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Prepayment, Salience, and Welfare

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Prepayment, Salience, and Welfare

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The timing of payment can enhance salience, making customers more price-responsive when paying before consumption rather than after. This study examines Indonesia's nationwide switch to prepaid electricity metering, impacting over 40 million households. We find that prepaid metering users are twice as price-elastic as postpaid users. We also find a positive willingness to pay for prepaid metering, suggesting consumer welfare gains. As prices rise, prepaid metering reduces excess burden by 1.5% and CO_2 emissions by nearly 6%. These findings suggest prepaid meters can support climate policy goals by promoting energy conservation without imposing significant burdens on consumers.
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Efforts to mitigate climate change hinge on rethinking energy consumption, especially in developing economies where infrastructure and policy constraints hinder efficient energy use. Among these challenges, electricity consumption remains a critical focus due to its outsized contribution to greenhouse gas emissions (International Energy Agency, 2023). While developed countries leverage advanced technologies such as automatic billing and in-home displays to promote efficient use of electricity (Gilbert and Zivin, 2014; Sexton, 2015; Jessoe and Rapson, 2014), developing economies face barriers to implementing similar technologies. These barriers include limited financing for infrastructure upgrades and persistent revenue shortfalls, which undermine demand management efforts. This paper addresses a pressing policy question: How can simple, low-cost technologies like prepaid electricity meters enhance the salience of electricity prices and reshape consumer behavior without reducing consumer welfare? By investigating these dynamics, we provide new insights into the price elasticity of electricity demand—a key policy parameter for designing effective energy policies—in resource-constrained settings.

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Economists have documented the importance of salience in consumption responses in various ways. For instance, payments made long before or after the purchase reduce consumers' attention to a product's cost (Gourville and Soman, 2002). Similarly, electronic toll collection reduces salience, making drivers less sensitive to toll prices (Finkelstein, 2009a). In primary sectors such as electricity, the role of salience-enhancing technologies like prepaid meters remains underexplored, particularly in developing countries where affordability and access constraints necessitate innovative solutions. Prepaid metering is an example of a simple technology that is 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 et al., 2017; Jack and Smith, 2020; Debasish Kumar and Stern, 2020; Beyene et al., 2022). Despite its promise, the mechanisms driving reduced electricity consumption under prepaid metering remain unclear, leading to unclear welfare implications. As prepayment obliges customers to make an upfront payment, we posit that prepaid systems heighten price salience, leading to more elastic electricity demand compared to post-payment systems.

In this paper, we investigate the differences in demand elasticity between prepaid and postpaid users, testing whether consumers under prepayment exhibit greater price salience than their postpaid counterparts, *ceteris paribus*. Estimating elasticity in developing countries presents several challenges (Khanna and Rao, 2009). Retail electricity prices often exhibit limited variability and are frequently set below marginal costs due to subsidies, fostering overconsumption and inattention to price signals (Del Granado et al., 2012).[2] As a result, several studies have adopted differing methodological approaches, often imposing strong assumptions, and reported a wide range of elasticity estimates, spanning from -0.85 and -0.04 (Khanna and Rao, 2009; Burke and Kurniawati, 2018; Durmaz et al., 2020; Uddin et al., 2023; Gillingham et al., 2016). We overcome these challenges by leveraging two regulatory changes in Indonesia: the large-scale conversion to prepaid meters and a subsidy reform that raised tariffs for certain consumers. These exogenous variations allow us to estimate price elasticity more flexibly and over a longer period than prior studies.

We estimate price elasticity using proprietary billing data from an Indonesian utility company at the service unit level for the years 2013-2020. To test our hypothesis that prepayment reduces electricity consumption, we employ a difference-in-differences (DiD) methodology on two similar customer groups who faced a similar probability of

[1] This payment system may improve demand management and lower the risk of excess consumption in settings where it is fully powered by renewable energy sources (International Renewable Energy Agency, 2020). It has also been implemented in other sectors like water utilities, mobile phones, internet access, transportation, and recently in cooking stoves (Shupler et al., 2021).

[2] Additionally, in some developing countries, electricity demand is constrained more by supply factors than by consumer demand, diminishing the role of price in the electricity demand equation (Khanna and Rao, 2009). Methodologically, estimating elasticity is complicated by endogeneity between consumption and average prices, as well as the common reliance on aggregated data in many studies Burke and Kurniawati (2018); Alberini and Filippini (2011a). Deryugina et al. (2020) point out similar issues in estimating short and long-run demand elasticity in developed countries.

being converted to prepaid meters. However, one group faced increased tariffs, while the other group faced no changes to their tariffs. 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,[3] and with a similar share of prepaid penetration rate. Our identifying assumption is that differences in electricity demand elasticity are driven primarily by prepayment adoption, supported by parallel pre-treatment trends.

We complement our main analysis with a battery of robustness checks. First, to address potential selection bias in prepaid metering driven by household preferences, we use the prepaid penetration rate from nearby service units to instrument adoption as it captures the program's expansion effort and is not directly related to household preferences. We also complement our DiD analysis with the matching estimator (Abadie and Imbens, 2006), using baseline electricity usage as the matching criteria. Furthermore, 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, our additional checks on the remaining identification threats–including selection into customer class, strategic behavior to minimize tariffs, and compositional changes–confirm that our conclusions remain robust.

We find that prices increased by 35% after the subsidy removal, faced by both postpaid and prepaid users over seven years. Due to the price change, the average usage for postpaid users decreased by only 4% compared to the 17% usage decline by prepaid users. Furthermore, our findings reveal that the estimated price elasticity of prepaid users declines from -0.14 in the first year to -0.47 after seven years, suggesting long-run behavioral changes. Overall, we find that our estimated price elasticity of prepaid users is two to four times lower than that of their postpaid counterparts.

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 households face liquidity constraints that prevent them from prepaying or if the technology itself generates negative utility that is independent of price effects. Firstly, liquidity constraint is not likely the main driver for the reduction in consumption because electricity bill constitutes less than five percent of total monthly spending, and the amount to prepay can be split into several small purchases. Secondly, 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 the certainty of the electricity bill amount. To gain a more comprehensive understanding of the net welfare implications of prepaid metering, we complemented our analysis with an incentivized choice elicitation method commonly utilized in the literature (Allcott and Kessler, 2019; Jack et al., 2022), and we find that the

[3]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.

net welfare effect (proxied by the willingness of consumers to forgo a monetary amount to continue using the prepaid meter) is positive.

Our results have significant implications for energy policy. Using an applied welfare analysis, we quantify that the transition from postpaid to prepaid meters, subject to a 35 percent price increase due to subsidy removal, results in efficiency gains of approximately 1.5 percent relative to baseline costs, primarily due to improved price salience. Importantly, the environmental benefits from reduced pollution are significant, with CO_2 emissions being almost six percent lower relative to the baseline. Although our estimates may not directly translate to other settings, the magnitudes of the gains in the CO_2 emission reductions are comparable to a few energy policies' impact on emissions in developed countries, such as carbon tax and renewable energy subsidy (Stechemesser et al., 2024).

Our findings provide the first evidence that prepaid meter users have a more elastic demand relative to postpaid users. Previous studies conducted in developing countries have shown that prepayment systems can reduce electricity consumption by up to 14 - 24% in residential settings (Qiu et al., 2017; Jack and Smith, 2020; Debasish Kumar and Stern, 2020; Beyene et al., 2022).[4] Our findings are consistent with these results, indicating a similar decline in consumption. By leveraging our variation in the tariffs, we move one step further than existing literature by identify the elasticity parameters that might explain the lower consumption of consumers under prepayment. Our 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 (Finkelstein, 2009b; Chetty et al., 2009). For instance, increases in taxes included in posted prices have a greater effect in reducing alcohol consumption compared to taxes applied at the register (Chetty et al., 2009). In the context of electricity demand, 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 has estimated long-run demand elasticity using dynamic panel models of aggregated state-level data (Alberini and Filippini, 2011a; 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 and the largest prepaid electricity meter conversion program in the world.

The rest of the paper proceeds as follows. In the next section, we provide the institu-

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

tional details. We then describe the dataset and the empirical analysis in Sections III and IV, respectively. Section V investigates further threats to the identifications. In Section VI, we perform an applied welfare analysis. Finally, we conclude the paper in Section VII.

I. 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).[5] *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. The total electrical energy sold by PLN in 2020 is 243 terawatt-hours (TWh), comparable to some high income countries like Australia, Spain, and South Africa (Ember and Institute, 2024). 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 sectors in Figure 1 are divided into different subclasses of customers based on contracted capacity in Voltage Ampere (VA).[6] The largest number of consumers is under $<=$ 1300 VA, about 70% of all customers in the country, but only consume 26% of the total consumption in 2019. We focus on these low VA customers because they were subjected to electricity tariff subsidies. The customer's VA indicates a maximum usage at any given time, thus comparing households within the same VA is important in ensuring comparability of their electricity consumption patterns. To put things in perspective, consider a 1 horsepower air conditioner that consumes 860 watts of electricity. Such an air conditioner can only be used by households with 1300 VA or above. A household with 900 VA will be able to use such an appliance only when all other appliances are switched off, as exceeding the allocated VA will trip the power.[7] Table S1 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 than those with 1300 or 2200 VA.

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

[6] Voltage Ampere (VA) is a measure of contracted capacity which indicates the maximum electricity that can be used at one moment in time. VA ranges from 450 VA for R1, B1, I1 to above 30,000 kVA for I4 customers.

[7] 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.

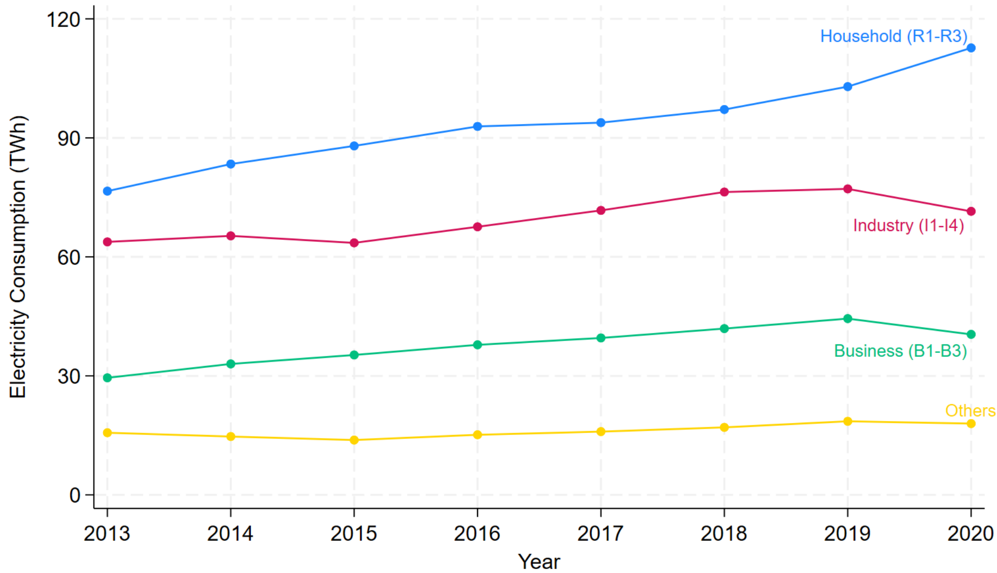


Figure 1. Growth in Electricity Consumption in Indonesia by Customer Sector

Note: Electricity consumption by sector using sales quantity (i.e., excluding on-site generation). The sectors include household or residential (R), business (B), industry (I), and the remaining sector we label as ”Others,” which includes public services and government offices. The number after the alphabet indicates the size of the customer. For instance, R1 covers customers with a capacity below 2,200 VA, R2 covers customers between 3,500 VA and 6,600 VA, and R3 covers customers above 6,600 VA. Similarly, B1 covers business customers with a capacity between 450 VA and 5,500 VA, B2 covers those between 5,500 VA and 200 kVA, and B3 covers those above 200 kVA. For industrial customers, I1 covers capacities between 450 VA and 14 kVA, I2 covers 14 kVA to 200 kVA, and I3 covers above 200 kVA.

A. Subsidy Removal and Resulting Tariff Hikes

Electricity tariffs in Indonesia have been politically determined and influenced by budgetary considerations (Burke and Kurniawati, 2018). The Minister of Energy and Mineral Resources sets these tariffs, including the level of subsidies allocated to each customer class. For many years, the Government of Indonesia has subsidized electricity prices for low VA households as a form of social protection. However, rising subsidy costs have prompted the Minister to remove price subsidies for the R1 1300 VA customer class. 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 B1 customer class within the same VA but were not affected by the tariff changes. We also use alternative counterfactual group discussed in Section III.

Figure 2 shows the tariff trends for R1 and B1. The first major price hike was due to the removal of the subsidy in mid-2014 while the second one occurred in 2016.[8] The

[8]These are based on the two regulations issued by the Ministry of Energy and Mineral Resources No. 30/2012 and

2016 regulation introduced monthly tariff adjustments based on a formula that accounts for changes in the exchange rate, fuel prices, and inflation. We treat these two regulations as the same regulation that exogenously increases tariffs. Customers under B1 1300 VA 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 amounted to approximately 35%.

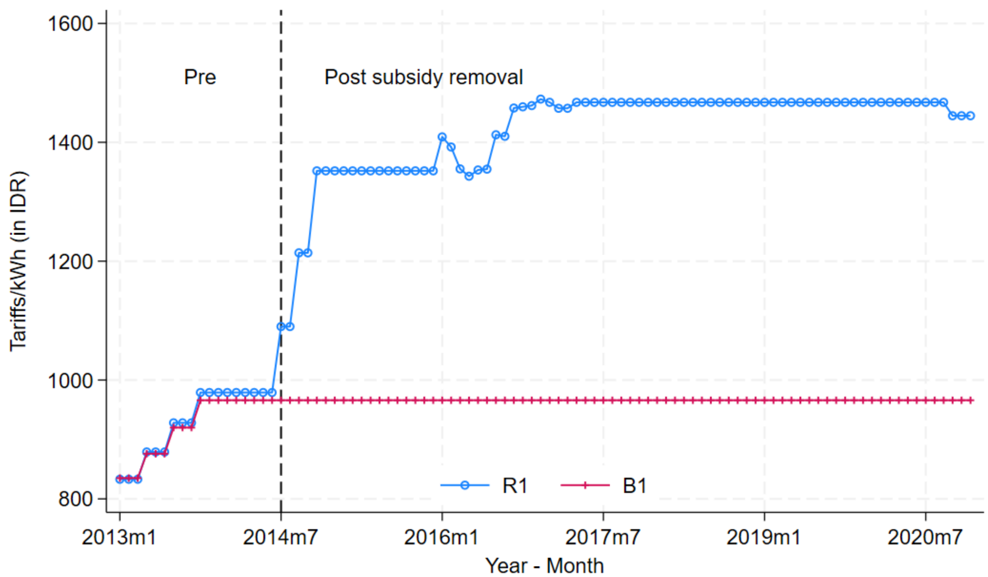


Figure 2. Electricity price for R1 and B1 customers classes = 1300 VA

Note: The figure plots the customers trends for R1 1300 VA and B1 1300 VA customer classes. The first major price hike was due to the removal of the subsidy in mid-2014 while the second one occurred in 2016.In 2013, we see a slight jump in the tariffs from the R1 1300 VA customer class due to a small tariff adjustment by the government (see footnote 8).

B. *Postpaid to Prepaid Metering Conversion Program*

Traditionally, all electricity users have been using postpaid meters (see right photo in Figure 3). 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 3).[9] 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,

No. 28/2016. Electricity tariffs have been increasing since 2013, but by a much smaller amount relative to the increase in tariff induced by the removal of subsidies.

[9] 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.

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 has the potential to improve revenue recovery of the utility company.

Figure 3. Postpaid and Prepaid Metering

Note: A typical postpaid meter (left) and prepaid meter (right) in Indonesia. The prepaid meter features numeric keys for entering 20-digit tokens to refill the balance. It displays the remaining balance, and if the balance reaches zero, the consumer cannot use electricity. In contrast, the postpaid meter shows the total consumption since its installation. Monthly consumption can be determined by subtracting the previous from the current month's reading.

