Efficiency and Equity Effects of Electricity Metering: Evidence from Colombia

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Abstract

Many households lack meters to measure their electricity or water consumption. I show that provision of electricity meters leads to a large reduction in electricity consumption over the first four months following meter installation. This is consistent with previous overconsumption by unmetered users facing a zero marginal price. However, it also reflects underconsumption by metered customers paying a marginal price exceeding marginal cost. I quantify these welfare effects using billing data from a large sample of mostly rural counties in Colombia. I show that the efficiency effects are relatively small compared to the distributional effect of metering. Very poor households, whose electricity consumption is low, would particularly benefit from meter provision.

JEL Classification: L94, Q41, Q56

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1 Introduction

Designing tariff structures for public utilities requires difficult trade-offs between opposing objectives. Prices must be set to recover costs of the utility firm, fairly allocate these costs across user types, while providing signals for efficient consumption. These choices are especially problematic for public utility pricing in developing countries, where many households still lack access to utility services. Poor rate design can discourage low-valuation households from receiving the service—or make it unprofitable for firms to provide it.

In this paper I analyze the transition between the two most common rate structures: fixed and volumetric charges. With a fixed charge, the amount that a consumer pays does not depend on their usage. This means that the marginal price of an additional unit of consumption is zero. Because the marginal cost of consumption is greater than zero, the consumption of users paying a fixed charge will be more than the efficient quantity. Conversely, fixed charges lead to suboptimal levels of access to the service. Households whose willingness-to-pay for the service is less than the fixed charge—but greater than the marginal cost of a connection—will not receive the service.

Volumetric charges face the opposite problem. With this type of tariff, consumption is metered and the amount that consumers pay is a function of their usage. The per-unit price includes both the variable costs of the service and an allocation of the fixed cost, which is often a large component of the total cost. Such charges lead to inefficiently low consumption because the marginal price for a unit of consumption exceeds marginal cost.[1] On the extensive margin, households with valuation for the service below the marginal connection cost will gain access. A further problem with volumetric charges is that they are more complex to administer than fixed charges, requiring an infrastructure to meter and bill based on consumption.

The maturation of infrastructure sectors in many countries involves a transition from fixed to volumetric pricing. Such a transition can be politically challenging. Households whose true consumption is high will be worse off when they are required to pay based on their consumption, instead of a fixed amount. Households with

[1]Davis and Muehlegger (2010) show large differences between price and marginal cost for residential and commercial natural gas customers in the United States. Puller and West (2013) use data from Texas to show that, even after the introduction of retail competition, retail electricity prices continue to exceed marginal cost.

low consumption will be better off under volumetric charges, but these households may have less political influence. Resistance from high consumption households will be particularly great if the volumetric charge is based on an increasing block price schedule.[2]

This paper uses administrative billing data from 13 electricity retailers in Colombia to quantify the welfare effects of the transition from fixed to volumetric charges. Household electricity bills are observed before and after the installation of a meter for more than 6,600 connections that were originally unmetered. I use an event study framework to study the pattern of consumption in the months following meter installation. Consumption falls by nearly 30 percent within the first four months. This result is robust to many possible alternative explanations for the decline in observed consumption.

I then use estimates of demand and marginal cost to compute the welfare effects of metering. The overall improvement in welfare, before considering the additional costs associated with metering, is shown to be relatively small: between \$0.50 and \$1.10 per household per month. This includes the reduction in the externalities associated with electricity generation. However, metering leaves most customers better off than they were before metering. The households who benefit the most are shown to be the ones with fewer appliances, smaller dwellings, and lower monthly expenditure. These are the ones whose true electricity consumption is lowest and who overpay the most when billed based on average consumption.

One obvious challenge for the analysis is that, by definition, I do not observe the consumption of unmetered users. I rely in particular on the first observation of metered consumption. The assumption is that, before the household receives its first metered bill, it has no information about its true consumption and how this will be used to calculate the total charge. Only after receiving its first metered bills will the household begin to optimize electricity consumption based on the non-zero marginal price.[3] This is consistent with the observed pattern in the data of a gradual

[2]This was not a problem for the development of volumetric charges in the United States after meters started to be used in the early decades of the twentieth century, because the first volumetric rate schedules were typically decreasing block price schedules. Customers with higher usage paid a lower marginal price for additional consumption (Watkins, 1916).

[3]Recent work in the United States has shown the importance of information provision for optimization of electricity consumption. Jessoe and Rapson (2013) use a randomized control trial to show that households exposed to real-time feedback on their electricity consumption are much more responsive to changes in electricity price.

decline in consumption during the first few months after meter installation. If instead all households immediately reoptimize their electricity consumption on the date of meter installation, there would be no subsequent change in consumption after meter installation.

There are at least three possible reasons why a household in Colombia would pay a fixed charge for their electricity service. Communities may be metered at the entry point to the settlement and individual dwellings charged based on their share of total consumption (similar to an apartment complex with no submetering). Dwellings may have a formal connection to the distribution network provided by the utility, but for a variety of reasons their consumption may not be metered. Finally, a household may install its own informal connection to the network, not officially sanctioned by the utility, which would also not be metered. These distinctions are important for engineers and lawyers. However, they are much less relevant for economists. In all cases the households face a zero marginal price for additional consumption and optimize their consumption accordingly.

There are many reasons why studying the effects of metering in low- and middle-income countries is important. First, the absence of individual meters is an important policy issue for utility regulators. In Ecuador, 22 percent of dwellings connected to the electricity distribution network lacked an individual meter in 2010.[4] There have been major protests about the installation of meters—or the absence of meters—in many parts of the world. In Colombia, there were 624,000 complaints to the public utility regulator about metering or the estimation of unmetered consumption in 2009, comprising 38 percent of all complaints.[5] Legal action against Colombian electricity retailers relating to charges for unmetered users have been heard by the Constitutional Court of Colombia.

While the analysis is focused on utility pricing in a developing country, there are many close parallels in developed countries. Even in the United States, many water and electricity consumers lack an individual meter and still pay a fixed charge for their usage.[6] For broadband internet service, fixed charges based on the connection

[4] Calculation based on data from Instituto Nacional de Estadística y Censos.

[5] Calculation based on data from the Superintendencia de Servicios Públicos.

