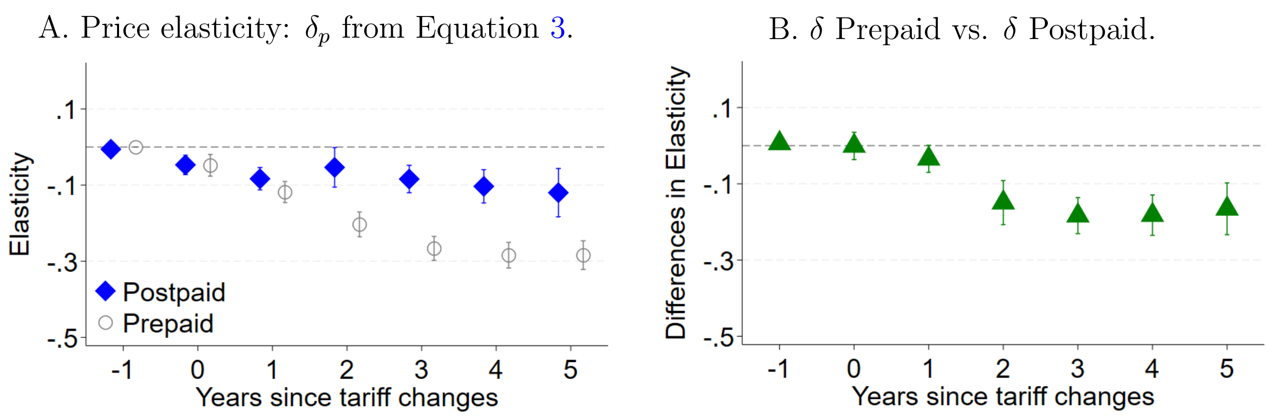
There are several explanations as to why the elasticity of demand for prepaid users may be higher compared to postpaid users. One possibility is due to the default program of the prepaid meter; households with prepaid meters might be those with newer houses, younger household members, more educated, or economically better off. While the default prepaid program was not targeted based on household preferences, some of these unobservables are associated with prepaid adoption and can influence electricity usage and thus remain in the error terms, leading

Table 4: The impact of tariff change on electricity demand by metering type

	Postpaid		Prepaid	
	(1)	(2)	(3)	(4)
Log(price)	-0.077		-0.20	
	(0.015)		(0.014)	
Year=2014 × Log(price)		-0.047		-0.048
		(0.013)		(0.014)
Year=2015 × Log(price)		-0.083		-0.12
		(0.015)		(0.014)
Year=2016 × Log(price)		-0.053		-0.20
		(0.026)		(0.016)
Year=2017 × Log(price)		-0.084		-0.27
		(0.018)		(0.016)
Year=2018 × Log(price)		-0.10		-0.28
		(0.022)		(0.017)
Year=2019 × Log(price)		-0.12		-0.28
		(0.032)		(0.019)
Service Unit	77	77	65	65
Mean usage	147.3	147.3	106.9	106.9
SD usage	52.4	52.4	59.3	59.3
Observations	1,395	1,395	1,801	1,801

Notes: This table reports δ from Equation 3, which is similar to Table 3 columns 2-3 and 5-6, but using matched sample. The number of matched samples by average usage at baseline year are 77 and 65 service units, instead of 138 service units in Table 3. Mean usage and standard deviation (in kWh) at baseline year are reported.

Figure 8: Elasticity Parameters for Postpaid and Prepaid with matched sample



Notes: Figure A plots the price elasticity (δ_p from Equation 3). Figure B compares δ Prepaid vs. δ Postpaid from Figure A. The whiskers indicate a 95% confidence level. It is similar to Figure 7, but the sample used the matched sample based on average baseline usage.

to omitted variable bias. While previous matching exercises attempt to improve comparability between prepaid and postpaid users, there could still be unobservables that are correlated with the metering type dummy and the log usage even after absorbing the time-invariant unobservables at the service unit level with service unit fixed effects.

We use log usage for all users regardless of the metering type. We then use the prepaid penetration rate within the service unit as the independent variable. Our identifying assumption is that prepaid share is uncorrelated with the demand-side predictors of log usage. As discussed in Section 2, prepaid penetration is primarily supply-driven and not demand-driven. Our idea is that regardless of metering type, tariff increase should decrease electricity demand, but the impact of tariff changes will be more pronounced as the prepaid share increases, as households improve their awareness of their own electricity consumption.

Table S1 in the Appendix provides some evidence that the prepaid conversion is not correlated with a set of household characteristics, and therefore supports the argument that the conversion to prepayment was not targeted based on household characteristics. Thus, we argue that the prepaid conversion program can act as a supply shifter for the prepaid status of the household. Then we do the below regression to estimate the price elasticity of electricity demand conditional on prepayment share.

$$\triangle \log(\text{usage})_{ict} = \beta_0 + \beta_1 \text{PreShare}_{ict} + \beta_2 \log(\text{price})_{ict} + \beta_3 \text{PreShare}_{ict} \times \log(\text{price})_{ict} + \gamma_t + \epsilon_{ict} \quad (5)$$

where PreShareict acts as the independent variable, representing the share of prepaid meters for customer i in service unit c and year t. The interaction term PreShareict $\times$ log(price)ict captures the combined effect of PreShare and log(price) on $\triangle$ log(usage). γ_t represents the coefficients for the year indicator variables and ϵ_{ict} is the error term clustered as service unit level.

Table 5 reports within-service-unit differences similar to Table 2, but using the 1300 VA sample without differentiating the metering type and the independent variable (in the leftmost column) is the prepaid share instead of the dummy variable indicating whether it is an aggregated bill based on metering type. The first four columns use only the 2014 sample, while columns 5-8 use samples from 2015-2020. Again, the results using 2014 data serve as our best effort to mimic the parallel trend test. The three rows in columns 1-4 indicate that, in 2014, prepaid share similarly influenced usage between R1 and B1 within service units, and prepaid share similarly affects the usage of R1 with B1. Columns 5-8 show the effects of tariff changes impact on log usage (regardless of metering type) conditional on prepaid penetration rate. The magnitude is consistent with all the results discussed in previous subsections.

Table 5: Balancing Test using Prepaid Share as Independent Variables

	2014				2015-2020			
	R1 1300VA		B1 1300VA		R1 1300VA		B1 1300VA	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within service units differences								
Prepaid Share	-0.58	(0.10)	-0.59	(0.16)	-0.64	(0.10)	-0.43	(0.08)
R1-B1	0.00 p-val: 0.103				-0.09 p-val: 0.000			
Prepaid Share R1-B1	0.01 p-val: 0.155				-0.15 p-val: 0.000			
Observations	552				1,754			

Notes: The table reports the mean difference similar to Panel B in Table 1, but differs in the sample is at the service unit, customer type, and 1300 VA levels without differentiating the metering type. The outcome variable is the indexed log usage as in Equation 1, and the independent variable (in the leftmost column) is the prepaid share instead of the dummy variable indicating whether it is an aggregated bill based on metering type.

We use an instrumental variable approach and obtain a similar conclusion. In the spirit of Bartik's shift-share instrument (Bartik 1991), the prepaid penetration of nearby customers class is plausibly exogenous to the 1300 VA household characteristics (satisfying the *exclusion restriction* assumption) and is a strong predictor for 1300 VA prepaid penetration due to supply side default program (satisfying the *relevance* assumption). Moreover, the prepaid penetration of other customer classes within the same service unit can only influence 1300 VA average consumption through prepaid penetration of 1300 VA customers. Then we can use the penetration rate of 450 VA and 900 VA as the instrument for prepaid penetration of 1300 VA customers. We keep the same fixed effects.