In 2010, PLN conducted a unilateral meter replacement initiative focusing on customers with contracted capacities of $<=$ 1300 VA (Natalia, 2014). As part of this program, the default option for new meters was prepaid, effectively making prepaid meters the only option offered. 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 affected customers with no alternative but to adopt prepaid electricity (Yuliani and Saputra, 2014).[10] These low VA customers were specifically targeted under this rule because they constitute PLN's largest customer base (mentioned earlier), and incur the highest billing costs per kWh sold.[11] While prepaid and postpaid users are subject to the same per-unit electricity price, the key difference lies in the

[10]Based on a survey conducted by one of the authors, houses can be identical and located next to each other (see Figure S1a and S1b in the Appendix), but one may use a prepaid meter while the other uses a postpaid meter, which can be attributed to idiosyncratic metering issues and broken rates.

[11]There are monthly fixed costs associated with sending staff to each home to record the meter, among other expenses.

metering system.[12]

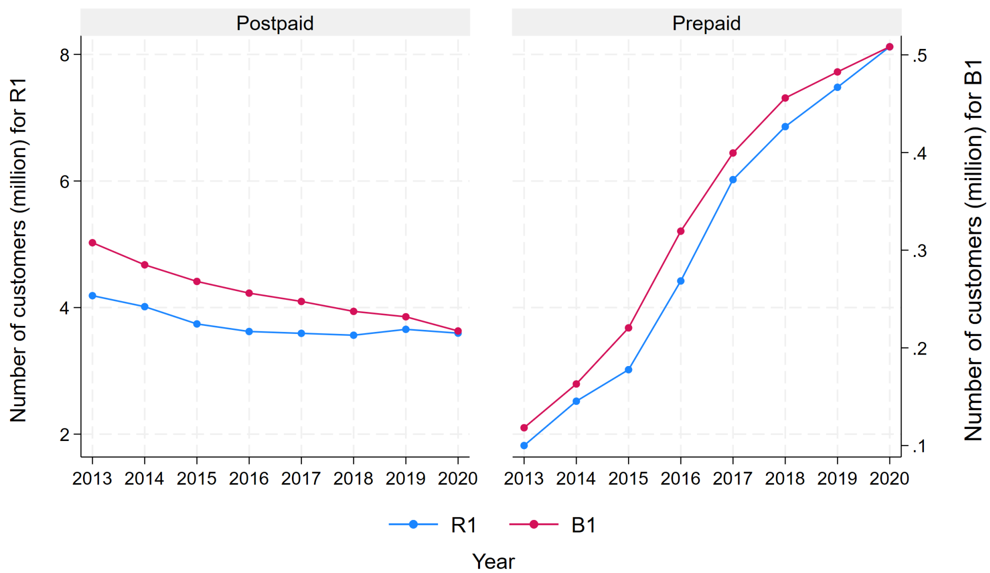


Figure 4. Number of Customers for R1 1300 VA and B1 1300 VA

Note: The figure plots the trends for the number of customers under R1 1300 VA and B1 1300 customer classes, for the years 2013 to 2020.

Figure 4 shows a substantial increase in prepaid metering customers from 2013 to 2020, rising from two to eight million households within the R1 1300 VA category alone. The prepaid penetration rates between R1 and B1 are similar as the program does not differentiate different classes of customers in this program (see Table S4 in the Appendix for the statistical test). 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 S3 in the Appendix). Moreover, Table S5 in the Appendix provides evidence that prepaid conversion is not systematically correlated with household characteristics, supporting the argument that prepaid adoption was not targeted based on household characteristics. Figure S4 in the Appendix 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 regions.

II. Conceptual Framework: Prepaid vs. Postpaid

The utility maximization problem for electricity consumers can be modeled under two distinct metering systems: prepaid and postpaid. Consumers derive utility $u(q)$ from the

[12]One exception is that those under 450 and 900 VA are subjected to a minimum usage of 40 hours.

consumption of electricity q, and their goal is to maximize this utility subject to a budget constraint that varies depending on the metering system. For prepaid users, the total expenditure on electricity is determined by:

$$I = s^{+}Pq, \tag{1}$$

where P is the price of electricity, q is the quantity demanded, and I is the total expenditure. The term s^{+} is a salience parameter that captures the awareness of costs for a prepaid user. On the other hand, the total expenditure on electricity for postpaid users is determined by:

$$I = \gamma s^{\times}Pq. \tag{2}$$

Similarly, $s^{\times}$ is the corresponding salience parameter for a postpaid user. We assume that the salience for postpaid consumers is lower than for prepaid users ($s^{+} > s^{\times}$), consistent with our survey results discussed in Section VI.A and Figure S5 in the Appendix. γ is a discount factor because postpaid users pay their bill after consumption (in our setting the gap between consumption and paying the bill is one month) and $\in (0,1]$. Prepaid users do not have γ as they have to pay before consumption (or think of them as having $\gamma = 1$). Given these budget constraints, the first-order conditions for utility maximization imply that prepaid users will choose a quantity q^{*} such that:

$$u'(q) = s^{+}P. \tag{3}$$

Similarly, the optimal consumption level for postpaid users is determined by the following equation:

$$u'(q) = \gamma s^{\times}P. \tag{4}$$

Since $s^{+} > s^{x}$, then $s^{+}P >> s^{\times}P$, suggesting that individuals under prepaid perceive a higher price than those under postpaid, consistent with findings from Sexton (2015). γ also reduces the perceived price of postpaid users, consistent with the lab experiment that suggests pay-later consumers over-consume relative to pay-as-you-go consumers (Werthschulte, 2023). Nevertheless, when facing the same price, Equations 3 and 4 suggest that the perceived price of electricity is higher for prepaid users than for postpaid users, regardless of the discount factor γ. Furthermore, combining these with Equations 1 and 2, we obtain the following relationship:

$$\frac{I}{s^{+}P} < \frac{I}{\gamma s^{\times}P}, \tag{5}$$

suggesting that, under the same budget, the quantity of electricity consumed by prepaid users (left side of the equation) is lower than that consumed by postpaid users (right side of the equation). This lower consumption is consistent with empirical findings, such as those in Jack and Smith (2020), Debasish Kumar and Stern (2020), Beyene et al. (2022), and Werthschulte (2023).

Finally, using Equations 3 and 4 and the fact that $s^{+} > s^{\times}$, we can easily see that prepaid users exhibit greater price sensitivity than postpaid users. That is:

$$\frac{\partial q^*}{\partial P} = \frac{s^{+}}{u''(q^*)} > \frac{\gamma s^{\times}}{u''(q^*)}. \tag{6}$$

Because salience is higher for prepaid users, any change in the price of electricity leads to a greater adjustment in the consumption of prepaid users relative to postpaid users. In other words, the higher perceived price leads prepaid users to react more strongly to price fluctuations, as their consumption is more tightly linked to the immediate visibility of costs.

This conceptual framework offers a potential mechanism through which prepaid electricity meters may lead to an increased price sensitivity, resulting in lower consumption than postpaid meters. In the following sections, we present empirical evidence supporting this.

III. Data and Identification Strategy

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.

A. Counterfactual Group

As discussed in Section I, our paper focuses on R1 1300 VA and B1 1300 VA customers. We posit that B1 customers are likely to respond to electricity price changes in a manner similar to R1 customers within the same 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 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. A qualitative survey conducted by one of the authors indicates that households generally are unaware of their classification as either R1 or B1 customers. This lack of awareness is unsurprising, given that historically, tariffs for R1 and B1 customers within 1300 VA and below were identical, providing no incentive for customers to distinguish between the two categories.[13] Based on this, we posit that these two customer classes are likely to exhibit similar patterns of electricity usage. In Section IV and V, we provide robustness checks that suggest our findings are robust to our choice of a control group.

Our "treated" group, which consists of the R1 customers affected by the tariff increases, while our "untreated" (or control) group consists of the B1 customers 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 (see Figure 2). 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 (first row in Panel B), (2) differences between R1 vs. B1 for postpaid and prepaid users (second and third rows in Panel B), and (3) the trends between prepaid vs. postpaid and R1 vs. B1 (fourth row). First, prepaid customers consume about 40% less electricity than postpaid customers. One reason for this difference is the variation in the accounting process: PLN initially records only 80% of the top-up balance and adds the remaining 20% after the second top-up, while postpaid meters rely on meter readings taken during staff visits to households.[14] Since this difference is static, we address it using a transformed average usage in our analysis below. This transformed variable is indexed by metering type (see Equation 7). 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.

B. Outcome Variable

As noted earlier, 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:

$$\triangle log(usage)_{ipct} = log\left(\frac{usage_{ipct}}{N_{ipct}}\right) - log\left(\frac{usage_{ipc2013}}{N_{ipc2013}}\right), \tag{7}$$

[13]This aligns with column 8 in Table S5 in the Appendix, which shows that prepaid penetration is unrelated to whether a household operates a home business, suggesting that prepaid status is not systematically associated with business activity.

[14]There can be other factors that explain this difference, such as technical aspects of the metering: a prepaid meter can only be used up to the filled balance, whereas a postpaid meter allows unlimited consumption within the maximum VA.

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 (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)	Mean (7)	SD (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			

Note: 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 since 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, the third row shows the differences between R1 and B1 among prepaid users, and the fourth row compares the differences between the second and third rows, along with the p-values of the differences.

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 customer group. Figure 5 shows that, visually, the indexed log usage (computed from Equation 7) 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.

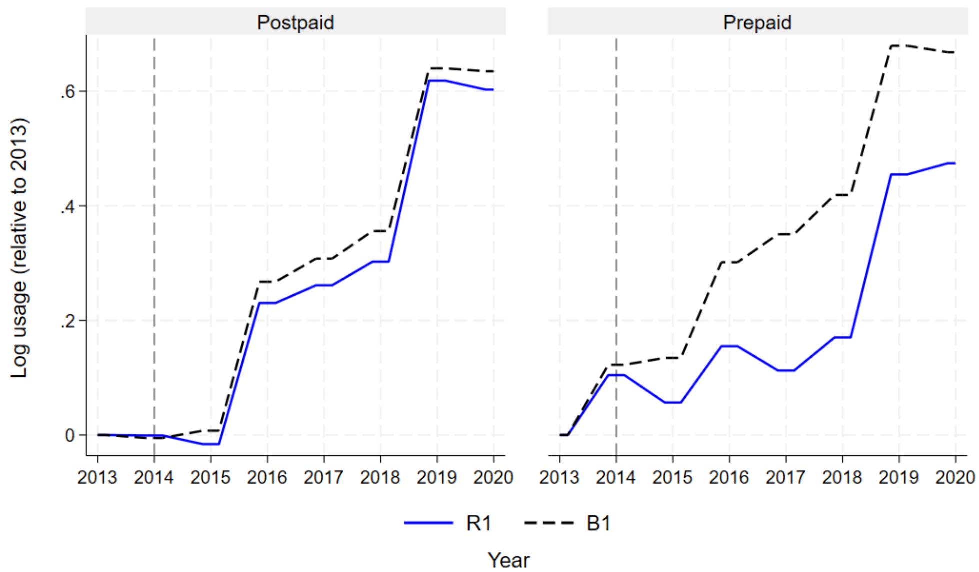


Figure 5. Usage of Prepaid and Postpaid Meters Before and After Tariff Changes

Note: The figure shows trends in the usage of prepaid and postpaid users before and after the tariff changes. The solid (dashed) line represents locally smoothed polynomials of year dummies on the indexed log usage, $\triangle log(usage)_{ict}$, for R1 1300 VA (B1 1300 VA) users. 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 1300 VA 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 1300 VA behave similarly to their postpaid counterparts. This is because B1 1300 VA users are not exposed to tariff changes.

C. *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 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, as noted in Alberini and Filippini (2011b). 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, ideally, we need to prepaid meter status that is independent of demand characteristics to not suffer from endogeneity bias. Thus, it is important to understand how many conversions to prepaid meters occurred due to household choice, as this will give rise to an endogeneity bias.[15] As discussed in Section I, we argue that the conversion to a prepaid meter is primarily driven by PLN regulation. Table S5 in the Appendix indicates that a broad range of socioeconomic indicators (such as education, home characteristics, and whether the household runs a home business, among others) are not significantly correlated with the prepaid share, except for marital status and age. This is because married couples and younger people are more likely to have recently acquired a new house and therefore require a new meter installation, which by default will be a prepaid meter. Nonetheless, their prepaid status is independent of household preferences, as there is no option for these new houses to choose a postpaid meter if they prefer it.[16] Nonetheless, in Section IV, we discuss several potential threats to the validity of our identification strategy and outline the methods we use to address each threat.

IV. Empirical Analysis

In this section, we report our main estimation of the elasticity parameters for each metering type following the DiD strategy. Then we perform additional analysis. In Section IV.B, 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. In Section IV.C, we aim to address the possibility of selection into a prepaid meter even further using instrumental variable approach. 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. Finally, in Section IV.D, 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 changes that interacted with the prepaid system. We discuss our empirical strategies in more detail in the subsections below along with the results.

A. *Price Elasticity of Electricity Demand by Metering Type*

We run ordinary least squares (OLS) regressions, 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:

$$\triangle log(usage)_{ipct} = c + \alpha_i + \beta_p T_c * Post_t + \gamma_t + \varepsilon_{ipct}, \tag{8}$$

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

[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.

[16] Anecdotally, new houses and old houses are not built differently with the goal of saving energy, as there is no need for heating or insulation in Indonesia. Additionally, there is no incentive to construct buildings to save electricity due to the low electricity prices.

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 7. 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 the subsidy removal led to a 15% decrease in electricity usage for prepaid users relative to postpaid users. This magnitude is somewhat similar to existing studies that merely compare postpaid vs. prepaid and did not exploit changes in electricity tariffs (i.e., 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)). It is clear that 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	
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			

Note: The table reports the mean difference similar to Panel B in Table 1, but using the indexed log usage as in Equation 7.

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:

$$\triangle log(usage)_{ipct} = c + \alpha_i + \delta_p log(price)_{ict} + \gamma_t + \varepsilon_{ipct} \tag{9}$$

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.[17] The δ_p coefficient is interpreted as the elasticity of demand under each metering type.

Table 3 reports β from Equation 8 (Columns 1 and 4) and δ from Equation 9 on for postpaid users (Columns 2-3) and prepaid users (Columns 5-6). Columns 1 and 4 are the same as Table 2 only that it uses all the years. 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.

Compared to the existing literature, Table 3 Column 2 shows a price elasticity that is similar in magnitude to existing studies (i.e., Ito (2014)) while Column 5 shows an elasticity that is larger than those in existing studies. This is expected, as most of the existing studies largely use conventional postpaid meters and do not examine elasticity in conjunction with the use of prepaid meters. These initial results show that there is a significant difference between how postpaid users and prepaid users respond to prices. To quantify the difference in the elasticity parameters between prepaid and postpaid, we include a prepaid dummy, *Pre*, to Equation 9. Hence, we have the following:

$$\triangle log(usage)_{ict} = \alpha_i + \delta log(price)_{ict} * Pre + \delta_0 log(price)_{ict} + \delta_1 Pre + \gamma_t + \varepsilon_{ict}. \tag{10}$$

Under the tariff changes, we compare how affected prepaid and postpaid consumers respond to these price changes. The left panel of Figure 6 plots Columns 3 and 6 of Table 3 while the right panel plots δ_p coefficients from Equation 10. These δ_p coefficients are the elasticity of demand of prepaid metering relative to postpaid.[18] The right panel of Figure 6 shows that prepayment leads to a more elastic demand by about 14 percent six months after the tariff changes.

We find that prepayment leads to up to four times greater price elasticity than the postpaid counterparts. Figure 6 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.[19] Note that after 2017, there were no more large tariff hikes (see Figure 2) but the difference in elasticities persists over time. This highlights the long-run dynamics of behavioral responses to prices under different

[17]The β coefficient in Equation 8 and the δ coefficient in Equation 9 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 (Std. Dev. = 0.005), suggesting that the tariff changes are 35% on average. As such, $\beta/0.35 \approx \delta$.

[18]Table S2 in the Appendix shows the δ_p coefficients from Equation 10.

[19]There is a slight elasticity increase in 2020 (six years after the tariff changes), which is possibly due to COVID-19 pandemic. If we omit the year 2020, our estimates remain within a very similar range.