[6] In New York, more than 250,000 apartments do not have individual electricity meters, and residents can leave their air conditioning running all day without have to pay for it (Dolnick, Sam, "Air-Conditioners That Run When Nobody's Home," *New York Times*, August 15, 2010). Most academic research has focused on the incentives for landlords and tenants, where often different agents pay for appliances, choose the level of utilization, and pay for energy. Davis (2012) shows

capacity instead of consumption are nearly universal.

Finally, the analysis of interval metering in Colombia has parallels to the debate in the United States about real-time metering and billing. Despite the widespread roll-out of real-time meters, as of 2013 few utilities offer real-time pricing of consumption to residential users. Instead, households are charged the average cost of consumption for all households in their utility's service territory. As discussed by Borenstein (2012), this creates a cross-subsidy from consumers with low consumption during peak periods, when costs are higher, to consumers with high consumption during peak periods. Introduction of real-time pricing and elimination of this cross-subsidy would make a small number of users much worse off, while reducing the bills for most users by only one or two dollars per month. This combination limits the political feasibility of real-time pricing. I find similar results for the introduction of metering in Colombia.

The remainder of the paper is organized as follows. In Section 2 I provide a simple illustrative model to frame the analysis of the effects of metering. In Section 3 I describe the data used for the analysis. Sections 4, 5 and 6 contain the empirical analysis of the effects of metering: with respect to consumption, efficiency, and redistribution respectively. Finally, Section 7 provides a discussion of the policy implications of the results.

2 Illustrative model

Figure 1 illustrates the effect of providing individual meters in a neighborhood with N households sharing a single meter. Total monthly electricity consumption in the neighborhood is $N\bar{q}$. Each household is billed for an equal share of total consumption, $\bar{q}$. The regulated price of electricity, P is set to recover the firm's total fixed costs and the constant marginal cost of electricity c.

With N sufficiently large, the effect of one additional unit of consumption on an individual household's bill is negligible. This is because the additional consumption is divided among all N users, so the bill will increase by P/N. In effect, the marginal price of consumption for the unmetered household can be treated as zero. The figure

that tenants are less likely to have energy-efficient appliances. Gillingham et al. (2012) show that occupants who pay for their own heating are 16 percent more likely to adjust their heating settings at night. Similarly, Levinson and Niemann (2004) find that tenants who do not pay for their own utilities use more energy by setting their heating thermostat higher.

shows the demand for a representative low-consumption household, $D^L(P)$, and a representative high-consumption household, $D^H(P)$. Because the marginal price is zero, the low consumption household consumes $q_1^L = D^L(0)$ and the high consumption household consumes $q_1^H = D^H(0)$.

The low consumption household would be better off with no electricity than it would be receiving electricity and paying for the unmetered connection. This is because the monthly bill $P\bar{q}$ is greater than the area under the demand curve $D^L(P)$.

Consider the effect of providing metered connections to the unmetered households in the diagram. With a meter, the marginal price increases from zero to P. Given the higher marginal price, the consumption of the low-consumption household will decrease from q_1^L to $q_2^L = D^L(P)$. Welfare increases by the area B less the area A. In effect, the meter causes the marginal price faced by the household to increase from an inefficiently low level (zero) to an inefficiently high level (greater than marginal cost).[7]

The high-consumption household consumes q_1^H, exceeding the quantity they pay for, $\bar{q}$. Based on the diagram, the high-consumption household is better off with the unmetered connection than they would be without any connection. After the meter installation, their consumption falls from q_1^H to q_2^H. However, note that the meter installation also makes the high-consumption household better off! This is because the marginal benefit of the units of consumption between q_2^H and q_1^H is low (area $G + J + K + N$) relative to the additional cost for the unmetered connection (area $G + H + L + J + K$). Consumer surplus increase by area $H + L - N$ with the meter. Overall welfare increases by the area $L + M - G$.

The discussion so far ignores the cost of the meters (which may be large compared to the welfare gains). It also does not consider the effect for the firm of the reduction in revenue due to the decline in consumption. If the price had been set to exactly recover the firm's fixed costs, then the regulated price may need to be raised. This would make all customers worse off. The assumption for the analysis is that the metering project only covers a small number of connections so that the effect on revenue (and any regulatory adjustments to price) are negligible.

The meter installation also affects the welfare analysis of the subsidies. With no meters, the subsidies are a transfer from governments to households.[8] The subsidies

[7]This point was first observed by Munley et al. (1990).

[8]This is true only if households pay their utility bills. For non-paying households, the subsidies are a transfer from the government to firms.

have no distortionary effect on consumption because the marginal price is already zero. After the meters are installed, the subsidy changes the marginal price of consumption and so does have a welfare effect. Because the pre-subsidy price exceeds marginal cost, the subsidy increases welfare by reducing the price toward marginal cost. This ignores the welfare effects of raising money to provide the subsidy.

3 Data

The primary data source for the analysis is the billing history from 2003–2008 for nearly all residential connections in 73 municipalities (equivalent to counties) in Colombia. These municipalities were chosen at random from a list of more than 600 municipalities in Colombia with available billing data and the complete long-form census microdata from the 2005–06 cenus. The billing data includes information on the billed quantity in kWh, the billed amount before and after subsidy transfers, any overdue amounts or interest payments, the meter type, the dwelling address, and the transformer identifier. Using the transformer identifer I can link this data to a separate database with monthly information all distribution transformers in Colombia. This data includes information on the location of each transformer, the number and total duration of outages by type, the number of customers connected to the transformer, and the total billed consumption of the transformer.

Table 1 shows the breakdown of the billing data sample for the 73 counties. In total there are 95,039 unique bill recipients and more than 4.6 million electricity bills. More than 76 percent of bill recipients are metered for the entire sample period. Slightly less than 10 percent of bill recipients are unmetered throughout the sample period. Particularly relevant for the current study are the 7 percent of bill recipients (6,646/95,039) who are initially unmetered but subsequently receive a meter.

The mean consumption of the previously-unmetered households is 95 kWh per month. This is slightly more than half of the mean quantity that these households were billed when they were unmetered (185 kWh per month). The households who switch have slightly higher metered consumption, on average, than the households who are always metered. Note that this does not adjust for the uneven geographical distribution of the switching households.