Table 6: Instrumenting with prepaid penetration under different VA within service units

	(1) OLS	(2) 2SLS
Prepaid Share	2.173**	2.350
	(0.844)	(2.323)
Prepaid Share X Log(price)	-0.374***	-0.329*
	(0.124)	(0.184)
Log(price)	0.058	
	(0.078)	
Observations	2,306	2,306
F-stat 1st stage Prepaid Share		63.98
F-stat 1st stage Prepaid Share X Log(price)		87.58

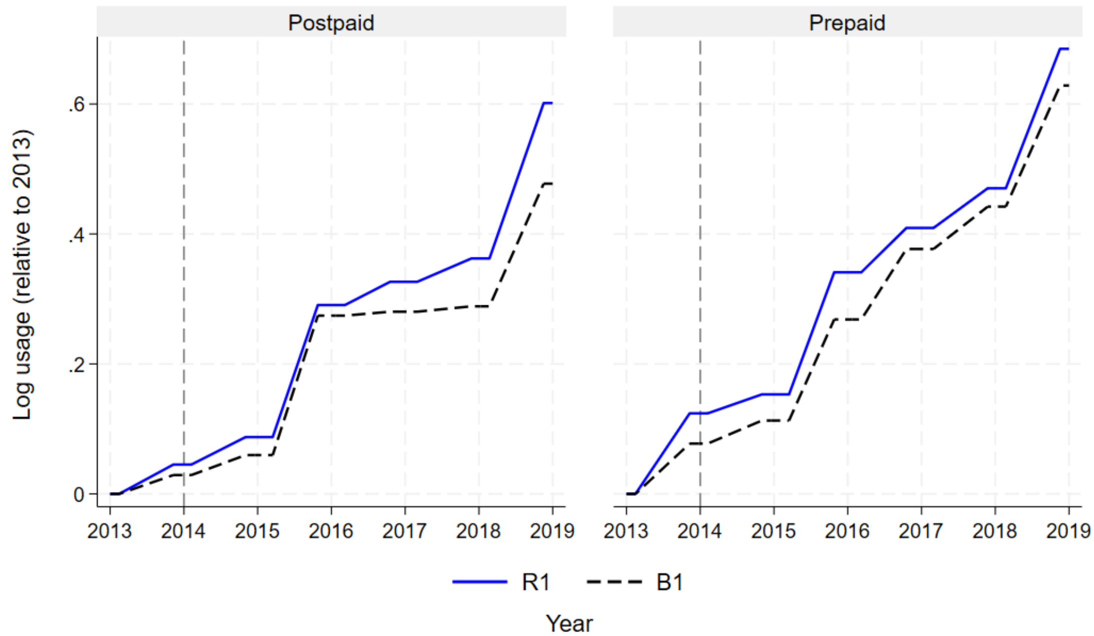
Notes: The table reports β_1, β_2, and β_3 from Equation 5. The sum of β_2 and β_3 captures the elasticity parameters conditional on the prepaid share (see Figure S6 in the Appendix for the estimated elasticity parameters across the share of prepaid penetration). The outcome variable is the indexed log usage (regardless of metering type) as in Equation 1. Column 1 uses OLS with the independent variable being the prepaid share of 1300 VA, column 2 uses 2-Stage Least Squares where we instrument PreShare and PreShare $\times$ log(price) using three instruments: share of 450 VA and 900 VA, log(price), and its interaction term. All the prepaid shares are measured within service units. The regressions are all controlled for year and service units' fixed effects.

4.5 Placebo Test

We conduct placebo checks using other VAs that do not experience price changes. These placebo checks help us rule out the possibility that the observed effects are driven by factors other than tariff change, such as economic growth or other concurrent changes that might influence electricity demand. Figure 9 reports β from Equation 2, which is the difference in the log usage between R1 450 VA and B1 450 VA.[18] They both did not experience price changes, therefore it is impossible to identify elasticity parameters. However, we can still observe the trends in the log usage. Figure 10 suggests that there is no significant difference in consumption patterns between the prepaid and postpaid customers in 450 VA customers. This provides reassurance that the changes in the log usage that we found earlier among prepaid users were driven by price changes.

[18] There is a minimum bill of 40 hours of usage applied to postpaid users for 900 VA and 450 VA, while none for prepaid meters. In 2013, monthly percapita usage was 74 hours (ESDM 2014). If postpaid households use their home as their residence, they would likely have consumed above the minimum usage and therefore face the exact same price as prepaid users.

Figure 9: Placebo Impact: Electricity Usage Trends without Tariff Changes

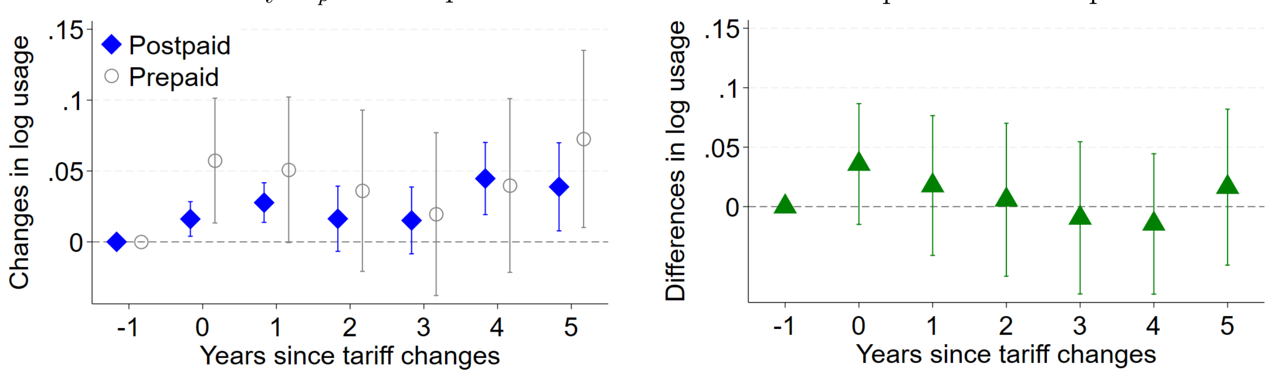


Notes: This figure plots the placebo impact of subsidy removal on usage using 450 VA where there are no changes in tariffs. The solid (dashed) line represents locally smoothed polynomials of year dummies on the indexed log usage ($\triangle log(usage)_{ict}$) for R1 450 VA users (B1 450 VA). The average usage of prepaid users seems to grow more, but there is no visible pattern difference between R1 and B1. We exclude the year 2020 due to concurrent policy occurring in 2020 - the COVID relief package affected this group.

Figure 10: Placebo Impact: Electricity Usage Trends without Tariff Changes

A. Price elasticity: δ_p from Equation 3.

B. δ Prepaid vs. δ Postpaid.



Notes: This figure plots the placebo impact of subsidy removal on usage using 450 VA where there are no changes in tariffs. Figure A plots the price elasticity (δ_p from Equation 3). Figure B compares δ Prepaid vs. δ Postpaid from Figure A. These A and B figures mimic Figure 7 A and B but using R1 450 VA vs. B1 450 VA). The whiskers indicate a 95% confidence level.