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

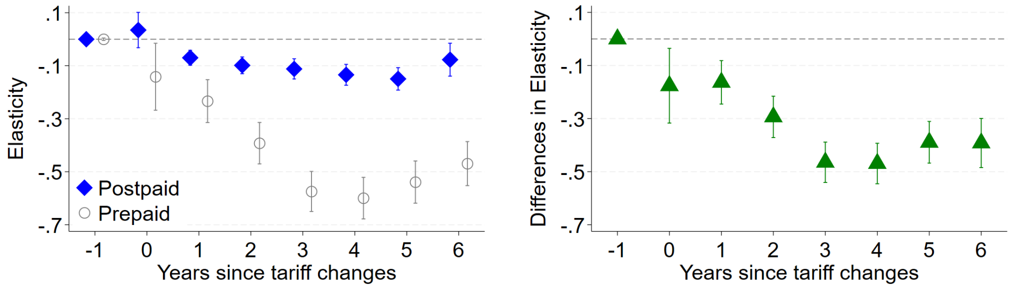
	Postpaid			Prepaid		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat=1 $\times$ Post=1	-0.037			-0.17		
	(0.0058)			(0.013)		
Log(price)		-0.11			-0.48	
		(0.016)			(0.036)	
Year=2014 $\times$ Log(price)			0.035			-0.14
			(0.034)			(0.064)
Year=2015 $\times$ Log(price)			-0.070			-0.23
			(0.014)			(0.041)
Year=2016 $\times$ Log(price)			-0.099			-0.39
			(0.016)			(0.040)
Year=2017 $\times$ Log(price)			-0.11			-0.57
			(0.019)			(0.038)
Year=2018 $\times$ Log(price)			-0.13			-0.60
			(0.020)			(0.040)
Year=2019 $\times$ Log(price)			-0.15			-0.54
			(0.021)			(0.040)
Year=2020 $\times$ 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

Note: We do the regression on subsamples of prepaid and postpaid users. Columns 1 and 4 report β from Equation 8 and Ccolumns 2-3 and 5-6 report δ from Equation 9. 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.

technologies that are long-lasting.

B. 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. To minimize this, we conduct a similar DiD regression but with a matched sample: prepaid and postpaid users with similar average consumption levels in 2013.



(a) Price elasticity: δ_p from Equation 9.

(b) δ Prepaid vs. δ Postpaid.

Figure 6. Elasticity Parameters for Postpaid and Prepaid

Note: Figure 6a plots the price elasticity (δ_p from Equation 9). Figure 6b compares δ Prepaid vs. δ Postpaid from Figure 6a. The treated group is the R1 1300 VA customer class and the control group is B1 1300 VA customer class (not exposed to subsidy removal). The whiskers indicate a 95% confidence level. Table S2 in the Appendix reports the results of Figure 6b in more detail.

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 more comparable to postpaid users with 900 VA at the level.

The results using our matched sample (Table 4) show similar results to the results using the unmatched sample (Table 3). In Table 4, we see more comparable mean electricity usage results between our prepaid and postpaid users, an improvement from Table 3 without matching. The average usage of postpaid users remains higher than prepaid users, but given the standard deviation (see row ”Mean usage” and ”SD usage”), 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 7 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.

C. Instrumenting the Prepaid Penetration Rate

As discussed in Section I, prepaid meter penetration is largely supply-driven. However, there remains a possibility that unobserved demand preferences correlated with prepaid status might still influence electricity consumption patterns. While previous matching

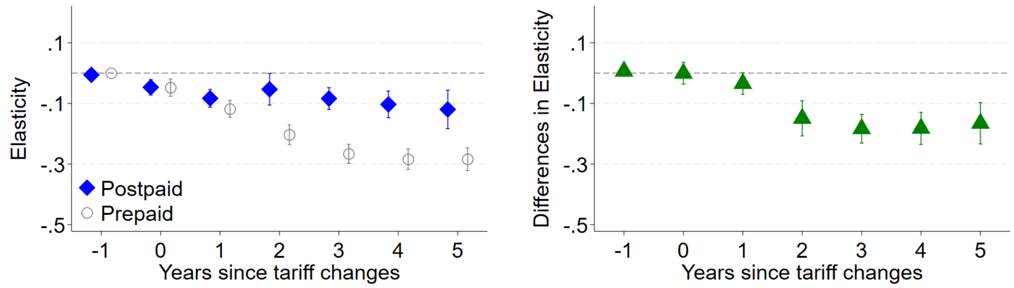
Table 4— Impact of Tariff Change on Electricity Demand by Metering Type

	Postpaid		Prepaid	
	(1)	(2)	(3)	(4)
Log(price)	-0.077		-0.20	
	(0.015)		(0.014)	
Year=2014 $\times$ Log(price)		-0.047		-0.048
		(0.013)		(0.014)
Year=2015 $\times$ Log(price)		-0.083		-0.12
		(0.015)		(0.014)
Year=2016 $\times$ Log(price)		-0.053		-0.20
		(0.026)		(0.016)
Year=2017 $\times$ Log(price)		-0.084		-0.27
		(0.018)		(0.016)
Year=2018 $\times$ Log(price)		-0.10		-0.28
		(0.022)		(0.017)
Year=2019 $\times$ 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

Note: This table reports δ from Equation 9, 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, suggesting a more comparable mean electricity usage results between our prepaid and postpaid users, an improvement from Table 3 without matching.

exercises aim to improve comparability between prepaid and postpaid users, unobserved factors correlated with metering type and log usage may persist, even after controlling for time-invariant unobservables at the service unit level using fixed effects.

To address this, we no longer use the metering type variable directly. Instead, we aggregate prepaid and postpaid usage and use the prepaid penetration rate as a proxy for the likelihood of conversion to prepaid metering. Consequently, our observation is half of our main specification in Table 3. We consider two alternative instruments: (1) prepaid penetration of other VA customers (450 VA and 900 VA) within the same service unit, and (2) prepaid penetration of other VA customers (450 VA and 900 VA) in nearby service units. The switch to prepaid among 450 VA and 900 VA customers is plausibly exogenous to the characteristics of 1300 VA households, satisfying the exclusion restriction (discussed below). Moreover, it is a strong predictor of 1300 VA prepaid penetration



(a) Price elasticity: δ_p from Equation 9. (b) δ Prepaid vs. δ Postpaid.

Figure 7. Elasticity Parameters for Postpaid and Prepaid with Matched Sample

Note: Figure 7a plots the price elasticity (δ_p from Equation 9). Figure 7b compares δ Prepaid vs. δ Postpaid from Figure 7a. The whiskers indicate a 95% confidence level. It is similar to Figure 6, but the sample used the matched sample based on average baseline usage.

due to program expansion[20], satisfying the relevance assumption. We prefer the second instrument because it mitigates potential neighborhood effects, where households may be influenced by their neighbors' decisions. Nearby service units are located in different cities, which minimizes direct neighborhood influence on prepaid choice. These service units are small enough to rule out differing local government policies yet large enough that households in the nearby service unit are not in the immediate vicinity of those in the primary unit.

Our identifying assumption is that the penetration of neighboring service unit j influences usage in service unit i only through prepaid penetration in i. It should not directly affect electricity consumption in i, except through its impact on prepaid adoption and tariff changes in i, controlling for service unit and year fixed effects. For trends to bias our results, these trends in electricity usage across service units with different prepaid penetration in neighboring units would need to vary systematically with year-to-year changes in price and prepaid penetration. However, such variation is unlikely given the supply-driven nature of prepaid adoption and the exogeneity of tariff changes. This design ensures that the observed effects on usage are driven by prepaid adoption and tariff changes rather than unobserved confounders.

We estimate the following regressions using service unit-yearly data, aggregating prepaid and postpaid users: (1) First-stage regressions:

$$S_{ict} = \alpha_0 + \alpha_1 S_{jdt} + \alpha_2 log(price)_{ct} + \alpha_3 S_{jdt} \times log(price)_{ct} + \gamma_t + \varepsilon_{ict}$$
$$[log(price)_{ict} \times S_{ict}] = \alpha_4 + \alpha_5 S_{jdt} + \alpha_6 log(price)_{ct} + \alpha_7 S_{jdt} \times log(price)_{ct} + \gamma_t + \varepsilon_{ict} \quad (11)$$

[20]PLN staff are more likely to convert nearby areas first rather than sporadically convert households to minimize transport costs.

(2) Second-stage regression:

$$\triangle log(usage)_{ict} = \beta_0 + \beta_1 \widehat{S_{ict}} + \beta_3 [S_{ict} \times \widehat{log(price)_{ct}}] + \theta_i + \gamma_t + \varepsilon_{ict} \tag{12}$$

where S_{ict} represents the prepaid meter penetration rate of customer class c in service unit i at year t, similarly S_{jdt} represents the prepaid penetration rate of customer class d in service unit j, where service unit j is the closest to service unit i. The interaction $S_{ict} \times \log(\text{price})_{ct}$ measures captures the combined impact of prepaid penetration and prices on electricity usage. Fixed effects θ_i and γ_t control for service unit and year specific factors. Standard errors are clustered at the service unit level. To improve interpretability, the prepaid shares and $\log(\text{price})$ variables are mean-centered at the service unit level. Thus, β_1 captures the local average impact of prepaid share on usage while β_3 captures the local average impact on price elasticity as the prepaid penetration rate increases.

Table 5 compares OLS (where we assume prepaid share and its interaction with tarif are exogenous) and 2SLS estimates. The F-statistics from the first stage for each endogenous variable suggest that the instruments are strong, mitigating concerns about weak instrument bias. In all specifications, an increase in prepaid share always leads to less consumption, consistent existing studies. More importantly, the interaction term indicates that the price elasticity of demand becomes even larger as the prepaid share increases. Our prefered specification indicates that the price elasticity of electricity demand is -0.69, larger than our main findings. The 2SLS estimates reflect the local average treatment effect (LATE) for compliers, who are those service units whose prepaid penetration rate (S_{ict}) is affected by the instrument (S_{jct}). By contrast, our DiD results in Table 3 include compliers and non-compliers which lead to smaller magnitude of the treatment effects.

D. 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 8 reports β from Equation 8, which is the difference in the log usage between R1 450 VA and B1 450 VA.[21] 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 9 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.

[21] 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 as mentioned in Footnote 12. 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.

Table 5— Instrumenting with Prepaid Penetration under Different VA within Service Units

	OLS	2SLS	
	(1)	(2)	(3)
Prepaid Share	-0.57	-0.43	-0.43
	(0.068)	(0.025)	(0.025)
Prepaid Share X Log(price)	-0.87	-0.68	-0.69
	(0.082)	(0.057)	(0.061)
1st stage F-stat (1)		287.11	254.36
1st stage F-stat (2)		646.22	410.19
Observations	2,306	2,306	2,306

Note: The table reports β_1 and β_3 from Equation 12. The dependent variable is the indexed log of total usage (aggregated across metering types) as specified in Equation 7. Column 1 uses OLS with the independent variable being the prepaid share of 1300 VA, column 2 uses prepaid penetration of other VAs (450 VA and 900 VA) within the same service unit and customer class as the instrument and column 3 uses similar instrument as in column 2 but in nearby service unit as the instrument, following Equation 11 and 12. The prepaid shares and log of price variables have been centered to ease the interpretation. The F-statistics from the first stage are reported for each of the endogenous variable.

V. 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, make better decisions. However, with the existence of the subsidy removal, households might behave in response to this independent of their response to their metering type. First, households in the R1 category might have different price responses to B1 independent of the metering type. Thus, we use other alternative control group R1M in replace of B1. Second, households may opt to switch from the R1 to the B1 category after they are aware of the subsidy removal in R1. The switch from R1 to B1 driven by the subsidy removal, 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. Third, households may be growing and economically better off and therefore those in 1300 VA upgraded to 2200 VA. While this upgrade request does not necessitate changing the metering type (thus it is independent of metering type), our analysis, which uses only 1300 VA, may include households that are economically worse off than those 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.

A. 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

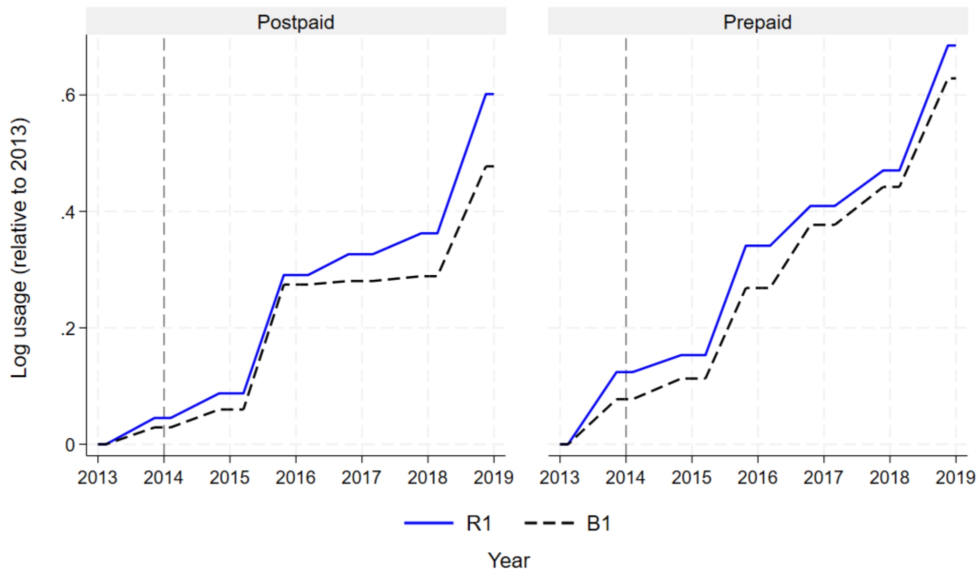
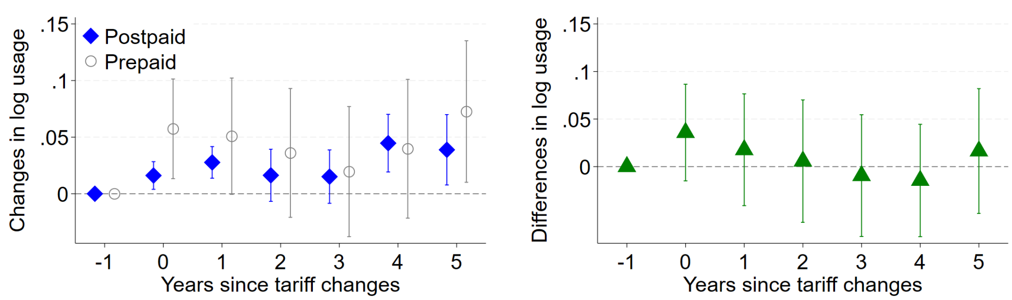


Figure 8. Placebo Impact: Electricity Usage Trends without Tariff Changes

Note: This figure plots the placebo impact of subsidy removal on electricity usage, using customers with 450 VA (i.e., 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 (B1 450 VA) users. The average usage of prepaid users seems to grow more, but there is no visible pattern difference between R1 450 VA and B1 450 VA. We exclude the year 2020 since a concurrent policy occurred in 2020 (i.e., the COVID relief package affected this group).



(a) Price elasticity: δ_p from Equation 9

(b) δ Prepaid vs. δ Postpaid

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

Note: This figure plots the placebo impact of subsidy removal on usage using 450 VA where there are no changes in tariffs. Figure 9a plots the price elasticity (δ_p from Equation 9). Figure 9b compares δ Prepaid vs. δ Postpaid from Figure 9a. Figures 9a and 9b mimic Figures 6a and 6b but using R1 450 VA vs. B1 450 VA). The whiskers indicate a 95% confidence level.

from selection bias. To test this, we performed a similar exercise using households within a similar category (R1). Due to a 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. This came as a surprise to households and starting from 2016 R1M 900 VA has to pay higher tariffs than R1 900 VA as they no longer receive subsidized tariffs (see Figure 2 in the Appendix for the trends in the tariff among 900 VA).[22] Figure 10 shows a similar figure to Figure 5 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. We also include B1 900 VA to show that the usage pattern is identical with R1 if they are equally not subject to any tariff changes.

To conduct the analysis on the 900 VA customer class, we use an event study as R1M only exists post-tariff changes.[23] The sample is R1M 900 VA as the treated group and R1 900 VA as the control group (not exposed to subsidy removal). Figure 11a compares β Prepaid vs. β Postpaid, capturing the trends in usage overtime similar to Figure 9b but using R1 900 VA vs. R1M 900 VA. Figure 11b compares δ Prepaid vs. δ Postpaid, capturing the price elasticity of demand similar to Figure 6b 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.

Since the magnitude of price elasticity remains consistent regardless of the control group used (as shown in Figures 6 and 11), it is likely that the larger price elasticity observed among prepaid users is driven by salience effect induced by prepayment technology rather than by confounding factors.