There are 269 connections with meters that measure the consumption of multiple users. These are located in only 7 counties. Unfortunately I do not have data on the number of users connected to each meter, nor the consumption of those users who subsequently receive their own meter. Therefore I exclude the multi-user meter observations from the analysis. Because many of the multi-user meters are converted to individual meters, the total number of electricity users who switch from being unmetered to metered will be greater than 7 percent.

In all categories a small minority of bills are estimated rather than based on a meter reading.[9] For the regression analysis, I drop all estimated quantities. I completely exclude all observations from connections for which more than 50 percent of the bills are estimated. The final category of excluded observation ("Other") includes households who switch from metered to unmetered, or who repeatedly switch between them.

Figure 2 provides a map of Colombia to show the location of the counties in the sample. Each circle corresponds to one of the 73 counties in the data, with the size of the circle scaled based on the total number of residential connections in the county. The size of the filled inner circle is scaled based on the number of connections switching from unmetered to metered. As can be seen on the map, these are not evenly distributed across the counties. Overall, the 10 counties with the greatest number of "switchers" make up 60 percent of the total switchers in the data.

Market data used for calculating marginal cost are from XM, the operator of the national transmission network and wholesale electricity market in Colombia. This data includes the hourly wholesale electricity price, the hourly generation from each grid-connected generation unit in Colombia, and the daily fuel consumption for each thermal generation unit. Monthly data on the components of the regulated electricity price in each market are from the energy sector regulator (CREG).

4 Consumption quantity after metering

In this section I analyze the quantity of electricity that is billed to a household in the months before and after the installation of a meter. I show that unmetered households are billed, on average, for quantities far in excess of their subsequent measured consumption. In addition, I show that there is a statistically significant decline in consumption in the months following meter installation. This result is

[9] Based on the regulatory definition, only customers with a meter can receive a bill based on a "estimated" quantity. In practice, some bills for unmetered customers are also labeled as "estimated".

consistent with households learning about their higher marginal price and adjusting their consumption accordingly. I show that the results are robust to several alternative measurement and behavioral explanations.

4.1 Base specification and results

The primary empirical specification models log billed consumption in an event study framework, in which the event is the installation of an electricity meter. Equation (4.1) shows the estimation equation.

$$\log q_{irt} = \beta n_{it} + \sum_{\tau=-12}^{12} \kappa_\tau I(T_i + \tau = t) + \lambda_i + \theta_{rt} + \varepsilon_{it} \tag{4.1}$$

In this equation q_{irt} is the billed consumption in month-of-sample t for household i located in region r. This will be equal to metered consumption for the months in which household i has an electricity meter. n_{it} is an indicator variable equal to 1 for the months t in which household i does not have an electricity meter. The base specification includes household fixed effects λ_i and region-specific month-of-sample fixed effects θ_{rt}.

T_i is the month of the sample in which household i receives an electricity meter.[10] The summation term includes 24 indicator variables for the 12 months before and 12 months after meter installation. The omitted month is the month of the first metered electricity bill. There are additional indicators for months on either side of the 25-month window around meter installation, as well as an indicator for households with no change in their meter type over the sample period.

The results from estimation of equation (4.1) are shown in Column 1 of Table 2. Only a subset of the coefficients are shown in the table. The full set of coefficients on both sides of the event window are plotted in Figure 3.

The most striking feature of the results in Figure 3 is that the consumption billed to unmetered households greatly exceeds the first metered consumption, by approximately 70 percent. By definition, it is impossible to know the true consumption of households for the months in which they do not have a meter. However, there

[10]In precise terms, T_i is the month of the first electricity bill received by the household in which the code for the type of meter reading is "R" (reading from an exclusive meter serving the subscriber) instead of "N" (estimated because of the absence of a meter). No information is available on the exact date of the meter installation.

are several reasons to think that little adjustment to consumption occurs in the first month after meter installation before the household receives their first metered bill. Before receiving the first bill, the household has little information about their true electricity consumption, the price of this consumption, and how these are used to calculate the billed amount. It would require a high degree of sophistication to read the quantities off the new meter, extract the non-linear price schedule from the old (unmetered) bills, forecast the future bill amount, and then optimize consumption behavior accordingly. Furthermore, the difference between the unmetered and metered quantities far exceeds any change in electricity consumption that has ever been observed.[11]

Consumption gradually fell in the months following the meter installation. Log consumption was -0.33 lower four months after the household received the first metered bill, relative to the first metered quantity. This corresponds to a reduction in consumption of 28 percent. This large decrease in consumption in the months after receiving the first metered bill support the above argument that little adjustment occurred immediately after meter installation. To the extent that such adjustment did occur, the effects of metering on consumption would be even larger than estimated here.

Although this effect appears large, it is consistent with anecdotal and empirical evidence about the consumption of unmetered users and the change in consumption from metering. Casillas and Kammen (2011) study the installation of individual meters in two non-grid-connected villages in Nicaragua that rely on diesel generation. They found that total load fell by 28 percent after metering. A case study of regularization of electricity service for a *favela* in Sao Paulo, including metering and billing, found that electricity consumption fell by 23 percent even before the implementation of an energy efficiency program (USAID, 2009). Munley et al. (1990) analyze an experiment in which some residents of a newly-submetered apartment complex began to pay for their own electricity, while a control group continued to receive electricity included in their rent. Mean consumption of the users who were paying for their electricity was 24 percent lower. In a similar setting, Dewees and Tombe (2011) find that electricity consumption declined by 20 percent in a Canadian condominium complex after the introduction of sub-metering.

[11]For comparison, Reiss and White (2008) show that electricity consumption in San Diego fell by 13 percent after prices more than doubled in 2000.

4.2 Robustness to potential measurement errors

There are several possible reasons why the decline in metered consumption described above may not correspond to a decline in the true electricity consumption of the households in the sample. In this section I provide evidence that these measurement issues may explain no more than a small part of the decline in metered consumption.

The first potential measurement issue is miscoding of the meter type. A household may have had a meter installed but the utility may still estimate consumption using its previous methodology until it updates its meter reading and billing processes. It is also possible that a household that has had a meter installed partway through a billing cycle could receive a bill that combines metered and unmetered components. This might be coded as either a metered or an unmetered bill.

Another possibility is that true electricity consumption may exceed metered consumption because of meter tampering. In this case, the observed decline in metered consumption over the first four months may not reflect a change in the consumption of the household, but instead learning by the household about how to alter the meter.[12] I report results from two estimations in which I attempt to exclude households with bills that suggest possible meter tampering.