5 Other threats to Identification

Our conjecture is that prepayment makes households more price elastic as they are more aware of their consumption and the price and, as such, they make better decisions. However, with the existence of prepaid default and subsidy removal, households might behave in response to this but not through their metering type. We identify three possible responses that, if found to be material, might bias our results downwards as these adaptation mechanisms plausibly minimize their exposure to tariff changes and therefore minimize their reactions. First, households in the R1 category might have different price responses to B1 even before the tariff changes. To address this we use an alternative control group. Second, households may opt to switch from the R1 to the B1 category after they are aware of the subsidy removal in R1. Third, households may be growing and economically better off and therefore those in 1300 VA upgraded to 2200 VA. Our analysis, using only 1300 VA, may consist of households that are economically worse off than their counterparts that moved to 2200 VA. We explain our detailed analysis of these three potential threats in the subsections below. To summarize the results below, we do not find that our results are largely biased due to these threats.

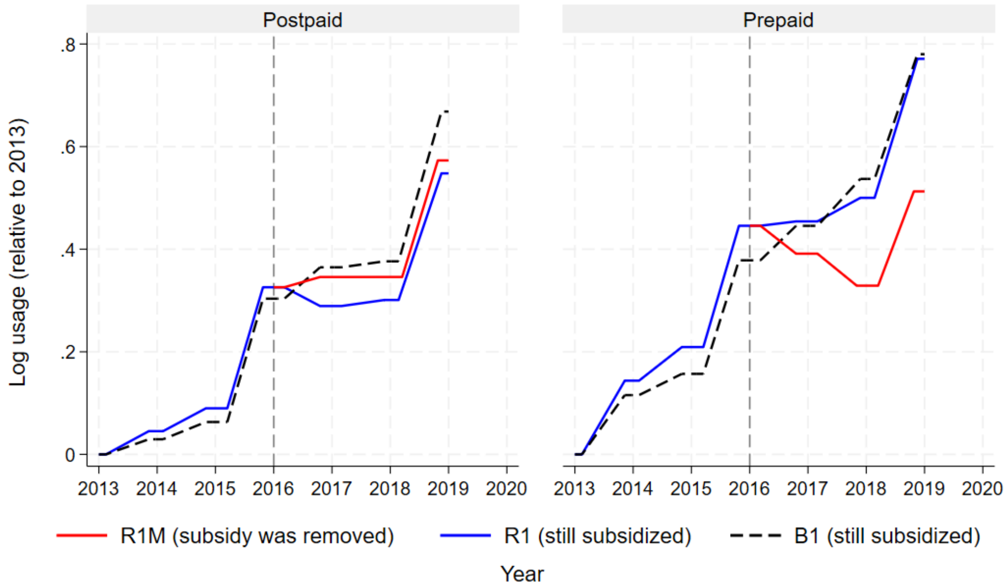
5.1 Selection between R1 and B1

There is a possibility that B1 is not a valid counterfactual group for R1 based on some unobservable characteristics. If this is the case, then this could cause our results to suffer from selection bias. To test this, we performed a similar exercise using households within a similar category (R1). Due to the new regulation, the R1 900 VA category was split into two in 2016: R1 900 VA and R1M 900 VA. The latter category did not exist before 2016, as there was only one category of R1 900 VA. The reason behind this split was the government wanting to remove some of the subsidy from R1 900 VA households. Therefore, R1M is the category for households that are likely to be less poor than their peers within the same 900 VA.[19] Figure 11 shows a similar figure to Figure 6 but using the 900 VA sample. It is clear that after the subsidy removal in 2016, among prepaid users, R1M 900 VA did not consume as much as R1 900 VA or B1 900 VA. This is not the case for postpaid users even though they were equally exposed to the subsidy removal.

To conduct the analysis on the 900 VA customer class, we use an event study as R1M only exists post-tariff changes. Figure A shows the impact of subsidy removal on usage (β_p from

[19] R1M stands for small residential "Mampu" or capable residential. The National Team for the Acceleration of Poverty Reduction (TNP2K) in Indonesia determined customers falling in this category using a proxy mean test (Alatas, Banerjee, Hanna, Olken and Tobias 2012), using household observable characteristics such as appliances they have, among others. Having received this list, PLN would then classify them as R1M. This came as a surprise to households, but households who disagree with this classification can submit disputes through an online application or by visiting the PLN office.

Figure 11: Trends in the usage of prepaid and postpaid users before and after tariff changes - 900 VA

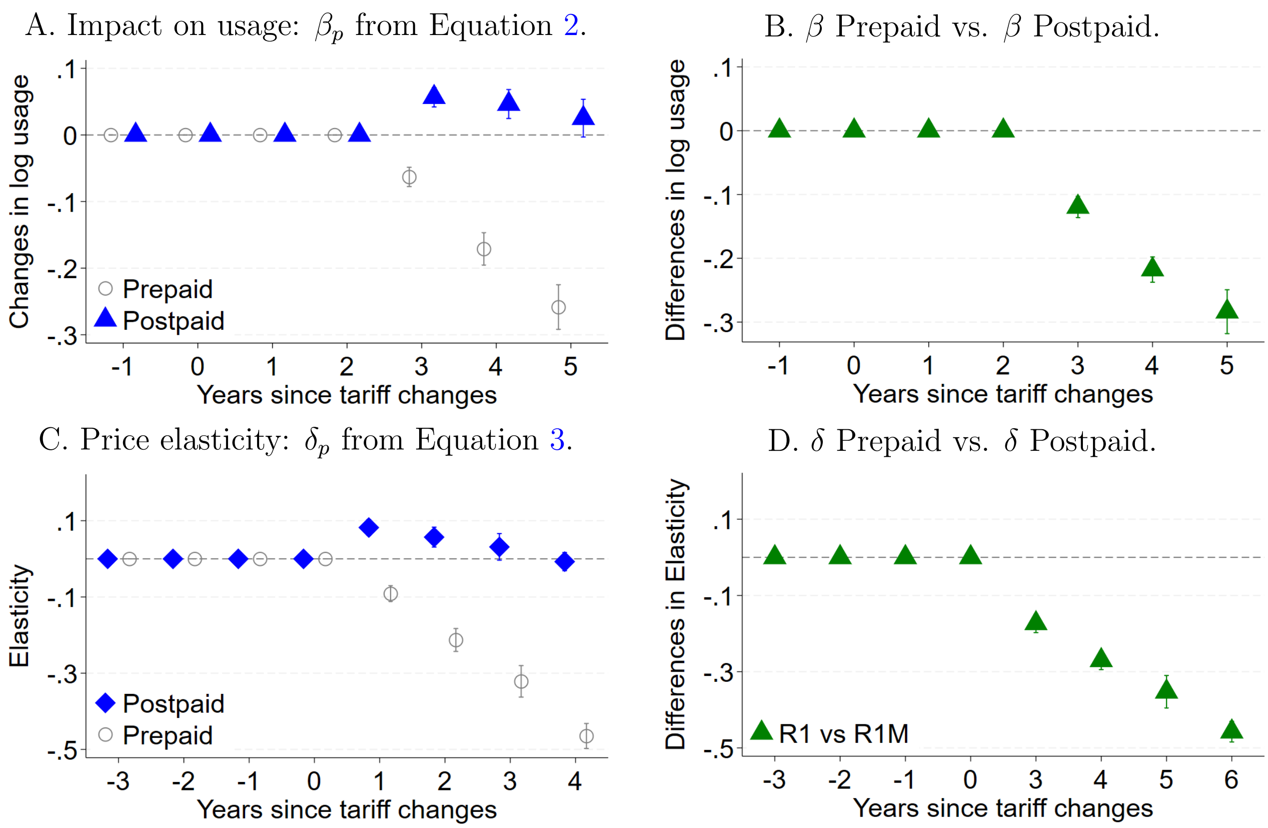


Notes: the lines indicate a local polynomial smooth of year dummy on $\triangle log(usage)_{ict}$. The year when the subsidy is removed for the exposed group is shown in the vertical dash line. Prepaid users consume less over time relative to postpaid users after the removal of the subsidy.