B. *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)

[22]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 et al., 2012); i.e., using household observable characteristics such as appliances they have, among others. Having received this list, PLN would then classify them as R1M. Therefore, R1M is the category for households that are likely to be less poor than their peers within the same 900 VA. Households who disagree with this classification can submit disputes through an online application or by visiting the PLN office.

[23]One of the limitations of using this sample is that we cannot test for parallel trends due to this.

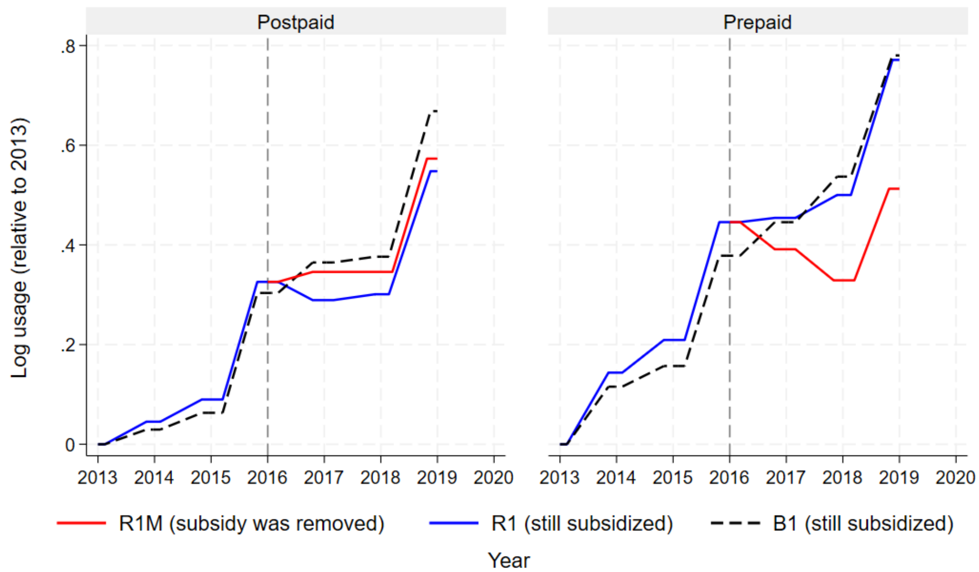
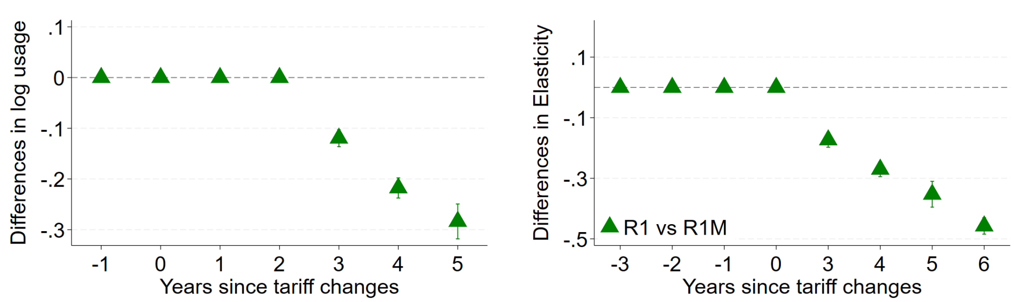


Figure 10. Usage of Prepaid and Postpaid Meters Before and After Tariff Changes, 900 VA

Note: 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. It also shows that B1 900 VA customers have a similar usage pattern with R1 given that they are both still subsidized and not exposed to tariff changes.



(a) β Prepaid vs. β Postpaid

(b) δ Prepaid vs. δ Postpaid

Figure 11. Using Alternative Counterfactual Group (R1 900 VA vs. R1M 900 VA)

Note: Figure 11a compares β Prepaid vs. β Postpaid, capturing the trends in usage overtime similar to Figure 9b but using R1 900 VA vs. R1M 900 VA. Figure 11b compares δ Prepaid vs. δ Postpaid, capturing the price elasticity of demand similar to Figure 6b but using R1 900 VA vs. R1M 900 VA. Years prior to tariff changes are zeros since R1 900 VA and R1M 900 VA are the same group. The whiskers indicate a 95% confidence level.

R1 customers may illicitly convert to B1 through bribery.[24] In either case, we anticipate an increase in B1 prepaid customers, but not in postpaid because, as previous evidence suggests, prepaid users are more aware of tariff changes and thus more likely to respond, including by reclassifying their tariff category.[25] To test this, we conduct the following regression:

$$\triangle log(N)_{ipct} = \alpha_i + \tau_c + \theta_p Y_t \times B1 + \gamma_t + \varepsilon_{ipct} \tag{13}$$

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. $B1$ is dummy variable for B1 customers and Y_t denotes year dummies, thus θ_p captures the trends of the customers of B1 relative to R1. Fixed effect γ_t accounts for time-related variation across all service units and customer classes in year t. The error term ε_{ipct} includes unobserved factors and random fluctuations in log usage at various levels - service unit, metering type, customer class, and year. Without strategic behavior to minimize taiff increase θ prepaid vs. θ postpaid should be the same, especially near the year when the tariff changed.

Figure 12 suggests that there was 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 for B1 1300 VA prepaid is 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. This could explain smaller price elasticity parameter one and two years after the tariff changes. Since our 2SLS estimates (Table 5) did not use the comparison between R1 and B1, we find larger price elasticity than the DiD estimates (Table 3) consistent with underestimation due to households reclassification.

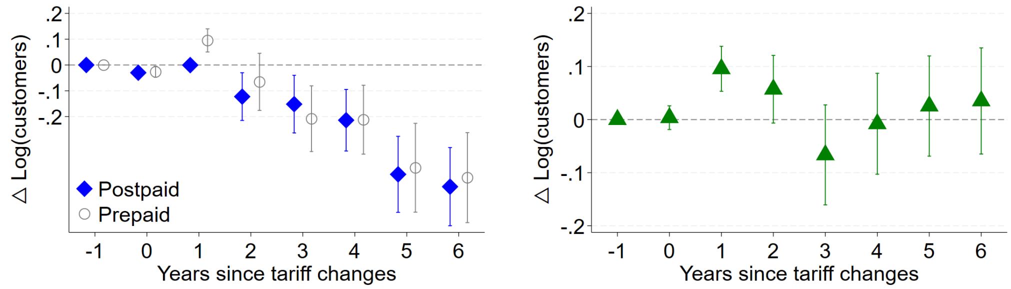
C. Compositional Changes

There are possibilities that households are economically better off over time and therefore upgraded to higher VAs. If 1300 VA households want more electric appliances and doing so would make them hit their maximum contracted capacity, they would want to upgrade to 2200 VA. This might drive compositional changes as tariffs are the same between 1300 VA and 2200 VA but those remaining in 1300 VA are poorer than similar households in 1300 VA. Similarly, 900 VA households might also upgrade to 1300 VA and they might be poorer than similar households in 1300 VA.[26] To test whether our results are sensitive to compositional changes, we include households under 2200 VA and do the same regression as our main analysis. Figure 13 shows our main results by

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

[25]In principle, households do not have to change their metering to change their customer class; thus, this reclassification does not mean they would be converted to prepaid due to the "default" nature of the program.

[26]For comparison of prices across VA, see Figure 2 in the Appendix.

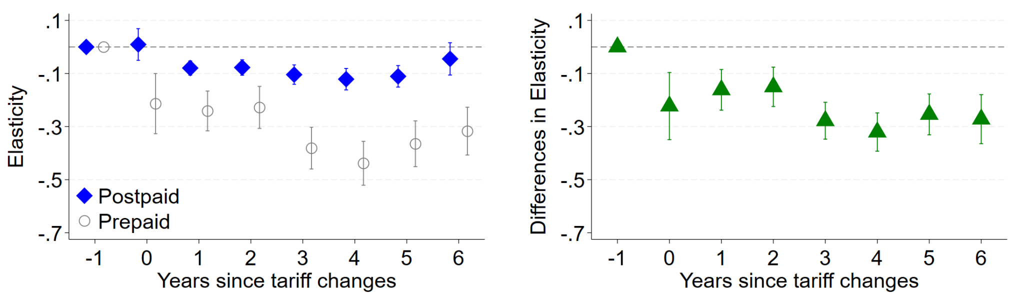


(a) Customer Growth: θ_p from Equation 13 (b) θ Prepaid vs. θ Postpaid

Figure 12. Customer Growth of B1 relative to R1

Note: Figure 12a plots θ_p from Equation 13. Figure 12b compares θ Prepaid vs. θ Postpaid from Figure 12a. 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.

including R1 2200 VA.[27] The results show a smaller magnitude of price elasticity (-0.3 compared to -0.48 from Table 3 Column 5). This is expected because those who upgrade their electricity capacity typically do so with the intention of increasing their electricity consumption. Thus, the consumption growth of prepaid users moving from 1300 to 2200 attenuates their responses to tariff changes.



(a) Price Elasticity: δ_p from Equation 9 (b) δ Prepaid vs. δ Postpaid

Figure 13. Elasticity Parameters for Postpaid and Prepaid

Note: Figure 13a plots the price elasticity (δ_p from Equation 9). Figure 13b compares δ Prepaid vs. δ Postpaid from Figure 13a. The sample is R1 1300 VA as the treated group and B1 1300 VA as the control group (not exposed to subsidy removal). Figures 13a and 13b figures mimic Figures 6a and 6b but using R1 450 VA vs. B1 450 VA). The whiskers indicate a 95% confidence level.

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

VI. Consumer Welfare Analysis

This section explores the implications of the empirical results on consumer welfare. From Section IV, we find that prepaid users are more price elastic than postpaid users. Based on a battery of checks, it appears plausible that the type of metering could make 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.[28] However, this improvement in welfare may be negated if the metering type affects consumer utility through other channels. For instance, consumer welfare may decrease: if households face liquidity constraints that prevent them from prepaying or if the technology itself generates negative utility that is independent of price effects.

Liquidity constraints could lead households to consume less electricity, as they may have difficulties prepaying for their consumption. However, several factors suggest that such constraints are unlikely to be significant. First, Table S7 in the Appendix indicates that the average monthly electricity bill accounts for only 2–5% of households' total monthly expenditures. This is consistent with the fact that electricity tariffs in Indonesia are among the lowest globally.[29] Second, prepaid users have the flexibility to purchase tokens in smaller denominations. This flexibility in smaller purchases likely helps alleviate liquidity constraints.[30] Finally, evidence from our survey, presented in Section 1.5 in the Appendix, suggests that liquidity constraints are unlikely to pose a significant issue for most households.

Prepaid metering may also generate non-monetary costs or benefits. For instance, a prepaid meter offers a commitment mechanism and less uncertainty about the total bill 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 VI.A. In particular, we use the Multiple Price Listing method (MPL) to elicit an individual's willingness to pay for either a prepaid or a postpaid meter. This approach allows us to estimate net consumer surplus by capturing the perceived non-monetary benefits associated with prepaid meters. If the willingness to pay is positive, it indicates a positive net consumer surplus that captures non-monetary benefits.[31]

[28]In general, we abstract away from the discounting parameter, as regardless of this parameter, our claim on the salience effect still holds, as discussed in Section II. Nonetheless, we include a discussion on the time value of money aspect in Section 1.5 of the Appendix.

[29]Moreover, Indonesia does not have winter and experiences relatively stable temperatures throughout the year. Therefore, electricity bills are generally stable across months, making it easier to budget each month.

[30]An additional concern might be that the transaction costs of purchasing prepaid tokens could lead customers to reduce electricity consumption to offset these costs. However, these costs are minimal, amounting to approximately $0.2 USD or 0.1% of the average monthly bill.

[31]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 (discussed in Section I). 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.

A. *Consumer Welfare: Evidence from a Multiple Price Listing Survey*

We ran an incentivized experiment among prepaid and postpaid meter users with home residences in cities in Central and East Java in Indonesia.[32] A total of 1,104 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 1.6. 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 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 prepaid meter + Rp. 40.000" (see Figure 14).[33] 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 15. Both prepaid and postpaid participants were asked to make such choices three times. However, if a participant chooses "Up" in Figure 15 and then chooses "Down", the experiment ends for that participant, regardless of whether he has made three such choices.

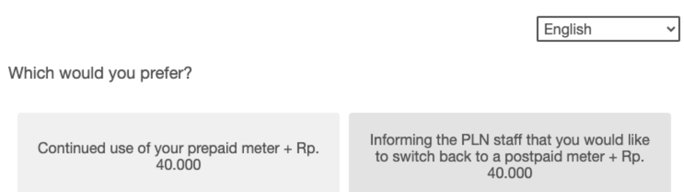


Figure 14. Sample Decision Screen of Participants

Note: Survey participants could only click on one of the boxes. If they click "Continued use of your prepaid meter + Rp. 40.000", they are then automatically moved to a new screen following the decision-tree outlined in Figure 15. Participants are not allowed to change their answers.

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,

[32]Human Subjects Board approval number 016/UN2.F6.D2.LPM/PPM.KEP/2022.
[33]40.000 IDR is 2.69 USD using the exchange rate of 14,870 IDR/USD.

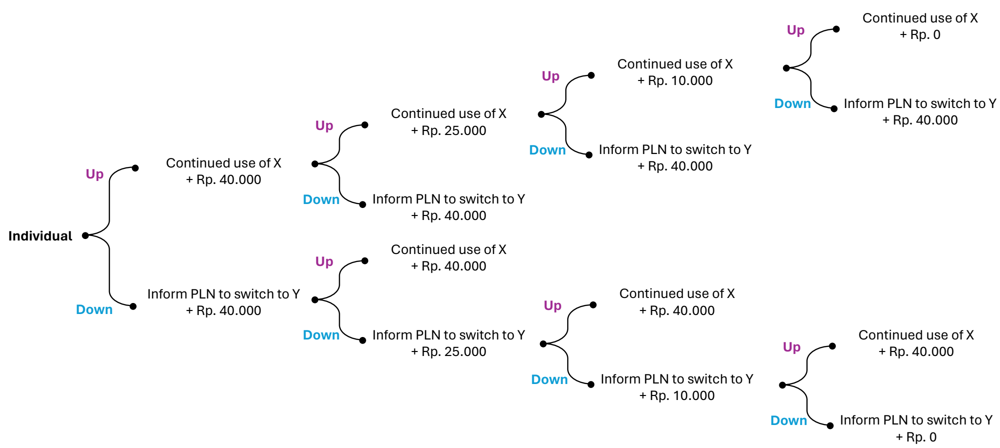


Figure 15. Participant Decision-Tree

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

we informed the PLN staff to make a switch. Moreover, out of 1,104 survey respondents, 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: (-∞, -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, ∞). 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 16 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 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.[34] Participants were asked to pick one of six choices and we lumped these answers

[34]Survey participants were specifically asked "Who initiated the change of your electricity meter from postpaid to

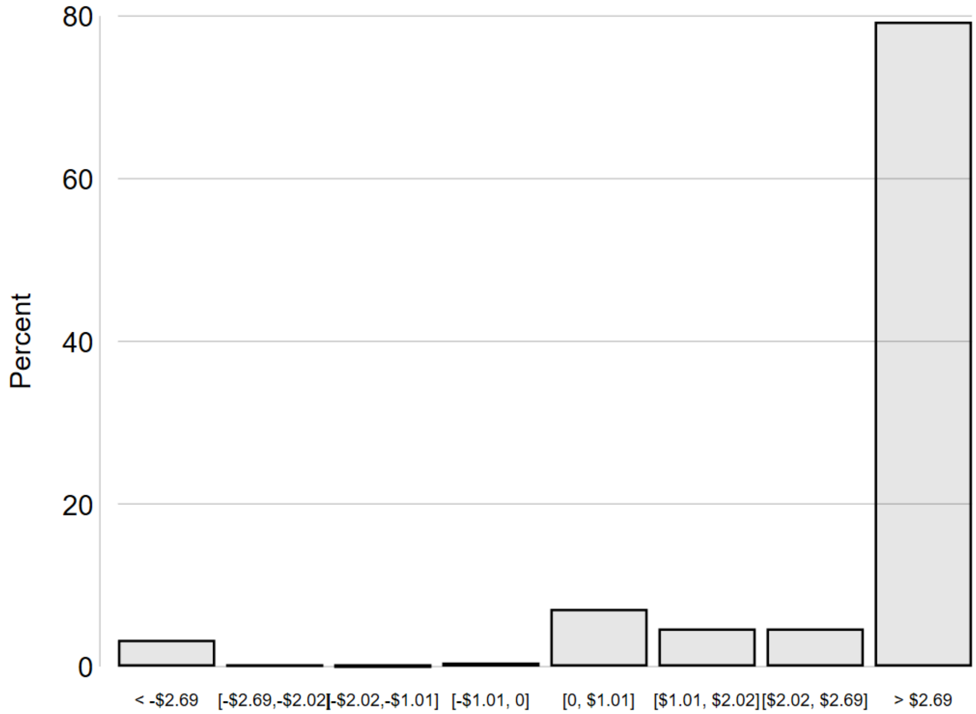


Figure 16. Individual Willingness-to-pay For Continued Use of Prepaid Meters

Note: 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.