A common approach used by utilities is to compare metered consumption of a household to that of similar households in the same area. Households or firms with consumption much lower than the average may receive surprise inspections to check that their meters are functioning correctly.[13] I calculate the mean metered consumption in each municipality, stratum, and month, and estimate equation (4.1) for only those metered observations in which consumption is between 50 and 150 percent of the mean. This excludes observations with unusually high or unusually low consumption.

The result of this estimation is shown in Column 2 of Table 3. The decline in metered consumption after four months is about 15 percent. The magnitude of the decline is much lower than in Table 2 but still economically significant. However, the difference between the two results will partly be due to the selection criterion, which

[12]Techniques used to alter meters include inserting thin sticks to prevent the dial from turning, placing magnets on the meter to slow it down, and installing a direct connection to the distribution network that bypasses the meter completely.

[13]The chief executive of Emcartago, the utility in the small city of Cartago, described how users with a consumption less than half the average in their sector receive an inspection. ("Alto robo de luz en Cartago", *El Tiempo*, September 18, 1998. `http://www.eltiempo.com/archivo/documento/MAM-839346`).

excludes many households who made large adjustments to their consumption after meter installation.

A second approach to reduce the likelihood that the results are caused by meter tampering is to eliminate households with any fines or quantity corrections on their bills over the entire sample period. If meter tampering is detected then households receive a fine and are billed for an estimate of the underreported consumption. In the sample, 40 percent of households have a fine or correction. Column 3 in Table 3 shows the results for the estimation excluding these households.

A final type of measurement error is that the initial metered consumption exceeds the household's true consumption because of informal supply to neighboring households. If one dwelling is unmetered, but the neighboring dwellings are metered, then the residents of those dwelling may use electricity from the unmetered connection. After all dwellings are metered, these connections would no longer be necessary and would eventually be dismantled, leading a reduction in the measured consumption of the newly metered household.

I check for this possibility using the subset of transformers with exactly one dwelling converted from being unmetered to metered over the sample period.[14] Column 5 of Table 3 shows the change in consumption after metering for the observations with a single new meter installation at a transformer. These results are consistent with the results from the full sample.

Column 6 of Table 3 then shows the change in log mean consumption for the other metered dwellings connected to the same transformer as the newly metered household. In the first two months after a dwelling receives a meter, the point estimate for the change in metered consumption of neighboring dwellings is positive and statistically significant. This is consistent with the story of always-metered households losing their free, informal electricity supply from unmetered neighbors. However, it could also be explained by improvements in network reliability occuring at the same time as the meter installation. Furthermore, the effect does not persist beyond two months. Overall, it seems unlikely that this effect could explain more than a small fraction of the observed decline in consumption after the meter installation.

[14]Where there are multiple houses with meters being installed, even in different months, it may be difficult to distinguish changes in metered consumption due to eliminating shared connections from lagged responses to metering.

4.3 Robustness to alternative behavioral explanations

The results so far are consistent with a model of households updating their electricity consumption decisions as they gradually learn about their marginal price. However, there are many other possible models that are consistent with this behavior. In this section I consider the evidence for these alternative explanations.

One particular concern may be the non-random assignment of metering. Although I do not explicitly model the (potentially) joint decision by the household and retailer to install a meter, it is possible that one factor that affects this decision is the path of future consumption. For example, suppose a household realizes that their electricity consumption will soon decline, due to a change in family composition or replacement of an inefficient appliance, for example. In such circumstances this household might be more likely to request an electricity meter. The subsequent observed decline in consumption would then be the cause, not the consequence, of the meter installation.

One way to rule out the possibility of idiosyncratic household shocks driving meter adoption is to look at areas where multiple dwellings had a meter installed at the same time. In these cases, it is much more likely that the metering decision was determined by the firm, for cost or network or regulatory reasons, rather than being determined by changes in household demand. Table 4 show the results for the subsample with at least three meters installed in one month among connections to the same transformer (Column 1) and the subsample with at least ten meters installed (Column 2). The results are comparable to those in Table 2, suggesting that reverse causality story is of limited concern in this setting.

All newly metered households face an increase in their marginal price. For households whose true consumption is lower than the average quantity that they had previously been billed, their total bill amount will decline after metering, even before any changes to consumption. This may be perceived as a decline in the average price. Conversely, households whose true consumption is higher than what they had been paying will observe an increase in their total bill amount and so an increase in their average price of electricity. If households in this setting respond to average price instead of marginal price (Ito, 2013), quantity demanded of the first group may increase and of the second group decrease.

To test for the potential responsiveness to average prices, for each household I calculate the mean metered consumption of all households at the same transformer over the sample period. I then split the sample of newly metered households into two groups. The first group contains households with neighbors whose consumption is lower than mean unmetered quantity that the household had been charged. This provides a proxy measure for those households who faced a lower average price as a result of metering. The second group contains households with neighbors whose consumption is higher than what the household had been charged. Many households in this group faced a higher average price after being metered.[15]

Column 3 of Table 4 shows the results for households who most likely faced a decrease in their average price and Column 4 shows those with an increase in their average price. In both cases the consumption quantity fell in the months after meter installation. However, the relative decline was much greater for the households with a decrease in their average price, compared to an increase. This is the opposite to what we would expect if households were responding to the average price of electricity. This result is not surprising. In this setting, the change in the marginal price, from zero to some positive level, will be particularly salient.

A final possibility is that the change in consumption quantity is not due to metering, but instead to changes in payment enforcement that occur at the same time as the meter installation. The decline in consumption may not be because of the increase in marginal price, but instead because the household has to pay anything at all for their electricity after metering. I use billing data on overdue amounts during the period in which the "switchers" were unmetered. Column 5 of Table 4 shows the consumption results for those households with an average unpaid balance exceeding $5. These are the households who would be most affected by a change in payment enforcement. Column 6 shows the results for households with an average overdue amont of less than $5. Both groups show a significant decline in consumption after metering. For the households that had been paying their bill, the consumption decline occurs faster, but the overall size of the decline is lower.

5 Efficiency effects of metering

The previous section demonstrated that metering led to a substantial reduction in electricity consumption for the households in the data. In this section I extend the analysis to estimate the welfare impacts from metering. This requires information

[15]It is not possible to split the sample based on the true change in average price, because this is jointly determined with the consumption quantity.

and assumptions on the marginal willingness to pay for electricity, the marginal cost of supplying electricity, and the associated environmental externalities from supplying electricity.