Equation 2). Figure B compares β Prepaid vs. β Postpaid from Figure A. Figure C plots the price elasticity (δ_p from Equation 3). Figure D compares δ Prepaid vs. δ Postpaid from Figure C. The sample is R1M 900 VA as the treated group and R1 900 VA as the control group (not exposed to subsidy removal). Figures C and D are similar to Figure 7 A and B but using R1 900 VA vs. R1M 900 VA). Years prior to tariff changes are zeros due to the fact that R1 and R1M are the same group.

There are no discernible differences in the magnitude of price elasticity in Figure 7 and Figure 12. This suggests that results in Figure 7 are not driven by unobservable differences between R1 and B1. It is important to note that R1M 900VA is likely richer relative to R1 900VA, as the classification into R1M is based on physical assets. Poorer households might exhibit greater price elasticity independent of metering type. Since the treated group is likely richer than the control, we can infer that the observed differences in price elasticity are likely a lower bound.

Figure 12: Using alternative counterfactual group (R1 900 VA vs. R1M 900 VA)



Notes: Figure A shows the impact of subsidy removal on usage (β_p from Equation 2). Figure B compares β Prepaid vs. β Postpaid from Figure A. Figure C plots the price elasticity (δ_p from Equation 3). Figure D compares δ Prepaid vs. δ Postpaid from Figure C. The sample is R1M 900 VA as the treated group and R1 900 VA as the control group (not exposed to subsidy removal). Figures C and D are similar to Figure 7 A and B but using R1 900 VA vs. R1M 900 VA). Years prior to tariff changes are zeros since R1 and R1M are the same group. The whiskers indicate a 95% confidence level.

5.2 Strategic behavior to minimize tariffs

After the removal of the subsidy, households may strategically behave to minimize the tariffs they face. For instance, households under the R1 category may request to move to B1 to benefit from the subsidy. This shift can transform treatment units into control units, biasing down the treatment effects of the subsidy removal. This likelihood hinges on how easily households can transition to another category. In practice, households intending to switch to B1 from R1 undergo document verification and field checks by PLN staff. While these procedures create layers of difficulty, two possibilities emerge: (1) R1 customers who have initiated small businesses at home may remain classified under R1 despite eligibility for B1, only realizing their eligibility due to tariff changes. (2) R1 customers may illicitly convert to B1 through bribery.[20] In either case, we anticipate an increase in B1 prepaid customers, but not in postpaid because,

[20] We label both actions as strategic manipulation, as they both strategically minimize tariff exposure.

as previous evidence suggests, prepaid users are more aware of tariff changes and thus more likely to respond, including by reclassifying their tariff category. To test this, we conduct the following regression:

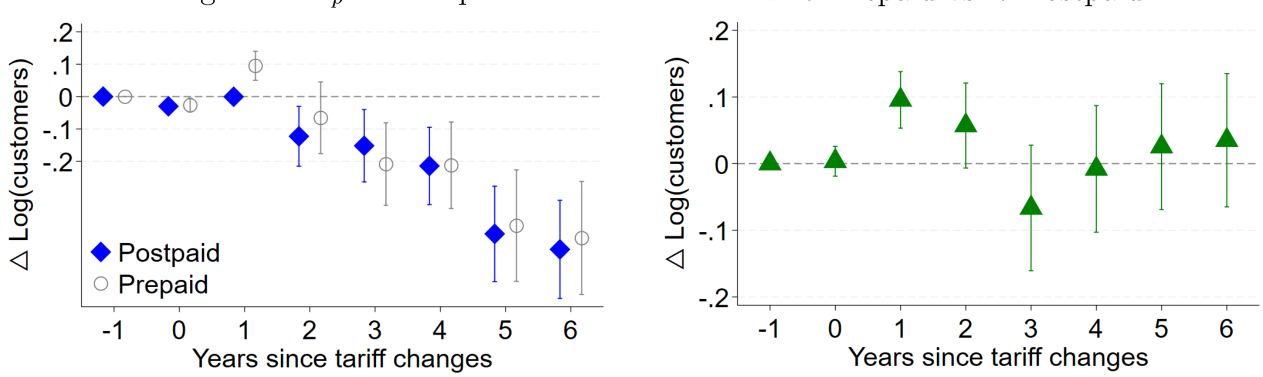
$$\triangle log(N)_{ipct} = \alpha_i + \tau_c + \theta_p Y_t * B1 + \gamma_t + \epsilon_{ipct} \tag{6}$$

where $\triangle \log(N) ipct$ the growth of number of customers in service unit i with metering type p within customer class c during year t, relative to the base year (2013). Fixed effects, α_i and τ_c, encapsulate heterogeneity at the service unit and customer class levels, respectively. The interaction term $\theta Y_t \times B1$ captures the trends of the customers of B1 relative to R1 and Y_t denotes year dummies. Fixed effect γ_t accounts for time-related variation across all service units and customer classes in year t. The error term $\epsilon ipct$ includes unobserved factors and random fluctuations in log usage at various levels—service unit, metering type, customer class, and year. If there is no strategic manipulation, the difference between θ_p prepaid vs. θ_p should be zero, especially near the year when the tariff changed.

Figure 13 suggests that there might be around a 10 percent increase in B1 customers one year after the tariff changes. As reported in Table 1, the average number of customers in 2014, B1 1300 VA - prepaid is around 14,100 households, thus 10 percent is less than 1,500 households. It is not hard to believe that these households "corrected" their customer class from R1 to B1. Our 2SLS estimate (Table 6) did not use the comparison between R1 and B1, and therefore we find smaller price elasticity (-0.3) than the main estimate (-0.4) in Table 3. Since our treatment group (R1) has about 218,000 households, in terms of magnitude, we think that this strategic behavior may lead to overestimating the price elasticity in the main analysis.

Figure 13: Customer Growth of B1 relative to R1

A. Customer growth: θ_p from Equation 6. B. θ Prepaid vs. θ Postpaid.



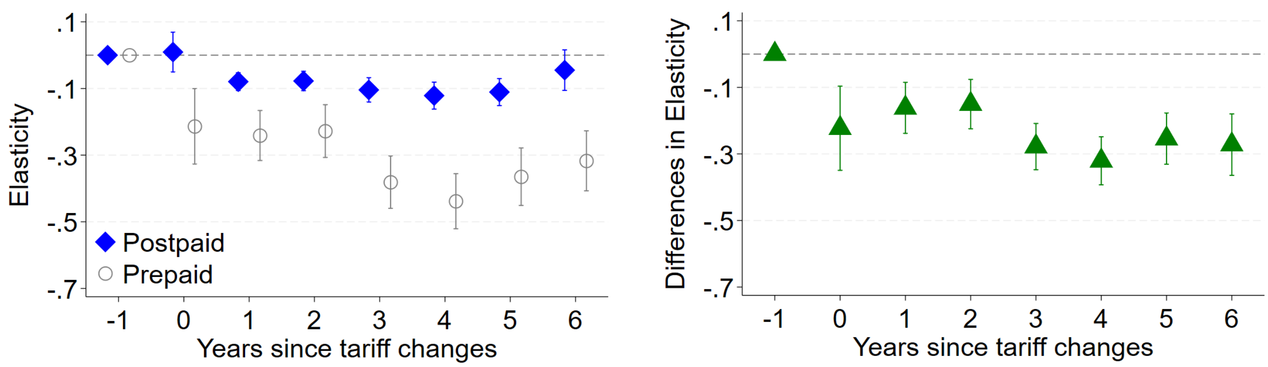
Notes: Figure A plots θ_p from Equation 6. Figure B compares θ Prepaid vs. θ Postpaid from Figure A. The sample is R1 1300 VA as the treated group and B1 1300 VA as the control group (not exposed to subsidy removal). The whiskers indicate a 95% confidence level.