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. Section 1.5 in the Appendix provides further explanation on why we observe positive willingness to pay from staying using a prepaid meter.

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 (see Figure S5 in the Appendix), 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 stud-

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.

ies (O'Sullivan et al., 2014). In particular, the results in Table S6 in the Appendix suggest that "no longer receiving unexpected bills" is one of the favorite features among prepaid meter users who reported a positive willingness to pay. Third, the discounting parameter is similar in magnitude to an experimental study that compares the pay-later group 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.

B. *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. Specifically, we calculate welfare changes resulting from this transition, drawing on methods from the tax literature on the excess burden in tax policy (Harberger, 1964). Finally, we assess the CO_2 emission implications of this transition.

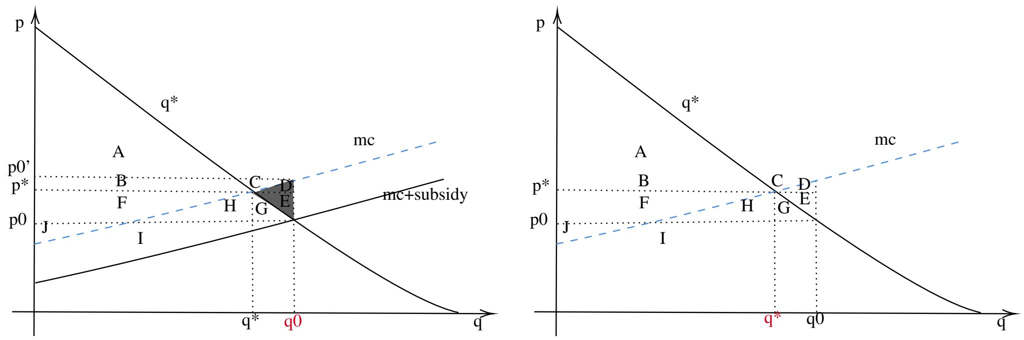
To derive an analytical solution for the welfare impact of postpaid to prepaid conversion, we impose a simple structure on our model described in Section II. We assume that the aggregate demand curves have constant elasticities in the form of $\alpha_d P^{-\beta}$, where α_d is the demand coefficient and β is the elasticity parameter. To fit our context, we assume that the producer offers electricity at marginal cost, mc, and consumers pay $P_0 = mc + subsidy$. 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 (shown in Table S7 in the Appendix). For the aggregate supply curve, we assume it to be $(mc/\alpha_s)P$. We calibrate the demand coefficient α_d and supply coefficient α_s with P_0 and q_0. The solid lines in Figure 17(a) illustrate these demand and supply curves.

Under the subsidy regime, a well-known inefficiency arises from overconsumption relative to the optimal level (q^*). This inefficiency is represented by the shaded triangle D and E in Figure 17(a). Removing the subsidy increases the price from P_0 to P^*, thereby eliminating the excess burden, as shown in Figure 17(b).

According to our empirical estimates, the price elasticity for prepaid users is greater than that for postpaid users ($\beta^+ > \beta^\times$). Therefore, the demand curve for postpaid users q is steeper than q^* (in Figure 18). The impact of converting postpaid to prepaid on the excess burden given the removal of the subsidy is represented by the previous triangle DE but excludes the small triangle k.

To quantify the excess burden from a tariff increase due to postpaid to prepaid conversion, we calculate the area represented by the triangle DE excluding k in Figure 18 under different values of prepaid elasticities. We set the slope of q fix at -0.1 (consistent with our empirical findings and existing studies' short-run price elasticity of electricity demand such as Ito (2014)), then we vary the slope of q^*, from -0.1 to -0.6. The results are shown in grey line in Figure 19.

The shift to prepaid meters reduces total electricity consumption relative to a counterfactual scenario without the conversion. This reduction has significant implications for emissions, given Indonesia's reliance on coal, which accounted for approximately 60%



(a) Excess burden under subsidy (b) Excess burden under removal of subsidy

Figure 17. Changes in excess burden due to removal of subsidy

Note: Figure (a) illustrates the changes in the excess burden under a subsidy, while Figure (b) shows the scenario after the subsidy is removed, both under the salient demand (q^*). The triangle DE represents the excess burden associated with the price subsidy, which disappears once the subsidy is removed.

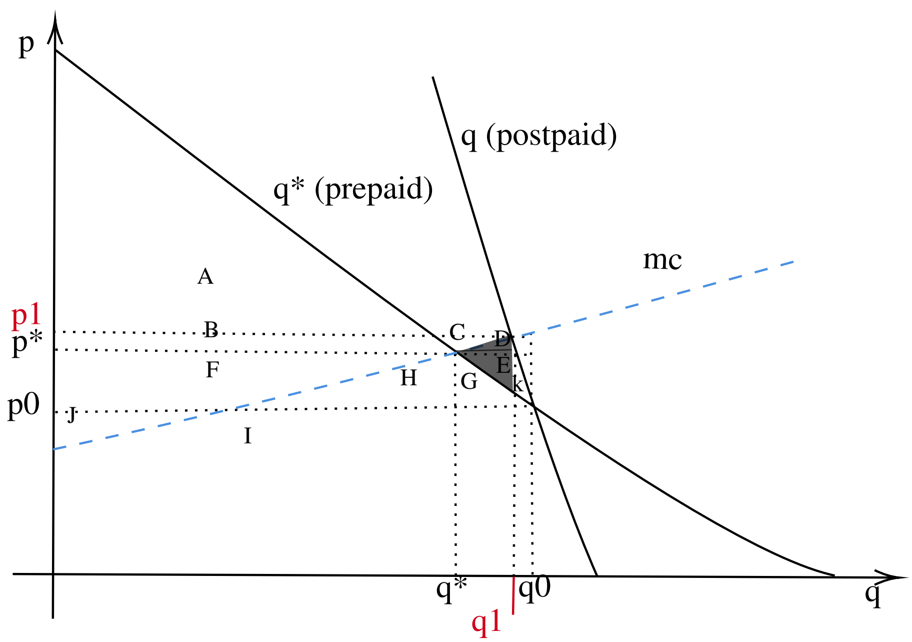


Figure 18. Excess burden under removal of subsidy and the conversion

Note: This figure illustrates the impact of converting postpaid to prepaid on the excess burden given the removal of the subsidy. The previous triangle DE, which represents the excess burden associated with the price subsidy, remains but excludes the triangle K.

of electricity generation in 2019 (Lolla and Yang, 2021). To quantify the environmental benefits, we calculate the avoided CO_2 emissions using the CO_2 emission factor for coal

(2.30 pounds of CO_2/kWh) from U.S. Energy Information Administration (2022). Using Indonesia's 2019 carbon credit price of IDR 69,600 ($4.51) per tonne (PwC Indonesia, 2023), we estimate the avoided cost of CO_2 emissions and normalize it relative to the total cost of carbon at baseline electricity consumption, q_0.

Our empirical estimates indicate that with $\beta^+ = 0.3$ and $\beta^x = 0.1$, and parameter values of $p_0 = 1000$ IDR/kWh, $p_1 = 1.35 \cdot p_0$ (reflecting a 35% tariff increase), and $q_0 = 41,136,476,384$ kWh (the 2013 aggregate consumption of R1 450, 900, and 1300 VA postpaid customers), the switch from postpaid to prepaid meters generates an efficiency gain of 1.5% of baseline expenditure relative to a scenario without the switch. This gain reflects the reduction in the excess burden due to behavioral responses to pricing and metering changes.

To further explore the environmental implications, we compute the avoided CO_2 emissions under different prepaid price elasticities. Figure 19 illustrates the impact of varying the prepaid elasticity on excess burden reduction and pollution abatement, while holding postpaid elasticity constant. With prepaid price elasticities of 0.3, the reduction in consumption is almost six percent. The results show that lower prepaid elasticities amplify both the welfare and environmental gains of the conversion. Given Indonesia's high emission intensity per unit of electricity generated, these findings highlight the substantial environmental benefits of reducing CO_2 emissions through the switch to prepaid meters. By decreasing electricity consumption, the conversion lowers CO_2 emissions and reduces the costs associated with carbon abatement.

VII. Conclusion

This study examines the role of prepaid metering in enhancing the price elasticity of electricity demand in developing countries. Using Indonesia's large-scale transition to prepaid metering and concurrent subsidy reforms as a natural experiment, we provide robust evidence that prepaid users exhibit significantly lower price elasticity than their postpaid counterparts. This finding underscores the importance of salience in influencing consumption behaviors and reveals a promising avenue for promoting efficient electricity use in resource-constrained settings.

Our results contribute to the broader literature on consumption and salience by offering one of the first empirical analyses of price salience in developing countries' electricity sector, where advanced technologies are often infeasible. By employing quasi-experimental methods and comprehensive robustness checks, we provide reliable demand elasticity estimates, demonstrating the sustained behavioral adjustments driven by prepaid metering systems. The accompanying survey evidence further highlights positive consumer welfare.

The implications of our findings extend beyond individual consumption patterns to broader energy policy and environmental goals. Prepaid metering not only enhances efficiency by aligning consumption with pricing signals but also contributes to significant reductions in carbon emissions, as evidenced by our applied welfare analysis. This paper highlights the dual economic and environmental benefits of prepaid systems, particularly in settings where affordability and access constraints limit the adoption of more advanced

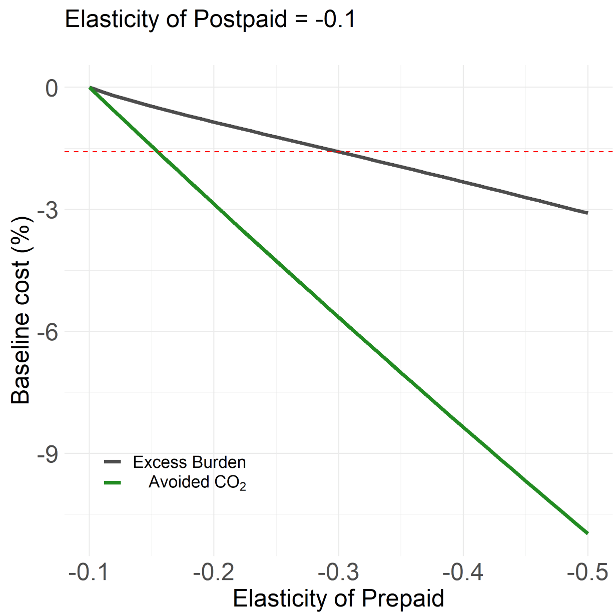


Figure 19. Gains from Postpaid to Prepaid Conversion

Note: This figure shows the sensitivity of efficiency gains 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 is normalized with baseline expenditure ($p_0 \times q_0$), while the magnitude of the avoided CO_2 is normalized by carbon price$\times q_0$.

demand-side technologies.

Since prepayment systems increase consumer price salience, this paper underscores the importance of setting electricity prices that accurately reflect the true social cost of carbon. If prices remain below this true cost—failing to account for environmental externalities—overconsumption may persist despite the adoption of prepayment systems. This highlights the need for policymakers to integrate environmental considerations into pricing strategies. Ensuring that prices align with the full social cost of electricity generation, including its carbon emissions, can further enhance the environmental and economic benefits of prepayment systems.

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Online Appendix:
Prepayment, Salience, and Welfare

Imelda, Abatayo, Resosudarmo

Contents

1 Appendix

1.1 Additional Tables

Table S1: Typical Appliances Per Voltage Ampere

	Typical appliances and its electricity consumption in Watt						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Lamps	Fridge	Rice cooker	TV	Fan	AC 1 HP	Iron
VA	10 W	130 W	100 W	60 W	100 W	860 W	400 W
450	4	1	1	1	1	0	0
900	5	1	1	1	1	0	1
1300	6	1	1	1	0	1	0
2200	7	1	1	2	2	1	1

Notes: There are four voltage amperes (VA) that we consider in our paper: 450, 900, 1300, 2200. Our analysis is mostly focused on households with 1300 VA and use the rest for robustness checks. The VA of a household indicates the maximum total watts that can be used at any given point in time. When a household's consumption exceeds the limit of VA, the miniature circuit breakers trip. The household will then need to restart the circuit breakers to get electricity again. As such, 450 or 900 VA households are least likely to use an AC with 1 horsepower (HP), while 1300 VA households are more likely.

1.2 Additional Figures

Figure S1: Prepaid and Postpaid Customers are Neighbors

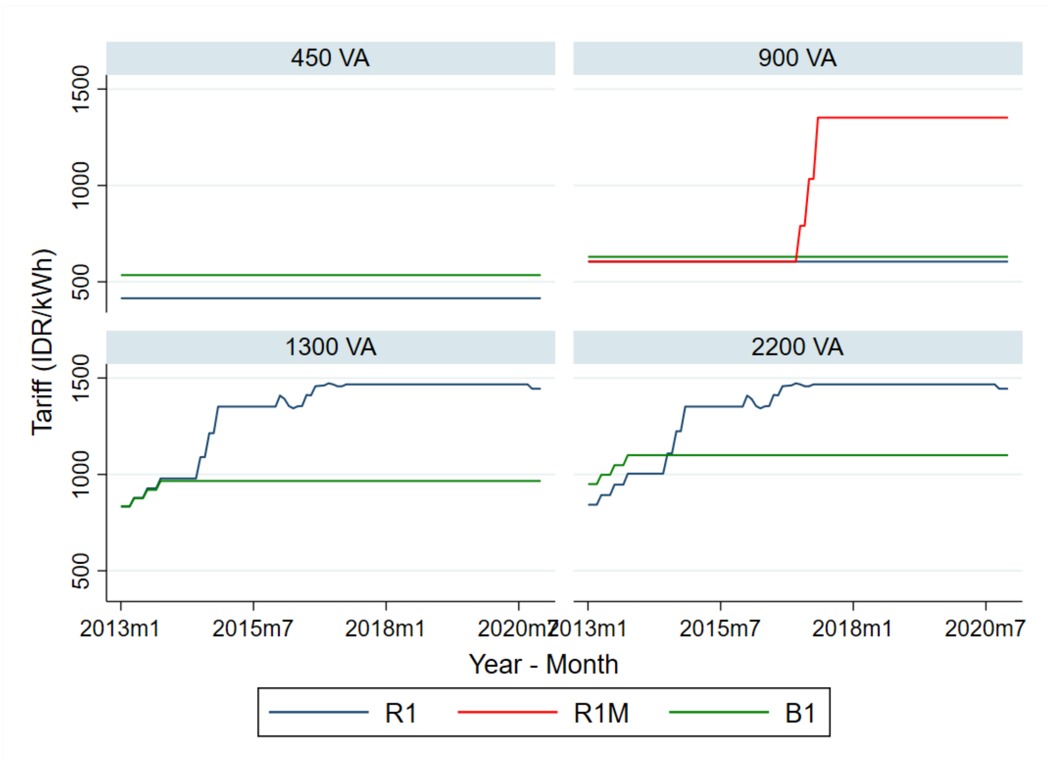
(a) R1 450 VA (b) B1 2200 VA

Notes: In Figure S1a, the building on the right is a prepaid customer while the building on the left is a postpaid customer. In Figure S1b, the building on the left and right are prepaid customers and the building in the middle is a postpaid customer.

1.3 Prepaid penetration of R1 1300 VA vs. B1 1300 VA

Table S4 reports within-service-unit differences similar to Table 2, but using the 1300 VA sample without differentiating the metering type. 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

Figure S2: Trends in tariffs for 450-2200 VA



Notes: The figure plots tariffs for customers under 450-2200 VA. The removal of the subsidy occurred for some R1 customers under 900 VA (R1M) started in 2017 and under 1300 VA started in mid-July 2014. R1M stands for small residential "Mampu" or capable residential, suggesting that the customers under this category are the least poor relative to other customers within the same 900 VA category. Source: Compiled by the author from several Regulations of the Minister of Energy and Mineral Resources of the Republic of Indonesia 2013-2020.