5.1 Demand model

I use a log-linear model for electricity demand as in equation (5.1). This functional form, with price entering linearly, is used because unmetered households (and metered households in their first month) face a marginal price of zero.

$$\log q_{irt} = \beta p_{it} + \lambda_i + \theta_{rt} + \varepsilon_{it} \tag{5.1}$$

As before, q_{irt} is the monthly metered electricity consumption of household i in region r in period t, λ_i is a household fixed effect, and θ_{rt} is a region by month-of-sample fixed effect. The difference between equations (5.1) and (4.1) is that the marginal price of electricity faced by household i in period t, p_{it}, replaces the metering event indicator terms. Based on the earlier discussion, for the households in the data who switch from being unmetered to metered, the marginal price is set to zero for the first month of metered consumption.

The major difficulty in estimating (5.1) is that the marginal price of electricity is a non-linear function of quantity. Most households face a two-part increasing block pricing schedule, with the price for the first block between 40 percent and 85 percent of the regulated base price, depending on the socioeconomic classification of the household. The size of the first block is based on altitude: 130 kWh per month for households above 1,000 meters and 173 kWh for households below 1,000 meters.[16] Households pay the regulated base price for all subsequent consumption.[17]

One method to resolve the problem of the dependence of prices on quantities is to estimate a discrete-continuous choice model. In this framework, the household's quantity decision is divided into two parts. First, there is a discrete decision of which part of the price schedule to locate on: either the first block, the second block, or the breakpoint between the two blocks. Second, conditional on the choice of price

[16] Before 2004 the size of the first block was 200 kWh for all households. This was reduced gradually between 2004 and 2007 to the current levels.

[17] Households in the two highest socioeconomic strata do not receive a subsidy and instead pay a 20 percent contribution towards the subsidy program. Most of these households are located in large metropolitan areas. Because this study uses data from rural areas, there are very few households in the high socioeconomic categories.

block (which determines both the marginal price and any "virtual income" from paying lower prices on inframarginal units), the household decides the quantity to consume. This methodology has been widely used for modelling electricity demand with nonlinear prices, for example, by Reiss and White (2005) in California and Medina and Morales (2008) and McRae (2015) in Colombia.[18]

There are several reasons why the discrete-continuous choice framework is difficult to apply in this setting. First, with only billing data available for most households in the sample, there are few covariates that can be used to predict the household's quantity choice. Because of the data limitations, I would like to exploit the panel structure of the data and use the repeated observations of households after they are metered, as in the previous section. However, estimating household fixed effects is computationally infeasible in large non-linear models.

Instead of estimating a discrete-continuous choice model, I instrument for the marginal price p_{it} using the width and height of the first pricing block (that is, the household's stratum and the subsidized quantity) as well as an indicator for the price being zero. This method was first used by Wilder and Willenborg (1975) and subsequently by, for example, Olmstead (2009). Within a household, there is variation in the shape of the price schedule over the sample period. This is not only because the newly metered households jump from a zero price to the price schedule, but also because the subsidized quantity is reduced for all households, and some households are allocated to different strata.

A second important issue is the sensitivity of the welfare results to the functional form for demand. Particularly important for understanding the effect of metering is the demand at very low prices. Does the additional consumption at a zero price have value to consumers? Or it is all "wasted" so that consumption would be much lower at any positive price? For example, if the additional consumption is caused by lights being left on when no one is at home, then it may be the case that any positive price would be enough to encourage people to turn them off.

The difficulty for the analysis is that over a wide range of prices, between zero and the lowest marginal price in the data (about 3.5 cents/kWh), we do not observe demand. Therefore the results will depend on the functional form of demand between these prices. In order to bound the true values I use an alternative demand

[18]The methodology is also commonly used for modelling water demand, which also often has complicated non-linear price schedules (Olmstead et al., 2007; Szabo, 2012).

specification given by equation (5.2).

$$\log q_{irt} = \beta p_{it} + \gamma I[p_{it} = 0] + \lambda_i + \theta_{rt} + \varepsilon_{it} \tag{5.2}$$

The additional term in this specification creates a discontinuous jump in demand at a price of zero.

The results from estimation of equations (5.1) and (5.2) are shown in Table 5. Column 1 shows the results for estimation of equation (5.2) without instrumenting for price. The coefficient on price is positive. This is because of the increasing block pricing under which price is an increasing function of quantity.

Columns 2 and 3 show the results from instrumental variables estimation of equations (5.1) and (5.2) respectively. In both cases price now has the expected sign. In Column 3, there is a jump in demand of about 13 percent at price of zero. The mean implied price elasticities of demand are shown at the bottom of the table. These are -0.37 in Column 2 and -0.27 in Column 3. These elasticities are consistent with the results found in other studies of electricity demand.

5.2 Marginal cost of electricity

The welfare analysis requires information on the marginal cost of the electricity consumed by the households being metered. I use the mean hourly wholesale market price over the corresponding month of the data, inflated by an estimate of transmission and distribution losses.[19] An alternative would be to use the wholesale procurement cost component of each retailer's regulated prices. Colombian electricity retailers are required to sign long-term forward contracts with generators, and the prices from these contracts are used to update the regulated retail rates every month.

Figure 5 shows the path of prices in Colombia over the sample period. The bottom line shows the seven-day moving average of wholesale market prices. The dashed line shows the monthly wholesale procurement costs of the retailers. Both prices are

[19] There are at least three reasons why this is an only approximation to the true marginal cost of electricity. First, as in many hydro-dominated systems, during particular hydrological conditions the market is not competitive and firms have an incentive to submit offers in excess of marginal cost. Second, there are times when transmission constraints are a serious problem in the Colombian electricity market. However, there is no locational marginal pricing in this market. Instead, as discussed by Wolak (2009), generators that run or do not run out of merit order receive positive or negative reconciliation payments. In the current analysis I ignore these payments. Finally, the input market is not competitive, and in particular the price of natural gas from the two largest fields is fixed by the government.

shown before adjusting for transmission and distribution losses. Except for a few isolated periods, the two price paths track each other closely, suggesting that there will be little difference to the results from using one or the other.