5.3 Compositional changes

There are possibilities that households are economically better off over time and therefore upgraded to higher VAs. If 1300 VA households want to have more electric appliances, they would want to upgrade to 2200 VA if they hit the maximum contracted capacity. This might drive compositional changes as tariffs are the same between 1300 VA and 2200 VA, but those who remain in 1300 VA are poorer households compared to similar households in the same VA bracket.[21] To test if compositional changes partly drive our results, we include households under 2200 VA and do the same regression as our main analysis. Figure 14 shows our main results by including R1 2200 VA.[22] The results show a smaller magnitude of price elasticity (about -0.3 compared to -0.48 from Table 3 column 5). One possible explanation is that the consumption growth of prepaid users moving from 1300 to 2200 attenuates the responses to tariff changes. Therefore, the magnitude is close to the estimates that account for the omitted variable (such as household economic growth), which is -0.329 results from Table 6 column 2.

Figure 14: Elasticity Parameters for Postpaid and Prepaid

A. Price elasticity: δ_p from Equation 3. B. δ Prepaid vs. δ Postpaid.



Notes: Figure A plots the price elasticity (δ_p from Equation 3). Figure B compares δ Prepaid vs. δ Postpaid from Figure A. The sample is R1 1300 VA as the treated group and B1 1300 VA as the control group (not exposed to subsidy removal). These A and B figures mimic Figure 7 A and B but using R1 450 VA vs. B1 450 VA). The whiskers indicate a 95% confidence level.

6 Consumer Welfare Analysis

This section explores the implications of the empirical results on consumer welfare. From Section 4, we find that prepaid users are significantly more price elastic than postpaid users. Based on a battery of checks, it appears plausible that the type of metering could play a role

[21]For comparison of prices across VA, see Figure 5 in the Appendix.

[22]We did not include B1 2200 VA as this group is not identified separately, and it was aggregated together with higher VA.

in making customers more aware of electricity prices. Consequently, in theory, prepaid meters should enhance consumer welfare by helping them make better decisions due to increased price awareness. However, this might not be the case if the metering type influences consumer utility through channels other than prices. We first show that the consumer utility from the non-price aspect is positive. First, we demonstrate that the consumer utility from non-price aspects is positive. We then calculate welfare changes from converting consumers from postpaid to prepaid, borrowing from tax literature on excess burden due to tax policy (Harberger 1964). In our case, instead of tax, prices increased due to the removal of subsidies. Lastly, we quantify pollution implications due to the conversion.

Prepaid metering may have non-monetary benefits or costs. For instance, a prepaid meter offers a commitment mechanism and less uncertainty in terms of billing while a postpaid meter offers the flexibility of deferring payment. We then compare the net gains or losses from choosing to use one type of metering system over another in Section 6.1. In particular, we use the Multiple Price Listing method to elicit an individual's willingness to pay for either a prepaid or a postpaid meter (see Section 1.2 in the Appendix for a more in-depth discussion of this method and channels on why we observe positive willingness to pay from staying using prepaid meters). If the willingness to pay is positive, it indicates a positive net consumer surplus that captures non-monetary benefits. We focus on the consumer's perceived willingness to pay and do not focus on the producer surplus, as we think producer surplus is unambiguously positive.[23]

6.1 Consumer Welfare: Evidence from an Online Survey

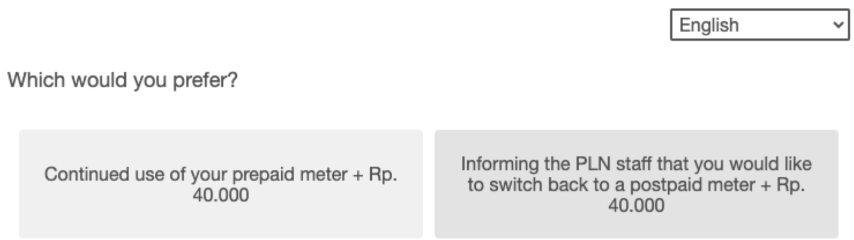
We ran an incentivized experiment among prepaid and postpaid meter users with home residences in cities in Central and East Java in Indonesia.[24] A total of 1104 participants completed the survey in August 2022. These participants were randomly recruited from the consumer panel database of the survey company, TGM Research. The experiment was administered online through a Qualtrics survey and was available to the participants in both Indonesian and English. A copy of the survey questionnaire in English can be found in the Appendix **??**. The Indonesian version of the questionnaire is available upon request.

We use multiple price lists (MPL), a common method to elicit individual willingness-to-pay (Allcott and Kessler 2019, Jack et al. 2022). Prepaid users were initially given the option for

[23] The reason is that the costs are likely lower than the gains. The substantive costs for producers are primarily related to the cost of metering (as the replacement cost is free for consumers) and the reduction in electricity sales. The gains for producers, however, encompass a variety of benefits, including lower billing costs due to the reduced need for staff to record the monthly consumption of each household, reduced improper usage of electricity and theft, lower debt and nonpayment, potential increases in the reliability of electricity during peak times, and a decreased need to build new generation capacity to meet growing demand.

[24] Human Subjects Board approval number 016/UN2.F6.D2.LPM/PPM.KEP/2022

Figure 15: Sample Decision Screen of Participants



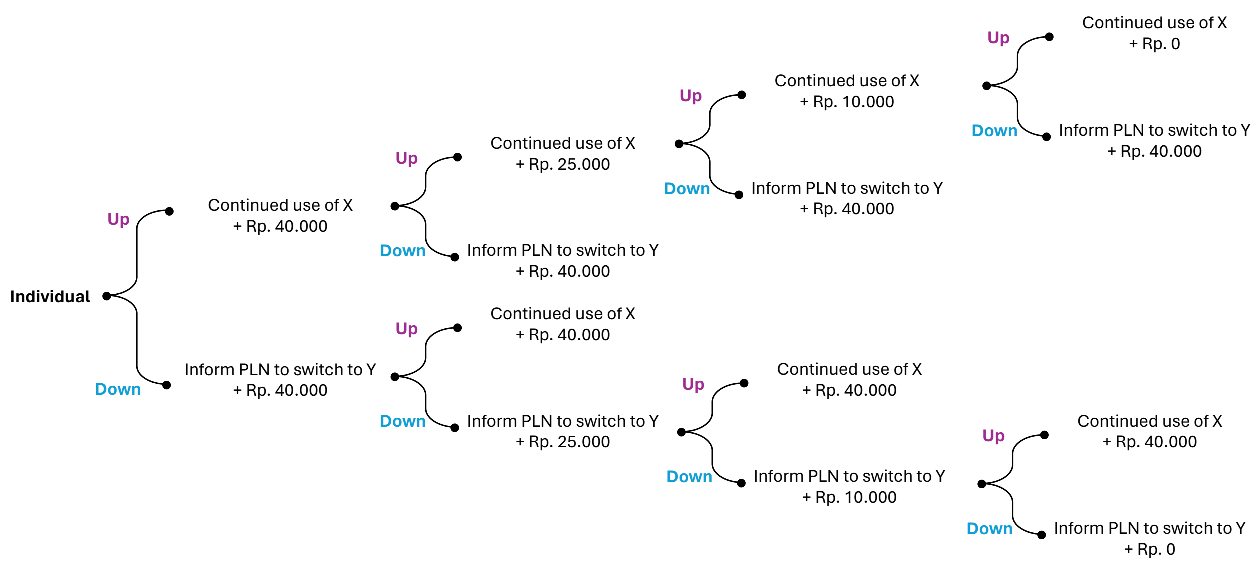
either "Continued use of your prepaid meter + Rp. 40.000" or "Informing the PLN staff that you would like to switch back to a postpaid meter + RP 40.000" while postpaid users were given the option for either "Continued use of your postpaid meter + Rp. 40.000" or "Informing the PLN staff that you would like to switch to a postpaid meter + Rp. 40.000" (see Figure 15).[25] Depending on which choice individuals make, they are then faced with a similar option but with their initial chosen option matched with a lower corresponding monetary amount, as depicted in the decision tree in Figure 16. Both prepaid and postpaid participants were asked to make such choices three times. However, if a participant chooses "Up" in Figure 16 and then chooses "Down", the experiment ends for that participant, regardless of whether he has made three such choices.