Table S2: The elasticity of demand of prepaid vs. postpaid

	Prepaid vs. Postpaid				
	(1)	(2)	(3)	(4)	(5)
Treat=1 × Prepaid × Post=1	-0.13	-0.13			
	(0.012)	(0.012)			
Prepaid × Log(price)			-0.36		
			(0.027)		
Prepaid × Year=2014 × Log(price)				-0.18	-0.18
				(0.070)	(0.071)
Prepaid × Year=2015 × Log(price)				-0.16	-0.16
				(0.041)	(0.041)
Prepaid × Year=2016 × Log(price)				-0.29	-0.29
				(0.039)	(0.039)
Prepaid × Year=2017 × Log(price)				-0.46	-0.46
				(0.038)	(0.038)
Prepaid × Year=2018 × Log(price)				-0.47	-0.47
				(0.039)	(0.039)
Prepaid × Year=2019 × Log(price)				-0.39	-0.39
				(0.039)	(0.040)
Prepaid × Year=2020 × Log(price)				-0.39	-0.39
				(0.046)	(0.047)
Service Unit FE	N	Y	Y	N	Y
Service Unit	138	138	138	138	138
Mean usage	165.4	165.4	165.4	165.4	165.4
Observations	4,590	4,590	4,590	4,590	4,590

Notes: The results of the table came from similar regressions to Equation 8 and Equation 9, but we added the prepaid dummy (Pre) to capture the relative difference between prepaid and postpaid. That is,

$$\triangle log(usage)_{ict} = \alpha_i + \beta_p T_c * Post_t * Pre + \beta_0 T_c * Pre + \beta_1 Post_t * Pre + \gamma_t + \epsilon_{ict}, \tag{1}$$

$$\triangle log(usage)_{ict} = \alpha_i + \delta_p \triangle log(price)_{ict} * Pre + \delta_0 \triangle log(price)_{ict} + \delta_1 Pre + \gamma_t + \epsilon_{ict} \tag{2}$$

Thus the table reports the results where we interact the left-hand side variable in Table 3 with the dummy of prepaid. Therefore it shows the price elasticity of prepaid users relative to postpaid.

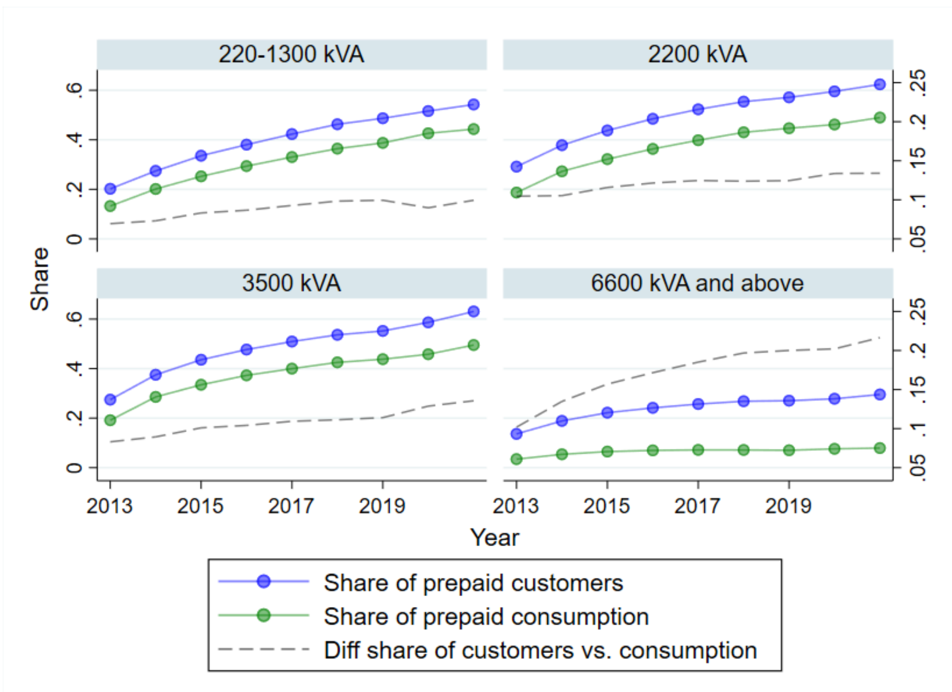
the parallel trend test. The three rows in Columns 1-4 indicate that, in 2014, prepaid share similarly influenced usage between R1 and B1 within service units, and prepaid share similarly affects the usage of R1 with B1. Columns 5-8 show the effects of tariff changes impact on log usage (regardless of metering type) conditional on prepaid penetration rate. The magnitude is consistent with all the results discussed in previous subsections.

Table S3: Do prepaid users poorer than postpaid users?

	(1) lowincome	(2) lowexpenditure	(3) loweducation
Prepaid users	0.0346	-0.0226	-0.00175
	(1.41)	(-0.73)	(-0.06)
Constant	0.146***	0.386***	0.381***
	(7.07)	(14.89)	(14.55)
Observations	1104	1104	1104

Notes: The table reports report the coefficient of whether prepaid users are poorer than postpaid users, using three different proxy: (1)lowincome: have income less than 2.5 Mio IDR per month (≈163 USD); (2) lowexpenditure: have expenditure less than 2.5 Mio IDR per month; (3) loweducation: do not have bachelor degree.

Figure S3: Shares of customers and consumption of prepaid users across different VAs for R1 and B1 customers

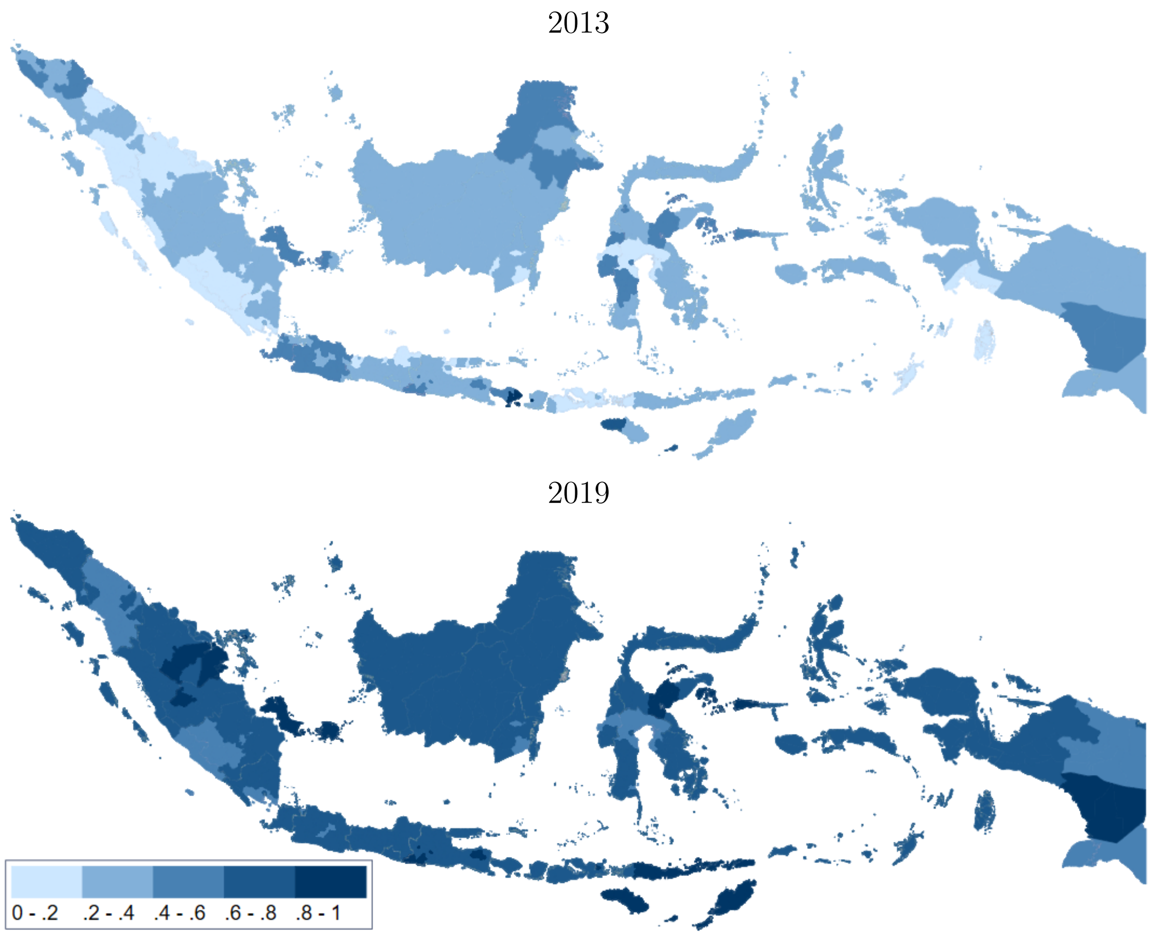


Notes: The share of electricity consumption of prepaid users is always lower than of postpaid users. This difference is even larger for larger customers, such as those consuming above 6000 VA. Source: PLN.

1.4 Selection into prepayment

To test whether the prepaid share variations are quasi-random within service units, we merge the National Socioeconomic Survey of Indonesia, a nationally representative survey in 2013 that contains socio-economic variables with the prepaid penetration rate in 2013 based on the location in which the households lived in 2013. We do not observe the household prepaid status in the survey. We rely on variations in the prepaid penetration rate across VA within municipalities. We then follow Equation 7 to test the correlation between prepaid share and

Figure S4: Increasing Prepaid Metering Shares Between 2013 and 2019



These figures map prepaid metering penetration for R1 1300 VA and B1 1300 VA customer classes in 2013 (top) and 2019 (below). Source: PLN.

Table S4: 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			

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 7, 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.

household characteristics.

$$Outcome_{icv} = c + \beta PrepaidShare_{cv} + Urban + \gamma_c + \epsilon_{icv}, \tag{3}$$

where the outcome of household i under VA v in municipality c which includes various socioeconomic indicators, including the highest education degree attained, home ownership status, presence of cement walls, ownership of air conditioning units, car ownership, participation in home businesses, usage of unsubsidized LPG, marital status, age, household size, and urban residency. The β coefficient indicates whether there is a statistical relationship between prepaid share and the outcome variables, conditional on VA fixed effects, urban fixed effects, and municipality and service unit fixed effects. The error term is clustered on the municipality level to allow for the correlation of socioeconomic variables within the municipality.

Table S5 indicates that a broad range of socioeconomic indicators are not significantly correlated with the prepaid share, except for marital status and age. Specifically, we observe higher penetration of prepaid usage among younger individuals and those who are already married, which aligns with the common scenario of starting a new household. Furthermore, our analysis in Table S3 reveals no significant difference in household wealth between prepaid and postpaid users based on self-reported income and expenditures from our survey. This finding provides additional evidence that prepaid shares within service units.

Table S5: The correlation between prepaid penetration and household characteristics

	(1) High School	(2) Secondary School	(3) Higher Education	(4) Owns Home	(5) Has Cement Walls	(6) Has Air Conditioner
Prepaid Penetration	0.028	0.021	-0.043	0.044	-0.064	0.032
	(0.043)	(0.013)	(0.038)	(0.039)	(0.067)	(0.029)
VA=900	-0.047***	-0.0088**	0.050***	0.024***	0.097***	0.025***
	(0.0073)	(0.0027)	(0.0059)	(0.0067)	(0.011)	(0.0038)
VA=1300	-0.17***	-0.011***	0.18***	0.045***	0.15***	0.20***
	(0.015)	(0.0031)	(0.014)	(0.013)	(0.015)	(0.014)
Urban	0.017***	0.0098***	-0.025***	0.093***	-0.10***	-0.022***
	(0.0040)	(0.0016)	(0.0041)	(0.0056)	(0.0092)	(0.0026)
Mean Dep. Var.	0.85	0.02	0.12	0.81	0.70	0.04
Observations	167,975	167,975	167,975	167,975	167,975	167,975

	(7) Owns Car	(8) Runs Home Business	(9) Uses Unsubsidized LPG	(10) Marital Status	(11) Age	(12) Household Members
Prepaid Penetration	-0.035	-0.0067	0.065	0.11**	-3.58***	0.13
	(0.033)	(0.018)	(0.058)	(0.038)	(1.02)	(0.16)
VA=900	0.078***	0.0022	0.088***	0.029***	-0.34	0.089**
	(0.0048)	(0.0033)	(0.0080)	(0.0050)	(0.17)	(0.028)
VA=1300	0.23***	-0.012*	0.26***	0.035***	-0.18	0.15***
	(0.012)	(0.0061)	(0.013)	(0.0076)	(0.30)	(0.039)
Urban	-0.023***	-0.028***	-0.064***	0.026***	-0.23*	-0.058***
	(0.0032)	(0.0028)	(0.0053)	(0.0027)	(0.092)	(0.017)
Mean Dep. Var.	0.09	0.07	0.15	0.85	45.71	3.99
Observations	167,975	167,975	167,975	167,975	167,975	167,975

Notes: each row is a separate regression following Equation 3 using the corresponding outcome variable on the left column. The mean of the outcome variable is listed in the right column. Source: PLN billing data and National Socioeconomic Survey of Indonesia (SUSENAS) 2013.

1.5 Consumer Welfare Channels

While we find that the net effect of prepaid metering on consumer welfare is positive, it is possible that the different channels through which prepaid metering affects consumer welfare vary in sign. Using data from the survey we conducted, we are able to test several hypotheses and shed light on the effect of a number of possible channels through which prepaid metering affects consumer welfare. In particular, we focus on investigating the influence of information feedback, time value of money, non-monetary features of prepaid meters, and liquidity constraints. As we dive into each of the channels below, we conjecture that the time value of money, certain non-monetary features, and liquidity constraints contribute negatively to consumer welfare. By examining each element, we provide an understanding of how prepaid metering affects consumer welfare through diverse welfare channels.

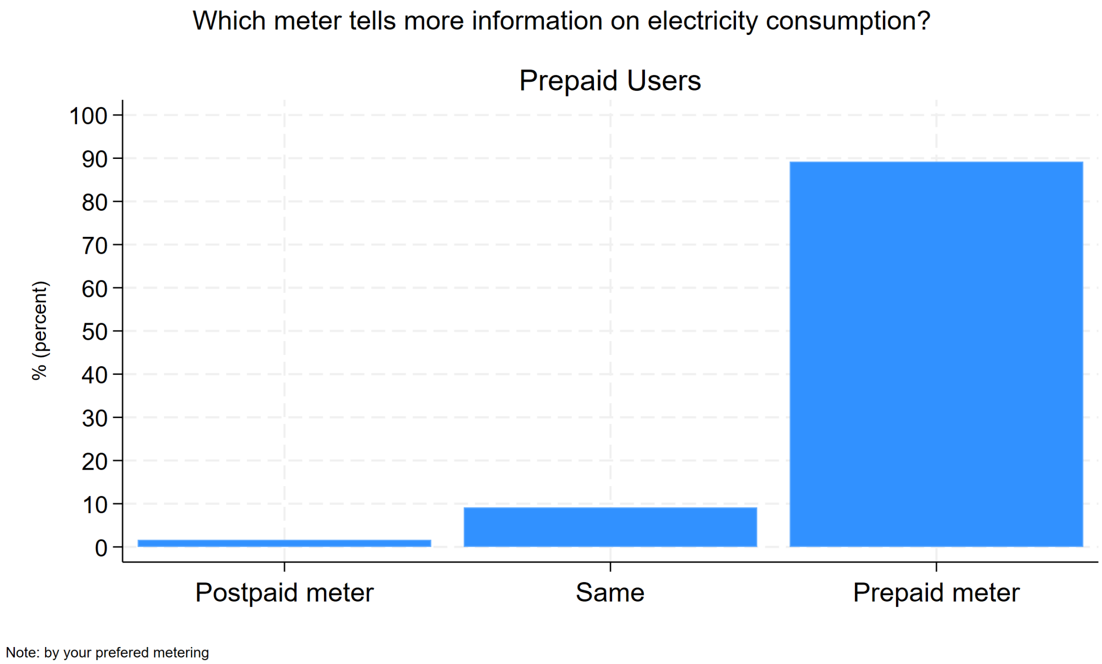
Information. We conjecture that prepayment enhances a household's awareness of electricity consumption, as individuals gain knowledge about their electricity usage before actual consumption occurs. This increased awareness makes households more energy efficient and hence, increases their welfare. To provide empirical support for this idea, we included a specific question in our survey for participants: "Which electricity meter allows you to know more about how much your electricity consumption is?". The results presented in Figure S5 suggest that among prepaid users, the overwhelming majority believe that prepaid meters offer them more information about their electricity consumption. It is important to acknowledge that there may be some inherent default bias, as respondents might tend to choose their current type of metering as the type that offers them the most information about their electricity consumption. Additionally, some postpaid users might not have had previous experience with prepaid meters and hence, are less likely to choose a prepaid meter as an answer to the question. Nevertheless, it is noteworthy that almost all of the prepaid users uniformly agree that prepaid metering enables them to be aware of their energy consumption. Moreover, in another survey question, 78% of our prepaid users answered that the statement "After using prepaid, I am more aware of my electricity consumption" best describes them. Only 22% of prepaid users were aware of their electricity consumption even before they switched to prepaid metering. This supports our conjecture above: that prepaid metering enhances a household's awareness of their electricity consumption.