The shaded region on the figure illustrates the range of the marginal prices faced by households in the sample. The bottom of the range corresponds to households in the region with the lowest regulated price, placed in the lowest socioeconomic category and receiving the highest subsidy. The marginal price for these households is lower than the marginal cost of generation (after adjusting for line losses) for many periods of the sample. Conversely, the top of the range correponsds to households receiving no subsidy in the region with the highest regulated price. Their price for electricity is far in excess of marginal cost.

The second component of the social marginal cost of electricity is the unpriced environmental externality associated with electricity generation. Overall, average emissions in the electricity sector in Colombia are low compared to the United States. This is because 80 percent of generation is hydroelectric. Natural gas comprises over 70 percent of the fuel used for thermal generation.

Because marginal emissions may be very different to average emissions, I use existing calculations of marginal emissions by regulators and consultants. These form an important input to the calculation of carbon credits for renewable energy projects financed under the Clean Development Mechanism. One type of calculation uses the average emissions factor for thermal unit, multiplied by the fraction of hours in the year in which system load exceeds mean hydro generation. A second type of calculation uses the average emissions factor for generating plants in the top 10 percent of the merit order. I use an emissions factor from these calculations of 0.2716 kg of CO_2 per kWh.[20].

An alternative approach would be to estimate the marginal emissions factor using data on fuel consumption and within-month-and-hour variation in system load. As shown in the attached appendix, the estimated emissions factors are less than half those used for the CDM calculations. However, the interpretation of these results is greatly complicated by the dominant role of hydroelectric generation in the Colombian market. Therefore, for the welfare calculations below I use only the higher number (0.2716 kg/kWh). I combine this estimate with a social cost of carbon of $40 per ton

[20]Unidad de Planeación Minero Energético, "Cálculo del Factor de Emisión de CO2 del Sistema Eléctrico Interconectado Nacional Para Determinar la Línea Base de Proyectos MDL", `http://www.siame.gov.co/`

of carbon dioxide.

Finally, I note that the only externality that I consider is carbon dioxide. Emissions of other pollutants may be also important, especially because the marginal effect on health of some types of emissions may be greater in developing countries (Arceo et al., 2012). Unfortunately, there is limited data available for Colombia on other emissions from electricity generation or their external costs.

5.3 Welfare calculation

In this section I use the demand estimates from Section 5.1 (including the household fixed effects) and the marginal cost estimates from Section 5.2 to simulate the effect of metering.

I present the results in terms of changes to consumer and producer surplus, calculated using Marshallian demand.[21] The reason for adopting this approach is that the non-linear price changes—from a fixed charge with zero marginal cost, to zero fixed charge and an increasing block tariff—make the calculation of equivalent and compensating variation much more challenging.[22] Furthermore, to understand the distributional effects of metering, it is important to allow for heterogeneity in consumer demand.

From the demand estimates, I generate three predicted quantities for each household and month in the data. These are based on three prices: zero, marginal cost, and the regulated increasing block price schedule.[23] For each firm and month, I compute the mean consumption quantity with the zero price. I assume that this quantity is billed to the unmetered households.

Table 6 shows two sets of results: all household-months and only the households who switch to being metered, in the month in which they are metered. Results are shown for the two demand equations. All calculations are undertaken separately for

[21] One cautionary note is that the use of consumer surplus may be less appropriate in the current setting than in related papers examining the welfare effects of energy price changes, such as Borenstein and Davis (2012) and Ito (2013). Income effects are likely to be more important for understanding energy price changes in Colombia than in the United States. Energy costs comprise a larger share of total income and the income elasticity may be larger.

[22] Reiss and White (2006) describe a tractable methodology that could be applied in this setting.

[23] For predicting consumption with the increasing block price schedule, I calculate the consumption quantity separately for the low price and the high price. The quantity consistent with being located on the corresponding tier is the predicted consumption. If neither quantity is consistent (so consumption at the high price is below the threshold and consumption at the low price is above the threshold), the household's consumption is set at the threshold between the price blocks.

each household and month. The numbers in each cell of the table are the mean for all households and months. Focusing on the subgroup of households being metered, consumption falls from 128 kWh/month when unmetered to 87 kWh/month when metered.

Metering eliminates the deadweight loss associated with excessive consumption from the zero marginal price. The mean value of this deadweight loss was \$0.40 per household-month for the log-linear model and \$0.84 per household-month for the discontinuity model. In the second model, much of the excess consumption has zero value to consumers, creating a larger deadweight loss. For the log-linear case, all of the excess consumption has some value to consumers, though less than the marginal cost.

In most cases, the metered household pays a marginal price for consumption that exceeds marginal cost. This means that their consumption is less than socially optimal, creating another deadweight loss. This deadweight loss for the metered household is \$0.27 for the first model and \$0.18 for the second model, again per household-month. The deadweight loss is relatively smaller for the discontinuity model because demand is more price inelastic, so pricing above marginal cost has less effect on consumption.

The change in the external costs (in this case, the cost of carbon) is also required for understanding the overall welfare effect of metering. Because of the decline in consumption, the external cost falls by \$0.44 per household-month. This comprises most of the welfare improvement in the log-linear model, and slightly less than half of the welfare gain in the discontinuity model.

The final block of Table 6 decomposes the welfare change by the change in consumer and producer surplus. On average, consumer surplus increases by \$3.06-\$3.72 per household-month as the result of metering. This is despite the unmetered consumers being charged, in aggregate, the correct consumption quantity!

In the current setting, with regulated prices held fixed, producers are left much worse off as a result of metering. This is because their profits decline by the difference between the regulated price and the constant marginal cost, multiplied by the reduction in consumption quantity. If the introduction of metering and the reduction in consumption occurred on a large-scale, it is possible that revenue after the change would no longer be sufficient to cover fixed costs. In that case, the regulated price would need to be increased. This would act as a transfer from the consumers and the government subsidy program to the firms. Given that prices are assumed to be constant, these results are best thought of as showing the marginal effect of metering a small number of additional households.

One important factor left out of the discussion so far is the cost of metering. This could be borne by either the consumers or the retailer. In either case, it is plausible that the capital and variable costs of metering are greater than the previously calculated increase in surplus from metering. This implies that, in many cases, metering may not be socially optimal.

6 Distributional effects of metering

Table 6 shows that metering increases consumer surplus by \$3.06-\$3.72 per household-month. However, this overall result masks a great deal of heterogeneity across households in the effect of metering. This section examines the differences between the households who are better off and the households who are worse off as a result of metering.