Participants were informed that upon completion of the survey, 200 respondents with valid and complete answers will be picked to receive payment based on the decision they made. This implies that, on top of the fixed fee that they received for completing the survey, they will receive this additional payment. This also means that if they chose to inform the PLN staff about a switch, either from prepaid to postpaid or postpaid to prepaid, we informed the PLN staff to make a switch. Moreover, out of 1104, 71% believed that the PLN staff would actually come and switch their electricity meter if a request were made.

The responses to the MPL categorize an individual's willingness to pay (in USD) into eight ranges, symmetrically distributed around zero: $(-\infty, -2.69]$, $[-2.69, -2.02]$, $[-2.02, -1.01]$, $[-1.01, 0]$, $[0, 1.01]$, $[1.01, 2.02]$, $[2.02, 2.69]$, and $[2.69, \infty)$. Focusing on prepaid users, as they are the ones with experience using prepaid metering, our analysis reveals evidence indicating a positive willingness to pay among these users. Figure 17 displays the histogram of willingness-to-pay among prepaid users, revealing that a substantial proportion of respondents (approximately 70-80 percent) are inclined to forgo monetary compensation in order to continue using prepaid metering. Additionally, based on responses to a hypothetical question in the survey, households currently utilizing prepaid meters express a reluctance to switch back to postpaid meters, with

[25] 40.000 IDR is around 3 USD.

Figure 16: Participant Decision-Tree



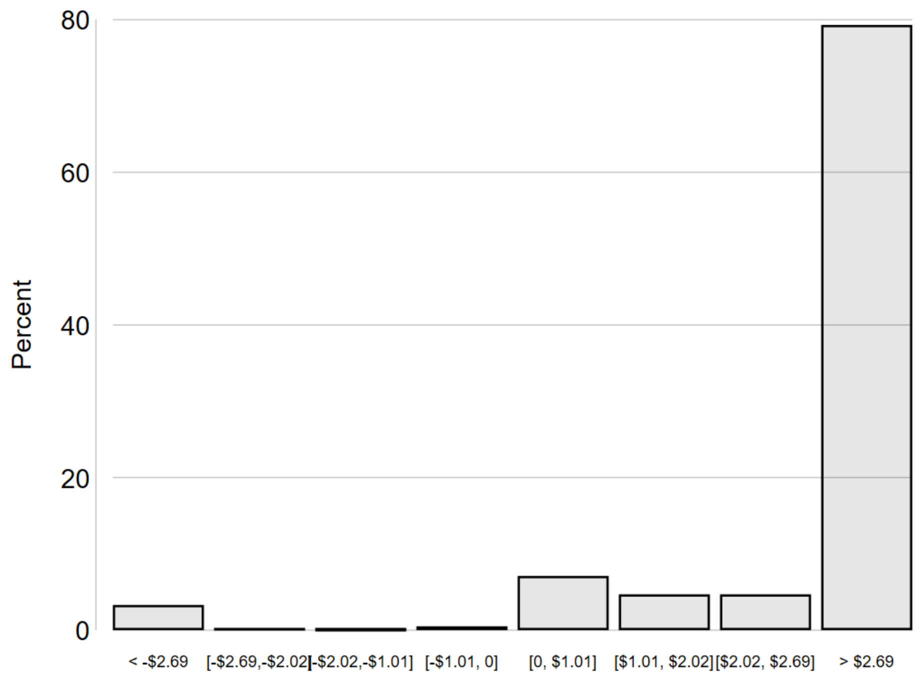
Notes: For prepaid users, "X" is replaced with "your prepaid meter" and "Y" is replaced with "a postpiad meter". On the other hand, for postpaid users, "X" is replaced with "your postpaid meter" and "Y" is replaced with "a prepaid meter".

the average estimated cost for such a switch exceeding a hundred billion USD. While this estimate may be considerably inflated, it underscores the strong disinclination of prepaid users to revert to postpaid metering.

One might be concerned about self-selection; that is, those who voluntarily converted to prepaid meters will, of course, have a positive willingness to pay for it. To address this concern, we ask our survey respondents who initiated their conversation to prepaid meters.[26] Participants were asked to pick one of six choices and we lumped these answers into three broad categories: those that were initiated by PLN, those that did not have a choice (because the house was newly built), and those who changed via their own initiative. We find that, regardless of who initiated the conversion, the majority of prepaid user respondents prefer to continue using prepaid meters rather than receive up to 3 USD in compensation for switching back to postpaid. Hence, regardless of who initiated the switch, we find positive consumer welfare. Section 1.2 in the Appendix provides further explanation on why we observe positive willingness to pay from staying using a prepaid meter.

[26]Survey participants were specifically asked "Who initiated the change of your electricity meter from postpaid to prepaid?" and participants could answer one of the following options: PLN personnel, my house was newly built so I had no choice, myself, my partner, my parent, or some other person.

Figure 17: willingness-to-pay to stay using prepaid metering



Notes: it shows the histogram of willingness-to-pay to stay using prepaid metering from prepaid users differentiated. Around 70 - 80 percent of respondents are willing to forgo the opportunity to get \$2.69 USD rather than to have their prepaid meter replaced with the postpaid meter. Source: an online survey conducted by authors.

Our survey results show consistency with several existing conjectures, reassuring that our respondents are not particularly different compared to other studies. First, prepaid users are largely more aware of their electricity consumption compared to postpaid users, consistent with our conjecture that the prepayment system leads to increased salience. Second, the qualitative aspects of prepaid metering that affect customers' satisfaction with prepaid metering are consistent with the existing studies (O'Sullivan, Viggers and Howden-Chapman 2014). Third, the discounting parameter is similar in magnitude to an experimental study that compares the pay-later group compared to the pay-as-you-go group in Germany (Werthschulte 2023), suggesting that postpaid users exhibit present focus over-consumption compared to the prepaid users. We discuss all of these aspects in more detail in the Appendix.

6.2 Applied Welfare Analysis

In this section, we develop a simple theoretical framework to assess the consumer gains from transitioning from postpaid to prepaid electricity meters. Let P denote the exogenous price of electricity, q. The utility function for an individual is given by $u(q) = V(q)$, where $V(\cdot)$ is a strictly concave and twice continuously differentiable function. Individuals maximize their utility subject to a budget constraint: $I = s^{+}Pq$ for prepaid users and $I = \gamma s^{x}Pq$ for postpaid users. Here, I represents the individual's total expenditure on electricity, $s \in (0, 1]$ is the salience parameter (with $s = 1$ indicating full salience), and $\gamma \in (0, 1]$ is the discount factor. The discount factor γ applies only to postpaid users because they pay for electricity after consumption, while it does not apply to prepaid users, who pay before consumption.