Time Value of Money. Another possible channel through which prepaid metering could affect consumer welfare is through the time value of money, where money today is worth more than the same amount of money in the future. We hypothesize that, because individuals with postpaid meters defer paying for their electricity until the end of the month, they are wealthier now, *ceteris paribus*, than their prepaid metering counterparts. As such, we conjecture a decline in electricity consumption among prepaid users that, in turn, declines their welfare. Below, we investigate whether this is the case in Indonesia.

Postpaid users have the advantage of being able to defer their payment to the end of the month, which discounts their electricity bill. In Indonesia, postpaid users also have the option to delay payment for up to three months before facing the consequences of electricity disconnection and a fine.[1] Despite this option to further delay payment without consequences, 46% of the

[1]According to the Regulation of the Ministry (*Peraturan Menteri Energi dan Sumber Daya Mineral Republik*

Figure S5: Information and electricity consumption



Notes: It shows the respondents' perception of which electricity meter allows them to know more about how much their electricity consumption is. Source: an online survey conducted by authors.

respondents in our survey report never being late in paying their bills while 22% admit to being late once or twice due to forgetfulness. Hence, given the limited duration of payment deferral and the relatively small proportion of customers who utilize this option, it does not seem like payment deferral is a significant factor affecting differences in consumer welfare between postpaid and prepaid users.

Prepaid users, on the other hand, cannot defer paying their electricity bill. They also incur additional costs in the form of transaction costs, ranging from 0 to 3.500 IDR depending on where they purchase their prepaid tokens.[2] Our survey respondents report having to purchase tokens 1-2 times each month. They also report that they do not mind paying these transaction costs, as these are small amounts.[3] This suggests that that additional upfront costs incurred by prepaid users hardly affects consumer welfare, as prepaid users hardly mind paying for them.

To further dig into whether paying upfront leads to significant declines in the welfare of prepaid users, we perform the following exercise. Customers will be indifferent to either using

Indonesia) Number 27/2017, households with a 1,300 VA connection are charged a fee of 5,000 IDR per month, equivalent to about 50 cents USD.

[2] https://www.cnnindonesia.com/ekonomi/20150908134432-85-77328/pln-tak-wajibkan-masyarakat-gunakan-listrik-prabayar.

[3] Survey respondents were asked to rate their level of agreement to the statement *"I am okay paying an admin fee for each prepaid meter top-up I bought, because it is small". Levels of agreement were between 1 to 100, with 1 signifying that they do not agree with the statement at all and 100 signifying that they agree with the statement a great deal. The average level of agreement for this statement is 72.*

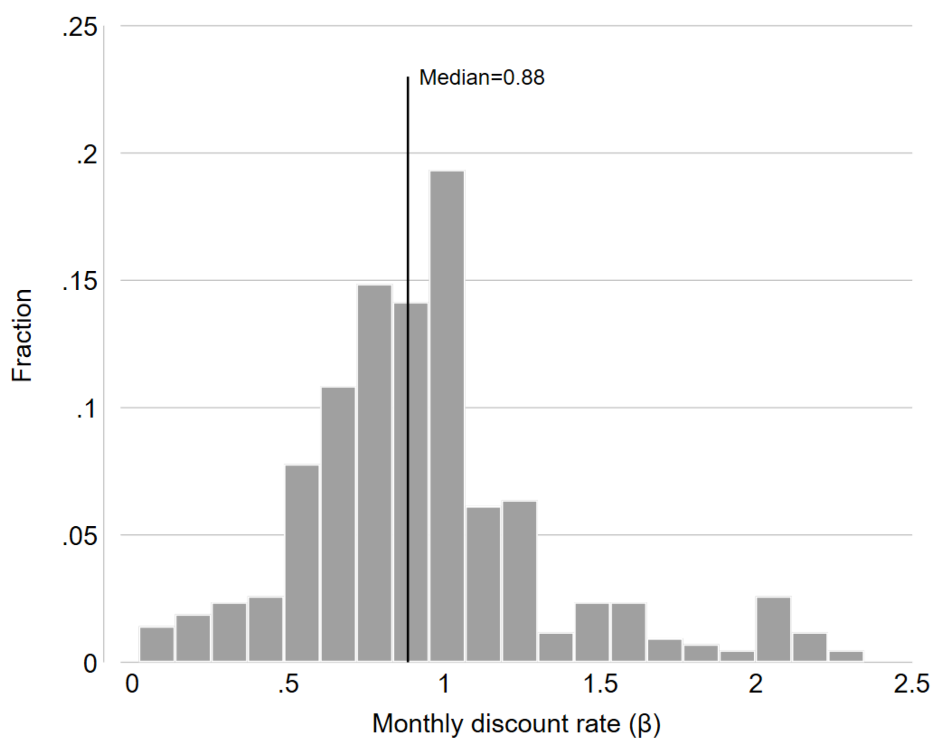
prepaid or postpaid meters when the following condition is satisfied:

$$\begin{aligned} \text{Cost for postpaid} &= \text{Cost for prepaid} \\ \beta * bill &= bill + (freq * \text{transaction cost}) \end{aligned} \tag{4}$$

where β is the discount rate, *bill* is the household's electricity bill, $freq$ is the number of times a household tops up their prepaid meter, and *transaction cost* is the administrative fee incurred from each top-up. If delaying one's bill payment does not significantly increase welfare, which also implies that paying upfront does not significantly decrease welfare, then β should be close to 1.

We ask our survey participants about their average monthly bill before and after their switch to prepaid metering. Figure S6 shows the distribution of individual β's computed using Equation 4. We find median individual β to be close to 1, which implies that because individuals do not discount the future much, we have additional support that delaying one's bill payment does not significantly increase welfare.[4]

Figure S6: Discount rates



Notes: it shows the computed β from Equation 4 and respondents' average bills under 1300 VA. We remove outliers below the 5th percentile. Source: an online survey conducted by authors.

To provide our final evidence on the role of the time value of money on the welfare of prepaid users, we examine the behavior of prepaid and postpaid users before the tariff changes using that data from PLN. We conjecture that if the time value of money plays a role, customers

[4] A β of 0.88 falls within recent average estimates from lab experiments on time preferences and discounting (Augenblick, Niederle and Sprenger 2015, Augenblick and Rabin 2019).

under the prepayment system should consume less relative to postpaid users. As shown in Figure 5, prepaid users behave very similarly to postpaid users in the absence of tariff changes. This provides further evidence of the role played by the time value of money in affecting the welfare of prepaid users.[5]

Non-monetary Features. Another channel through which switching to prepaid metering may affect consumer welfare, is through various non-monetary features offered by prepaid metering that influences individual utility. These are things such as the increase in utility at being able to manage one's cash flow better, the decrease in utility at getting disturbed by the meter's beeping sound when the balance is low, or the decrease in utility because of the additional effort required to top-up one's prepaid meter balance.

To shed light on this non-monetary features, we examine a set of questions where our survey respondents were asked to rate their agreement to certain statements from 1 to 100 (1 - not agree at all, 100 - agree a great deal). These statements are features, based on anecdotal evidence, that differentiate prepaid meters from postpaid meters.[6] The results are presented in Table S6, illustrating the level of agreement among individuals for each statement listed in the left column. Each feature's value is measured by the deviation from the individual's mean score for all other features. A negative value indicates disagreement with the statement, while a positive value signifies agreement. The feature that received the highest rating was "I no longer receive high and unexpected bills because of using prepaid meters," suggesting that this aspect of a prepaid meter is particularly appealing to the respondents. We could also observe several less appealing features of prepaid meter such as the admin fees and the sounds coming from the meter when the balance is low.

What we are interested in is testing whether the positive willingness-to-pay for prepaid metering that we see is due to any or several non-monetary features of prepaid meters. As such, we divide subset between those with positive and negative willingness-to-pays and test whether those with positive willingness-to-pays differ from those with negative or zero willingness-to-pays in terms of how much they agree with each prepaid meter feature.

[5] In the survey, we also directly measured respondents' discount rates through MPL method, we also find majority of them fall within 0.4-0.6 for both prepaid and pospaid users, consistent with above discussion.

[6] We rely on some of the anecdotal benefits of prepaid models include convenience, flexibility, affordability, and control over spending, while some of the anecdotal costs of using prepaid include worries of running out of balance, mental pain of prepayment, or discomfort and shame due to sounds generated by prepaid meters when the balance is low.

Table S6: Users' perception of prepaid metering features

Prepaid features	Prepaid WTP<=0		Prepaid WTP>0		Difference	
	Mean	SD	Mean	SD	Coef	p-val
Believe the prices are the same	-1.81	(18.68)	-11.61	(23.19)	-9.90	(0.000)
Admin fees do not bother me	-8.86	(20.40)	-7.61	(21.93)	1.46	(0.521)
Do not have difficulties in paying forward	3.98	(16.85)	5.00	(14.23)	1.19	(0.512)
No unexpected bills	3.00	(20.76)	8.60	(14.01)	5.77	(0.010)
Cashflow management	5.45	(15.93)	6.84	(14.22)	1.29	(0.470)
Easy to refill	9.59	(19.12)	7.79	(16.57)	-1.96	(0.363)
Do not worry it runs out of balance	2.10	(17.84)	5.15	(15.99)	2.74	(0.159)
Do not disturbed by sounds from low balance	-13.45	(25.46)	-14.17	(26.73)	-0.59	(0.835)
Observations	89		699			

Notes: The table reports the mean and standard deviations of each statement on the left column. The value for each feature is measured by its deviation away from the individual's mean of all other features. A negative value means that individual disagrees with the statement, while a positive value means they agree. Note: online survey.

The results presented in Table S6 show that there are only two features that are statistically significantly different across our two groups. The first is on the belief that prices are the same between prepaid and postpaid meters. On average, both groups disagree that prices are similar across these two types of meters, but those with positive willingness-to-pays disagree statistically significantly more, suggesting a misconception regarding the price but also lending to the possibility that individuals find prices more salient with prepaid meters than with postpaid meters. The second is on no longer receiving unexpected bills because of prepaid metering. While both groups agree that this is the case, those with positive willingness-to-pay agree with this statement more. This, again, seems to point at the possibility that prepaid metering increases welfare due because prices are more salient.

Liquidity Constraint. There are two main survey questions that are relevant to shed light on possible liquidity constraints among prepaid users. First is the statement that participants were asked to rate from 1 (not agree at all) to 100 (agree a great deal): "I always have money on hand so I don't have difficulty in buying prepaid meter top-ups". Second is a more direct question asking participants "[o]n average, how much is your total monthly prepaid top-up for a month." When combined with each participant's self-reported monthly income and expenses, we are able to say something about whether prepaid users are liquidity-constrained.

On average, our survey respondents agree with the statement that they always have money on hand and that they don't have difficulty buying prepaid meter top-ups (mean: 83, std. dev.: 20). On average, respondents pay 263.956 IDR each month, less than 5% of their median monthly income and 8% of their median monthly expenditure of our respondents. Majority of our respondents have a monthly income of 5 - 10 million and a monthly expenditure of 2.5 - 5 million. Hence, not only are prepaid meters really just a small percentage of both average monthly expenditure and average monthly income, average household expenditures are also only half of average monthly income. This provides evidence that prepaid users are not liquidity constrained.

We also look at a nationally representative survey of Indonesia (National Socioeconomic Survey) for the year 2013 and compute the average electricity bill relative to total expenditure. Table S7 suggests that monthly electricity bill is, on average, around 2 - 5% of households' monthly expenditure. This is perhaps not surprising, as electricity tariffs in Indonesia are among the lowest relative to other countries.[7] We do not negate that there is a possibility that households may apply mental accounting to their electricity budget and therefore are responsive to price changes even though the electricity bill share is small relative to their total expenditure. Regardless, this exercise provides further evidence that prepaid users in Indonesia are not liquidity constrained.

Table S7: Summary Statistics for Socioeconomics Characteristics

	450 VA		900 VA		1300 VA		2200 VA	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Expenditure (IDR)	2121.5	(1709.3)	3135.0	(2945.6)	4966.3	(4694.3)	7846.8	(7883.1)
Electricity (IDR)	41.6	(30.9)	81.9	(55.7)	168.4	(125.9)	300.5	(240.8)
Share (%)	2.3	(1.5)	3.0	(1.7)	3.8	(2.1)	4.2	(2.4)
Usage (kWh)	16.3	(377.6)	27.4	(605.3)	44.8	(271.9)	54.4	(171.9)

Notes: The table reports the mean and standard deviations of each variable. Expenditure and electricity bills are the monthly averages for the year in thousand IDR. The average usage in kWh is also a monthly average. Source: Susenas 2013.

[7] https://www.theindonesia.id/news/2022/04/06/133000/indonesias-electricity-price-lowest-in-asean-ministry.

1.6 Survey Questionnaire

English

Screening Question

Thank you for participating in this survey. This is a research project conducted by J-PAL Southeast Asia (SEA) based at the Faculty of Economics and Business, Universitas Indonesia (LPEM FEB UI) supported by researchers from the Geneva Graduate Institution, Australian National University, and Wageningen University. Answering all questions will take approximately 15 minutes.

By participating in this research:

- You give permission to the researchers of the Geneva Graduate Institution, Australian National University, and Wageningen University to let you participate in this research and to use the information you provide in this survey for the research related to users' satisfaction using prepaid metering in Indonesia.
- You understand that your data will only be used for research purposes and that this will be done completely anonymously.
- You understand that your participation is voluntary and that you are free to stop participating at any time, without having to give a reason.
- You understand that the information you provide will be kept securely by the researcher in accordance with the guidelines.
- You understand that it is possible that your data will be used for follow-up research, possibly by other researchers.
- You will not directly benefit from this survey. However, your answers will help us understand more about users' satisfaction using prepaid metering.

If you have any questions about this project, please contact imelda@graduateinstitute.ch.

I understand the procedure explained above and I agree with the above statements. If you need the copy of this form for your own record, you can print this screen now or export this page to pdf after you choose your answer.

Not agree	Agree
○	○

I am the head of the household or the spouse.
I am 18 or older.
I live in Indonesia
I live in a resident that I or my spouse own and I am not currently renting.
My home is used as a residential place and not for commercial purposes.

- ○ All statements about me are correct.
- ○ At least one statement about me is not correct.

Which electricity metering you are currently using?

Prepaid meter
A type of electricity meter in which you have to buy an electricity token before you can use it.

○ 

Postpaid Meter
A type when you pay your electricity consumption after usage (at the end of each month).

○ 

True or False: I have **never** used a postpaid meter in the past.

- True.
- False, I have used postpaid in the past.

What year did your electricity meter change to prepaid?

- 2010 or before
- 2011-2013
- 2014
- 2015
- 2016
- 2017
- 2018
- 2019
- 2020
- 2021
- 2022
- I don't remember

Who initiated the change of your electricity meter from postpaid to prepaid?

- PLN personel
- My house was newly built, so I had no other option other than using prepaid
- Myself
- My partner
- My parent
- Some other person

What is the city you're residing in?
(If you do not live in the city, please choose the closest city to your residence)

- Blitar

- Kediri
- Surabaya
- Malang
- Madiun
- Mojokerto
- Pasuruan
- Probolinggo
- Batu
- Other city

What city?