Figure 6 shows the distribution of the estimated changes in consumer surplus, for the households in the data who receive a meter. Most households are slightly better off: nearly three quarters of households have an increase in consumer surplus of between \$0 and \$10 per month. However, a minority of households are worse off, and some of these are extremely worse off. About 2 percent of newly metered households have a drop in consumer surplus of more than \$20 per month. These correspond to those households with high consumption who then have to pay for true consumption after being metered.

Table 7 shows the characteristics of households split by the quartile of consumer surplus change from metering. The first quartile, which contains all of the households who are worse off, has much higher electricity consumption both before and after being metered. The decline in consumption is greatest for this group: about 96 kWh per month, compared to less than 30 kWh per month for the other quartiles. By comparison, there is no consistent pattern in consumption changes across the three quartiles of households who are better off from metering.

The remaining blocks of Table 7 use census data matched to the billing data for a subset of the newly-metered dwellings. Reported monthly expenditure (coded from eight categories on the census questionnaire) is lowest for the quartile which benefits most from metering. The households in the bottom quartile of consumer surplus change have more people and larger dwellings.

Finally, the bottom block shows the proportions of households in each of the quartiles who own one of six appliance types. Those households with the reduction in consumer surplus from metering have greater ownership of every type of appliance considered: fridge, washing machine, fan, air conditioner, computer, and television. There is a strikingly large difference in the appliances of the quartiles who benefit most and least from metering. For example, 27 percent of the households with the greatest benefit from metering own a fridge, compared to 84 percent of the households who are worse off. These results are consistent with the poorest households having the most to gain from metering. They own few appliances, live in small dwellings, and generally have low electricity consumption. As a result, they are particularly worse off from being charged for the mean consumption of all users.

7 Discussion

As shown in Section 6, most households served by the utility were better off as a result of the meter installation. Yet grid upgrade and metering programs are perceived as deeply unpopular in Colombia and other developing countries. What explains the apparent discrepancy between these distributional results and the unpopularity of metering?

One explanation is that unrest is fomented by the small percentage of households who are worse off after metering. 2.3 percent of households had bills that more than doubled after they had a meter installed. They would have a very strong incentive to oppose the changes. By comparison, most households are better off, but only by a small amount. For policy, it would be useful to understand the reasons for the high consumption of the users who are made worse of. If consumption is high because of inefficient appliances (which previously the unmetered household could ignore), it may make sense to combine the metering program with energy efficiency initiatives.

A second possibility for the unpopularity of metering is that meter installation may be combined with changes in other utility policies such as bill collection practices. Unmetered users may have been billed for high quantities, but faced little penalty for non-payment. Although their bill is lower after metering, in many cases it is more strictly enforced. This is consistent with the results in Table 4 for the users with and without large overdue amounts. It is also possible that the utility tries to recover past overdue amounts (often for unmetered consumption that never took place) through the bills of newly metered users. Households may associate the effects of the policies, occurring contemporaneously with meter installation, with the effects of metering itself. This would lead them to reject the metering policy, which by itself would leave them better off.

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Table 1: Summary statistics for household and billing types

Classification	Number of	Number of Bills				Mean Q (kWh/mth)	
	Connections	Total	% Met.	% Unm.	% Est.	Met.	Unm.
Estimation obs.							
Always metered	72,347	3,645,665	94.2	0.0	5.8	87.1	.
Always unmetered	8,751	323,292	0.0	96.4	3.6	.	208.9
Switch to metered	6,645	314,195	54.9	39.5	5.5	95.2	184.8
Excluded obs.							
Multi-metered	269	8,336	31.4	0.0	68.6	.	.
Frequent estimates	1,852	87,398	29.8	1.8	68.4	88.4	147.2
Other	5,184	284,946	81.1	12.0	6.8	147.9	140.0
Total	95,048	4,663,832	83.0	9.6	7.4	91.2	197.6

Note: The estimation sample includes connections that are always metered throughout the sample period, connections that remain unmetered, and connections that switch from being unmetered to metered.

Table 2: Estimation results for billed quantity before and after metering

	(1) Un/Met Hh FE	(2) Un/Met Trans-mth	(3) Metered Hh FE	(4) Metered Trans-mth
Unmetered −2 months	0.587*	0.583*		
	(0.014)	(0.019)		
Unmetered −1 month	0.523*	0.540*		
	(0.014)	(0.019)		
Metered +1 month	-0.143*	-0.146*	-0.159*	-0.129*
	(0.014)	(0.021)	(0.013)	(0.022)
Metered +2 months	-0.246*	-0.255*	-0.268*	-0.242*
	(0.015)	(0.022)	(0.014)	(0.023)
Metered +3 months	-0.316*	-0.291*	-0.345*	-0.272*
	(0.016)	(0.023)	(0.015)	(0.024)
Metered +4 months	-0.330*	-0.281*	-0.350*	-0.262*
	(0.018)	(0.023)	(0.015)	(0.024)
Household FE	Y	.	Y	.
Dept × month-of-sample	Y	.	Y	.
Transformer × month-of-sample	.	Y	.	Y
Observations	3,747,441	3,747,439	3,618,837	3,618,837
No. of households	87,621	371,173	87,588	363,381

Note: The dependent variable is the log of billed consumption. Columns 1 and 2 include observations with both unmetered and metered consumption. Columns 3 and 4 include only metered observations. All estimations include 12 indicator variables for the 12 months after initial installation of a meter; Columns 1 and 2 also include 12 indicator variables for the 12 months before installation. The excluded variable is the month of meter installation. Only a subset of these results are shown in the table. Figures 3 and 4 shows the full set of estimated coefficients for Columns 1 and 3.