Under the first-order condition, individuals consume q^{*} such that $u'(q) = s^{+}P$ for prepaid users and $u'(q) = \gamma s^{x}P$ for postpaid users. Our survey results indicate that prepaid users exhibit higher salience ($s^{+} \gg s^{x}$) than postpaid users, thus the perceived price is effectively lower for postpaid users, leading to a relative underreaction to price changes relative to prepaid users, consistent with findings from (Sexton 2015). Moreover, γ reduces the perceived price even more, consistent with the lab experiment that suggests pay-later consumers over-consume relative to pay-as-you-go consumers (Werthschulte 2023)

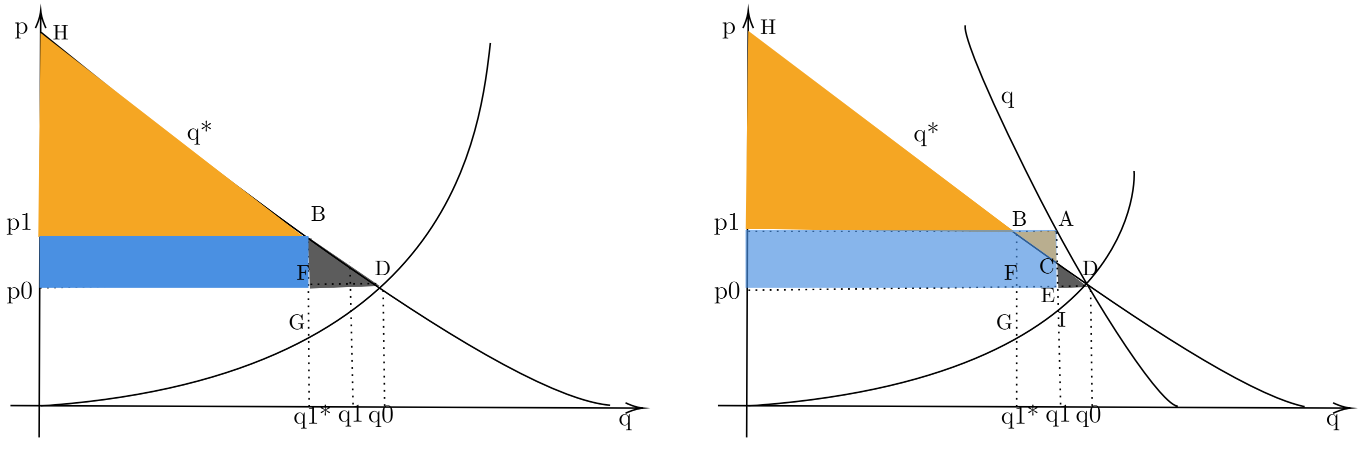
To derive an analytical solution for the welfare impact of postpaid to prepaid conversion, we impose a simple structure on our model. We assume that the aggregate demand curves have constant elasticities in the form of $\alpha P^{-\beta}$, where α is the demand coefficient and β is the elasticity parameter. To fit our context, we assume that the producer offers electricity at marginal cost, c, and consumers pay $P_0 = c+$subsidy. When the government removes the subsidy, the price increases such that $P_1 = P_0-$subsidy. Furthermore, we also assume no income effect, as electricity bills constitute less than five percent of monthly expenditure.

According to our empirical estimates, the price elasticity for prepaid users is greater than that for postpaid users ($\beta^{+} > \beta^{x}$). Therefore, the demand curve for prepaid users is flatter compared to that of postpaid users. Utility derived from less salient demand is q (analogous to postpaid) and from more salient demand is q^{*} (analogous to prepaid) is illustrated in Figure 18. When the price increases from P_0 to P_1, Figure (a) illustrates that the salient agent will choose $q1^{*}$, while (b) illustrates that the less salient agent will underreact to price changes, resulting in the consumption of q_1 instead of q_1^{*}. In (a), focusing only on consumer and government surplus, q_1^{*} generates the excess burden triangle of BDF, while Figure (b) generates the excess burden triangle of CDE.[27] This can be computed by subtracting the triangle BDF with consumer surplus by the triangle ABC, then adding the increase in government surplus by the rectangle ABEF. This suggests that inattention reduces the deadweight loss area and lowers consumer surplus. This is consistent with the theoretical findings of Chetty (2009), who found that inattention reduces excess burden when there are no income effects.[28]

[27] See footnote 23 on why we do not discuss producer surplus.

[28] However, inattention may raise the excess burden when there are income effects. For more discussion on this, see Chetty et al. (2009).

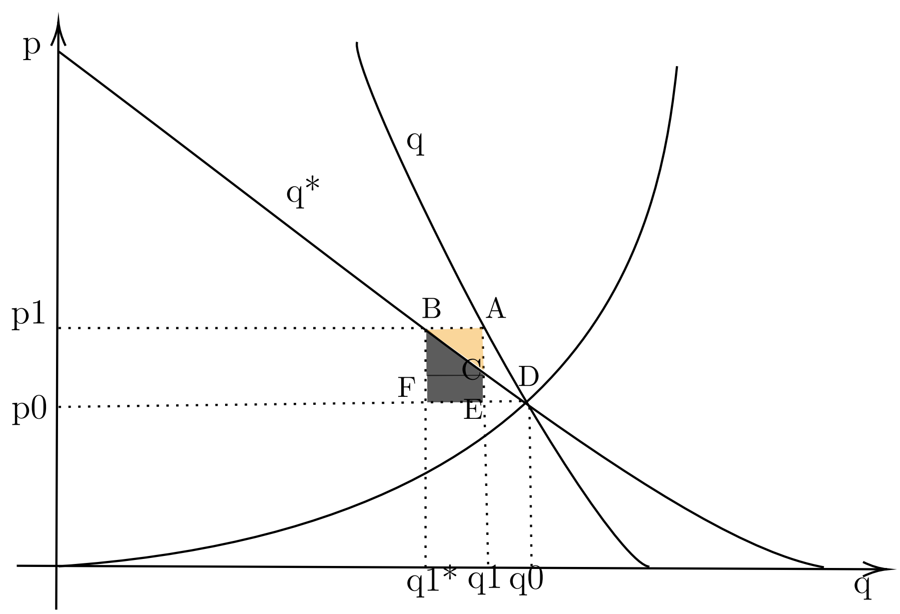
Figure 18: Changes in consumer surplus and government revenue



(a) More salient demand (q^*) (b) Less salient demand (q)

Notes: Figure (a) illustrates the changes in consumer surplus and government surplus under salient demand (q^*), while Figure (b) shows these changes under less salient demand (q). In Figure (a), focusing only on consumer and government surplus, the excess burden is represented by the triangle BDF. The consumer surplus in Figure (b) is the surplus in Figure (b) but reduced by the area ABC due to underreaction to the price increase. The government surplus in Figure (b) is higher than in (a) due to additional government revenue generated by the underreaction to the higher price, represented by the rectangle ABEF. Finally, the triangle CDE is the excess burden for q.

Figure 19: Excess burden and consumer gains due to the conversion



Notes: This figure illustrates the impact of converting postpaid to prepaid on the excess burden and consumer surplus. It summarizes the results from Figure 18. The upper triangle ABC illustrates the consumer gains, while the lower trapezium ABCF indicates the efficiency loss due to the conversion. The relative size of these two areas depends on the slope of q and q^*.