Screening-Exit

For this survey, we need Indonesians who are either the head of the household or the spouse and who are currently using prepaid meters in a house or apartment that they own.

Thank you for your time!

Introduction

Tell us what you think and earn a reward up to Rp. 40.000!

The information obtained from this survey will give insights into perceptions of individuals regarding prepaid metering. The survey is composed of **4 parts**. At the beginning of each part, you will be given instructions about the type of decisions you are required to make.

Note that you cannot go back and revise your answers.

Part 1: leisure vs. work

Imagine the following hypothetical situation. It is now Sunday 9AM and you have 1 hour of free time until 10AM. You will be asked to choose between

"enjoy your free time" OR **"work for 1 hour and receive some money as a compensation"**

If you choose to work, you will be asked to paint some furniture during the 1 hour by yourself.

leisure0

Which would you prefer?

Enjoy free time 1 hour + Rp 0
(This means you will receive Rp 0 but you can enjoy your free time)

○

Work for 1 hour + Rp 20.000
(This means you will receive Rp 20.000 but you have to do some work and you no longer have your 1 hour free time)

○

leisure+1

Which would you prefer?

Enjoy free time 1 hour + Rp 0

○

Work for 1 hour + Rp 40.000
(Now, you are offered **Rp 40.000** to compensate for your 1 hour doing the work.)

○

This is an example of the type of choices you will have to make and how your choices will affect the reward amount you will receive. Based on your previous answer, you will receive Rp 40.000.

Note, this is a testing question, therefore no monetary reward will be paid. However, in

the next part, you will be asked a similar type of question and monetary award will be paid.

This is an example of the type of choices you will have to make and how your choices will affect the reward amount you will receive. Based on your previous answer, you will receive Rp 0.

Note, this is a testing question, therefore no monetary reward will be paid. However, in the next part, you will be asked a similar type of question and monetary award will be paid.

Thank you for your answers.
Part 1 of the survey ends here.
You will now begin with Part 2.

work+1

Which would you prefer?

Enjoy free time 1 hour + Rp15.000
(Now, you are offered **Rp 15.000** and you can still enjoy your 1 hour free time.)

○

Work for 1 hour + Rp 20.000

○

This is an example of the type of choices you will have to make and how your choices will affect the reward amount you will receive. Based on your previous answer, you will receive Rp 15.000.

Note, this is a testing question, therefore no monetary reward will be paid. However, in the next part, you will be asked a similar type of question and monetary award will be paid.

This is an example of the type of choices you will have to make and how your choices will affect the reward amount you will receive. Based on your previous answer, you will receive Rp 20.000.

Note, this is a testing question, therefore no monetary reward will be paid. However, in the next part, you will be asked a similar type of question and monetary award will be paid.

Thank you for your answers.
Part 1 of the survey ends here.
You will now begin with Part 2.

Part2

Part 2: Prepaid Meter vs. Postpaid Meter

This part of the survey is the same as in the previous part.

You will be repeatedly asked to choose between two options. Unlike the previous survey, you will now be asked to choose between "**continued use of your prepaid/postpaid meter" + money** and "**informing the PLN staff that you would like to switch to a postpaid/postpaid meter" + money**.

A. Monetary Payment

Upon completion of the survey, 200 respondents randomly picked, with valid and complete answers, will receive an additional amount of reward based on your chosen amount. If you qualified, the amount will be directly paid to you upon finishing the survey.

B. Your Choices

There are two types of electricity meters that are involved in the choices you will be offered.

(1) This is a Prepaid Meter.

In a prepaid meter, you pay your electricity consumption **before** usage. A prepaid meter will need to be refilled by inputting a 20-digits electricity token before usage.

(2) This is a Postpaid Meter.

In a postpaid meter, you pay your electricity consumption **after** usage. You pay your bill at the end of each month.

C. Consequences of your choice

We are working closely with PLN. Thus, if you choose to **"informing the PLN staff that you would like to switch to a postpaid/postpaid meter"**, you authorize us to let PLN know your intention. **By**

choosing this option, you confirm that you agree with this.

HoltLaury-Initial

Which would you prefer?

Continued use of your prepaid meter + Rp. 40.000

○

Informing the PLN staff that you would like to switch back to a postpaid meter + Rp. 40.000

○

Which would you prefer?

Continued use of your postpaid meter + Rp. 40.000

○

Informing the PLN staff that you would like to switch to a prepaid meter + Rp. 40.000

○

HoltLaury-Up1

Which would you prefer?

Continued use of your prepaid meter + Rp 40.000

○

Informing the PLN staff that you would like to switch back to a postpaid meter + **Rp 25.000**

○

Which would you prefer?

Continued use of your postpaid meter + Rp 40.000

○

Informing the PLN staff that you would like to switch to a prepaid meter + **Rp 25.000**

○

HoltLaury-Up2

Which would you prefer?

Continued use of your prepaid meter + Rp 40.000

○

Informing the PLN staff that you would like to switch back to a postpaid meter + **Rp 10.000**

○

Which would you prefer?

Continued use of your postpaid meter + Rp 40.000

○

Informing the PLN staff that you would like to switch to a prepaid meter + **Rp 10.000**

○

HoltLaury-Up3

Which would you prefer?

Continued use of your prepaid meter + Rp 40.000

○

Informing the PLN staff that you would like to switch back to a postpaid meter + **Rp 0**

○

Which would you prefer?

Continued use of your postpaid meter + Rp 40.000

○

Informing the PLN staff that you would like to switch to a prepaid meter + **Rp 0**

○

HoltLaury-Down1

Which would you prefer?

Continued use of your prepaid meter + **Rp 25.000**

○

Informing the PLN staff that you would like to switch back to a postpaid meter + Rp 40.000

○

Which would you prefer?

Continued use of your postpaid meter **+ Rp 25.000**

○

Informing the PLN staff that you would like to switch to a prepaid meter + Rp 40.000

○

HoltLaury-Down2

Which would you prefer?

Continued use of your prepaid meter +**Rp 10.000**

○

Informing the PLN staff that you would like to switch back to a postpaid meter + Rp 40.000

○

Which would you prefer?

Continued use of your postpaid meter + **Rp 10.000**:

○

Informing the PLN staff that you would like to switch to a prepaid meter + Rp 40.000

○

HoltLaury-Down3

Which would you prefer?

Continued use of your prepaid meter + **Rp 0**

Informing the PLN staff that you would like to switch back to a postpaid meter + Rp 40.000

Which would you prefer?

Continued use of your postpaid meter + **Rp 0**

Informing the PLN staff that you would like to switch to a prepaid meter + Rp 40.000

Part3_electricity

Based on your answer your reward is ${e://Field/reward}

Hypothetically, how much monetary compensation do you want to be **willing to change to postpaid meter**? (in Rupiah, write down numbers only without dots nor commas)

Hypothetically, how much monetary compensation do you want to be **willing to stay using prepaid meter**? (in Rupiah, write down numbers only without dots nor commas)

If the PLN staff came to your home and offered you to switch to a Prepaid Meter (no fee, same voltage), will you accept the offer?

- Yes
- No

Why you do not want to accept the offer?

Hypothetically, how much monetary compensation do you want to be **willing to switch to a prepaid meter**? (in Rupiah, write down numbers only without dots nor commas)

Do you believe that the PLN staff will actually come and switch your electricity meter if requested?

- Yes
- No

Thank you for your answers.
Part 2 of the survey ends here.
You will now begin with Part 3.

Part 3: Electricity Usage Questionnaire

In this part of the survey, you will be asked to answer questions regarding your electricity usage. We value any information you will be able to provide for us.

Which of the following do you prefer using:

- Prepaid meter
- Postpaid meter
- Indifferent, either prepaid or postpaid

What are the things you like about prepaid meters?

What are the things you dislike about prepaid meters?

How much did you pay to change from postpaid to prepaid meter? (input just numbers and without commas or dots). Put zero if you did not pay anything.

In your household, whose income is used to pay for electricity?

- Mine
- My partner's
- My child's
- My parent's
- Others

In your household, who executes the top-up purchases for most of the time?

- Myself
- My partner
- My child
- My parent
- Some other person

Which of the following statement describes you?

- **After** using prepaid, I am **more aware** of my electricity consumption
- **After** using prepaid, I am **less aware** of my electricity consumption
- **Before and after** using prepaid, I always **aware** of my electricity consumption
- **Before and after** using prepaid, I **never aware** of my electricity consumption

Which of the following statement describes you?

- I am always **aware** of my electricity consumption

- I am **never aware** of my electricity consumption

Which electricity meter allows you to know more about how much your electricity consumption is?

- Prepaid meter
- Postpaid meter
- I think they are the same

True or False: My prepaid top up includes tax.

- True, it does
- False, it does not
- I don't know

True or False: My electricity bill includes tax.

- True, it does
- False, it does not
- I don't know

These statements measure your perceptions regarding **prepaid meters**. How much do you agree with the following statements (1 - Not, 100 - Agree)

	None at all		A little		A moderate amount		A lot		A great deal		
	0 10	20	30	40	50	60	70	80	90	100	
It is easy to input 20 digit codes to refill a prepaid meter.											
I always have money on hand so I do not have difficulty in buying prepaid meter top-ups											

	None at all		A little		A moderate amount		A lot		A great deal		
	0 10	20	30	40	50	60	70	80	90	100	
I believe that price per Kwh of electricity is the same between prepaid and postpaid meter											☐
I am not afraid that my electricity is completely off as topping up the prepaid meter is fast											☐
Prepaid meter helps me to manage my cash flow											☐
I am not annoyed with the notification sound that comes from prepaid meter when the balance is low											☐
I no longer receive high and unexpected bills because of using prepaid meter											☐
I am okay paying an admin fee for each prepaid meter top-up I bought, because it is small											☐

Did you reduce your electricity consumption in the last one year? If yes, why?

- ○ No, I did not reduce my electricity consumption
- ○ Yes, because I am afraid of running out of prepaid balance
- ○ Yes, because I do not have money on-hand to buy top ups
- ○ Yes, because I care about the environment

- ○ Yes, because of the limitation in the voltage (daya)
- ○ Yes, because of other reasons

What is the reason?

Did you reduce your electricity consumption **because** you switch to prepaid meter?

- ○ Yes
- ○ No

These statements measure how much you currently **trust the PLN staff**. Please rate how much do you agree with the following statements (1 - Not, 100 - Agree)

	None at all		A little		A moderate amount		A lot		A great deal		
	0	10	20	30	40	50	60	70	80	90	100
I believe that my current meter recording is reliable and accurate.											
I believe that PLN staff are genuine in helping me and do not expect me to pay them if I ask for their help											
PLN has not done anything that I think is wrong											
In the past, PLN staff have recorded my postpaid meter accurately and timely											

On average, **how much** is your **total** monthly prepaid meter top-up for a month (in **Rupiah**, input just numbers and without commas or dots)?

On average, **how many times** do you top-up your prepaid meter?

- 1 time every month
- 2 times every month
- 3 times every month
- 4 times or more every month
- 1 time every 2 months
- 1 time every 3 months
- Other

When you were previously using a postpaid meter, were you ever fined due to late payment?

- Never late
- Late once or twice, because I forgot to pay
- Often late paying my bills because I do not have money to pay
- Other reasons

What is the reason?

Thank you for your answers.
Part 3 of the survey ends here.
You will now begin with Part 4.

Part4_demographic

Socio-Demographic Questions

In this part of the survey, you will be asked to answer questions regarding some general information on you and your household characteristics. We value any information you will be able to provide for us.

If you purchase a light bulb and you have 2 options with identical brands, identical bulb brightness, different wattages, and different bulb prices, which bulb are you most likely to buy?

Non-LED bulb 15W - Rp 10.100

LED bulb 6W - Rp 35.000

How often do you leave the following electronics ON when you are not using them:

	Often	Sometimes	Never	I do not have it
Television				
Fan				
Air condition (AC)				

A smart meter is an electronic device that records your home's daily electricity consumption real-time. By checking the mobile apps connected to the smart meter, you will know how much Kwh you consume.

If you currently do not have this device, and have the chance to own it, how much will you be willing to pay for this device (including the installation and the mobile apps)?

- Rp 0
- Rp 10.000 - Rp 90.000,-
- Rp 100.000 - Rp 290.000,-
- Rp 300.000 - Rp 490.000,-
- Rp 500.000 - Rp 690.000,-
- Rp 700.000 - Rp 890.000,-
- Rp 900.000 - Rp 1.090.000,-
- Rp 1.100.000 - Rp 1.200.000,-

What is your gender?

- Male
- Female

What is your age?

- 20 - 24
- 25 - 34
- 35 - 44
- 45 - 54
- 55 - 60
- above 65

What is you highest educational qualification?

- Did not go to school
- Elementary/Primary School
- Junior High School
- High School
- Undergraduate
- Masters
- PhD

How many people are living in your residence (including you)?

- 1
- 2
- 3
- 4
- >=5

How many individuals in your households are elderly (requiring assistance) or young children?

- 0
- 1
- 2
- >=3

On average, what is your household's gross monthly income (**total for all members** in your household in a month)? If your income is not regular, try to sum it to annual income and then divided it by 12.

- Below 500,000 IDR
- 500,001 - 1,000,000 IDR

- 1,000,001 - 2,500,000 IDR
- 2,500,001 - 5,000,000 IDR
- 5,000,001 - 10,000,000 IDR
- 10,000,001 - 20,000,000 IDR
- More than 20,000,000 IDR

On average, what is your household's total monthly expense (**total for all members** in a month)?

- Below 500,000 IDR
- 500,001 - 1,000,000 IDR
- 1,000,001 - 2,500,000 IDR
- 2,500,001 - 5,000,000 IDR
- 5,000,001 - 10,000,000 IDR
- 10,000,001 - 20,000,000 IDR
- More than 20,000,000 IDR

Whose income is mainly used to pay the majority of household expenses?

- Myself
- My partner
- My child
- My parent
- Some other person

From memory, how much was your average monthly bill **when you were using a postpaid meter**? (In Rupiah, input just numbers and without commas or dots)

What type of work did you do last month?

- 1. Self employed
- 2. Self employed with part time /freelance employee

- 3. Self employed with full time employee
- 4. Full time labourer/employee
- 5. Freelance
- 6. Unpaid work in family-owned enterprise
- 7. Unemployed/ house wife

What is your main occupation sector last month?

- 01. Rice Farming & secondary farming
- 02. Horticulture
- 03. Plantation
- 04. Fisheries
- 05. Livestock
- 06. Forestry & other agriculture
- 07 Mining & Excavation
- 08. Processing Industry
- 09. Electricity & Gas
- 10. Building construction
- 11. Commerce
- 12. Hotels and restaurants
- 13. Tranportation & Warehousing
- 14. Information & Communication
- 15. Finance and insurance
- 16. Education services
- 17. Health services
- 18. Community, government & individual services
- 19. Other

Why are you using your current metering?

- I want to because I prefer my current meter and I have no complain
- I do not have time to request for a change eventhough I want to
- I don't know if I can change my current meter

- I requested for a change but no action has been taken from PLN
- Other reason

What is the reason?

What is your main cooking fuel?

- Electricity
- Piped gas
- LPG 12kg
- LPG 3 kg subsidized (green cylinder)
- Kerosene
- Firewood
- Others

What is the current wattage of your house?

- 450 watt
- 900 watt
- 1300 watt
- 2200 watt
- > 2200 watt

Payment

Before we end the survey, we want to know one last thing.
This is a series of hypothetical questions.

Suppose you are rewarded Rp 40.000, would you rather receive the payment of 40.000 now or receive the payment of 42.000 one month from now.

	Receive Rp. 40.000 today	Receive Rp. 42.000 next month
Offer 1	○	○
	Receive Rp. 40.000 today	Receive Rp. 45.000 next month
Offer 2	○	○
	Receive Rp. 40.000 today	Receive Rp. 49.000 next month
Offer 3	○	○
	Receive Rp. 40.000 today	Receive Rp. 55.000 next month
Offer 4	○	○
	Receive Rp. 40.000 today	Receive Rp. 63.000 next month
Offer 5	○	○
	Receive Rp. 40.000 today	Receive Rp. 71.000 next month
Offer 6	○	○

Thank you for all your answers.

Your number is **${e://Field/RandomID}**.

If your number is between 1 to 200, you are selected to get an extra reward ${e://Field/reward} based on your choice.

Powered by Qualtrics

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