To quantify the excess burden from a tariff increase due to postpaid to prepaid conversion, we calculate the area represented by the trapezium BCEF in Figure 19:

$$\int_{q_1^*}^{q_1} \left(\frac{\alpha}{q}\right)^{\frac{1}{\beta}} \mathrm{d}q - p_0(q_1^* - q_1) \tag{7}$$

To quantify only the consumer gains from a tariff increase due to inattention, we compute the integral above the q^* curve, which is the area represented by the triangle ABC in Figure 19:

$$\triangle CS = p_1(q_1^* - q_1) - \int_{q_1^*}^{q_1} \left(\frac{\alpha}{q}\right)^{\frac{1}{\beta}} \mathrm{d}q \tag{8}$$

Due to the conversion, the quantity produced will be q_1^*, which is less than q_1, resulting in emission implications. We compute how much CO_2 emission is avoided due to the conversion. Approximately 60% of electricity in Indonesia was generated from coal in 2019 (Lolla and Yang 2021). Thus, we use the CO_2 emission factor (pounds of CO_2/kWh) for coal, which is 2.30 pounds per kWh, from U.S. Energy Information Administration (2022). Additionally, we use the Indonesian carbon credit price of IDR 69,600 (approximately \$4.51) per tonne Indonesia (2023). We then compute the avoided cost of CO_2 based on these parameters and normalize it to the total cost of carbon at q_0.

Using our empirical estimates of $\beta^+ = 0.3$ and $\beta^x = 0.1$, and parameter values of $p_0 = 1000$ IDR/kWh, $p_1 = p_0 \times 1.35$ to represent a 35 percent tariff increase, and $q_0 = 41,136,476,384$ Kwh, which is the 2013 aggregate consumption of R1 450, 900, and 1300 VA postpaid. The demand coefficient α can be computed using p_0, β^+, and q_0. Our results indicate that, due to the switch to prepaid meters for R1 1300 VA customers from postpaid meters, the efficiency loss arising from a 35 percent price increase is 23 percent of baseline expenditure, while the consumer surplus loss reaches 31 percent of baseline expenditure. The magnitude of the gain/loss is normalized with baseline expenditure ($p_0 \times q_0$), which is approximately USD 2,742 million, while the magnitude of the avoided CO_2 is normalized by carbon price$\times q_0$, which is approximately USD 200 million.[29]

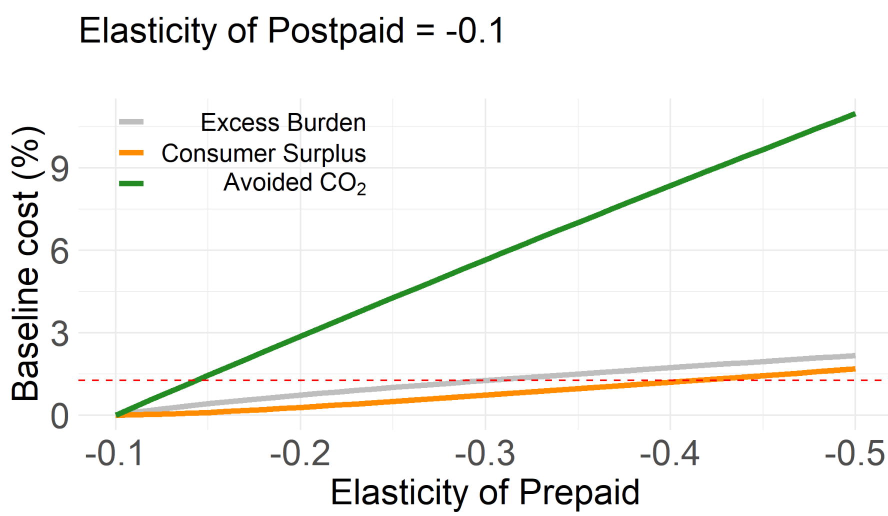
As the size of the gain and loss depends on the elasticity parameters, we then illustrate how the excess burden (Equation 7), consumer gains (Equation 8), and pollution externalities vary by elasticity parameters. We set the slope of q fix at -0.1 (consistent with our empirical findings and existing studies standard short-run price elasticity of electricity demand such as Ito (2014)), then we vary the slope of q^*, from -0.1 to -0.6 and compute the values of the gains and losses for each of the values.

Figure 20 illustrates the impacts of varying the prepaid price elasticity parameter on ex-

[29] using USD 1 = IDR 15,000.

cess burden, consumer gains, and pollution avoided, while holding the postpaid price elasticity constant. We can see that the higher the elasticity of prepaid, the larger the efficiency loss. Similarly, the higher the elasticity of prepaid, the larger the consumer surplus. However, the gains from avoided pollution are notably higher than both the efficiency loss and consumer surplus. This indicates that the environmental benefits of the conversion are substantial, especially due to the high emission intensity per unit of electricity generated. By reducing the quantity produced, the conversion has the potential to reduce CO_2 emissions, lower the costs associated with carbon, and ultimately promote climate change mitigation and improve public health.

Figure 20: Sensitivity of Efficiency and Consumer Surplus to Prepaid Price Elasticity



Notes: This figure shows the sensitivity of efficiency loss (computed from Equation 7) and consumer surplus (computed from Equation 8) given different values of prepaid price elasticity, with other parameters fixed. The horizontal lines correspond to values according to our main assumption on the elasticity parameters. The magnitude of the gain/loss is normalized with baseline expenditure ($p_0 \times q_0$), while the magnitude of the avoided CO_2 is normalized by carbon price$\times q_0$.

7 Conclusion

This study offers critical insights into the role of prepaid metering in enhancing the price elasticity of electricity demand in developing countries. By focusing on the Indonesian context, where a significant transition from postpaid to prepaid metering systems occurred alongside the removal of electricity subsidies, we provide empirical evidence that prepaid users demonstrate a more elastic demand response to price changes than their postpaid counterparts. This finding underscores the importance of salience in influencing consumer behavior, suggesting that the immediacy of financial consequences under prepaid systems heightens consumer awareness and prompts more efficient electricity usage.

Our results align with the broader literature on the impact of salience on consumption, contributing novel evidence from a developing country context where advanced metering technologies like in-home displays are often infeasible. The study's methodological rigor, including the use of event studies and difference-in-difference approaches, supports the robustness of these findings, offering a reliable estimate of price elasticity that is crucial for policymakers. Furthermore, our incentivized survey reinforces the hypothesis that increased salience under prepaid systems leads to a more conscious and controlled energy consumption pattern, with positive implications for consumer welfare.

The policy implications of this research are significant. As developing countries continue to grapple with the dual challenges of rising energy demand and the need for sustainable growth, prepaid metering systems emerge as a cost-effective tool for promoting energy conservation. By making electricity demand more elastic, these systems can help align consumer behavior with broader climate policy goals, such as reducing carbon emissions and enhancing energy efficiency. Policymakers and utility companies can leverage these insights to design effective pricing strategies and subsidy reforms that not only optimize energy use but also support the equitable and sustainable development of the electricity sector.

Our analysis reveals that the transition to prepaid meters, combined with a 35 percent price increase due to subsidy removal, leads to notable changes in both efficiency and consumer surplus. The heightened responsiveness of prepaid users to price changes results in consumer surplus gains, despite the efficiency losses stemming from reduced government revenue recovery. However, the benefits from avoided pollution significantly surpass these effects. This underscores the substantial environmental advantages of the conversion, especially given Indonesia's high emission intensity per unit of electricity generated. These findings highlight the critical need to consider consumer behavior and environmental impacts in policy decisions regarding prepaid conversion and price adjustments.

Future research could investigate the potential spillover effects of prepayment systems on other aspects of household behavior, such as energy-efficient appliance purchases and investment in renewable energy. Moreover, more research is needed to understand the long-term impacts of prepayment systems on consumer behavior and welfare. Overall, our findings highlight the importance of considering the behavioral drivers of electricity consumption and the potential effectiveness of prepayment systems in reducing consumption and promoting sustainable development.

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