Table 3: Effect of metering on consumption quantity: data robustness checks

	(1) Largest Δ in month 0	(2) 0.5<Q<1.5 mean Q	(3) No fines or rebill	(4) Combine $1-3$	(5) 1 meter install	(6) Q other 1 meter
Metered +1 month	-0.061*	-0.050*	-0.157*	-0.016	-0.123*	0.033
	(0.014)	(0.007)	(0.014)	(0.009)	(0.043)	(0.022)
Metered +2 months	-0.300*	-0.103*	-0.315*	-0.161*	-0.200*	0.051*
	(0.018)	(0.008)	(0.016)	(0.013)	(0.045)	(0.024)
Metered +3 months	-0.387*	-0.155*	-0.411*	-0.212*	-0.213*	0.009
	(0.021)	(0.009)	(0.017)	(0.015)	(0.043)	(0.023)
Metered +4 months	-0.388*	-0.168*	-0.414*	-0.236*	-0.206*	0.009
	(0.022)	(0.010)	(0.018)	(0.017)	(0.045)	(0.024)
Household FE	Y	Y	Y	Y	Y	Y
Dept $\times$ month-of-sample	Y	Y	Y	Y	Y	Y
Observations	3,522,869	1,707,531	2,006,407	929,424	497,995	491,589
No. of households	84,089	80,080	49,750	42,926	13,466	13,348

Note: The dependent variable in Columns 1 to 5 is the log of billed consumption. Columns 1 and 4 only include observations for which the largest month-to-month change in billed consumption occurred in Month 0 when the meter code appears on the bills. Columns 2 and 4 only include quantity observations between 50 and 150 percent of the mean metered quantity in that department, month, and stratum. Columns 3 and 4 exclude all observations from households with a fine or rebilled quantity in any month of the sample. Column 5 includes only transformers with exactly one household that has a meter installed during the sample period. The dependent variable in Column 6 is the log mean consumption of the metered households connected to the same transformer after the household receives its meter.

* $p < 0.05$ (two-tailed test for difference from zero). Standard errors in parentheses are clustered by household.

Table 4: Effect of metering on consumption quantity: robustness to alternative models

	(1) $\geq$ 3 users metered	(2) $\geq$ 10 users metered	(3) Av. price decrease	(4) Av. price increase	(5) $\geq$ \$5 mean overdue	(6) < \$5 mean overdue
Metered +1 month	-0.161*	-0.168*	-0.180*	-0.137*	-0.158*	-0.226*
	(0.014)	(0.020)	(0.015)	(0.031)	(0.014)	(0.033)
Metered +2 months	-0.280*	-0.309*	-0.336*	-0.118*	-0.308*	-0.265*
	(0.016)	(0.022)	(0.016)	(0.034)	(0.016)	(0.035)
Metered +3 months	-0.361*	-0.417*	-0.434*	-0.097*	-0.397*	-0.281*
	(0.017)	(0.024)	(0.018)	(0.035)	(0.017)	(0.036)
Metered +4 months	-0.379*	-0.411*	-0.442*	-0.105*	-0.411*	-0.266*
	(0.017)	(0.025)	(0.018)	(0.036)	(0.018)	(0.036)
Household FE	Y	Y	Y	Y	Y	Y
Dept $\times$ month-of-sample	Y	Y	Y	Y	Y	Y
Observations	698,917	228,070	128,821	41,073	118,464	51,419
No. of households	20,598	7,824	5,456	1,411	4,954	1,912

Note: The dependent variable is the log of billed consumption. Columns 1 and 2 only include observations where at least three and at least ten connections to a single transformer were metered in the same month. Columns 3 to 6 are estimated using only the same of switchers. Column 3 shows those switchers for which the average quantity of other users at the same transformer is less than the quantity billed to the user while unmetered; Column 4 shows the opposite case. Column 5 shows only those switchers with an average outstanding balance of greater than \$5 while unmetered; Column 6 shows the results for the remainder.

* $p < 0.05$ (two-tailed test for difference from zero). Standard errors in parentheses are clustered by household.

Table 5: Demand estimation results

	(1)	(2)	(3)
Price (00 pesos/kWh)	0.662*	-0.211*	-0.156*
	(0.001)	(0.005)	(0.009)
I[Price = 0]	1.440*		0.127*
	(0.009)		(0.017)
Household FE	Y	Y	Y
Year-of-sample	Y	Y	Y
Instrument for price	.	Y	Y
Observations	3,605,640	3,605,640	3,605,640
No. of households	87,587	87,587	87,587
Implied elasticity	1.16	-0.37	-0.27

Note: The dependent variable in all equations is the log of metered consumption. Unmetered observations are excluded. The price is the marginal price faced by the household in that month, which is determined from the nonlinear price schedule from the household's consumption quantity. Marginal price is set to zero in the first month after meter installation. In columns 2 and 3, marginal price is instrumented by the zero price indicator, the household's stratum (which determines the height of the subsidized block) and the width of the subsidized block.

* $p < 0.05$ (two-tailed test for difference from zero). Standard errors in parentheses are clustered by household.

Table 6: Welfare effects of metering

Per customer-month	Full Sample		Switchers Only	
	Log-linear	Discont.	Log-linear	Discont.
Consumption (kWh)				
Unmetered	115.8	115.8	127.7	127.7
Metered	76.9	76.7	87.4	86.8
Difference	-38.9	-39.1	-40.3	-40.9
Decomposition 1 (USD)				
Unmetered				
DWL (P $<$ MC)	0.42	0.83	0.40	0.84
External cost	1.26	1.26	1.39	1.39
Metered				
DWL (P $>$ MC)	0.35	0.24	0.27	0.18
External cost	0.84	0.83	0.95	0.94
Change in welfare	0.49	1.02	0.57	1.10
Decomposition 2 (USD)				
Change in CS	1.01	1.61	3.06	3.72
Change in PS	-3.11	-3.27	-6.37	-6.58
Change in govt subsidy	2.17	2.26	3.44	3.51
Change in external cost	0.42	0.42	0.44	0.44
Change in welfare	0.49	1.02	0.57	1.10

Note: The table shows the components of the welfare effects from metering, expressed in US$ per customer-month. The log-linear columns are calculated using the demand results from Column 2 of Table 5. The "discontinuity" columns are calculated using the results from Column 3 of Table 5, with a discontinuity in demand at a price of zero. The first two columns show the mean results for all customers and months in the billing data, simulating their consumption with and without metering. The last two columns show the means only for the customers who have a meter installed (and in the month of meter installation).

Table 7: Household characteristics by quartile of consumer surplus change

	Quartile of change in consumer surplus			
	1	2	3	4
Change in CS	-5.6	3.2	6.1	11.2
Consumption (kWh)				
Unmetered	263.2	92.2	75.3	90.6
Metered	166.2	63.6	52.4	65.0
Difference	-97.0	-28.6	-22.9	-25.4
Household characteristics				
Monthly expenditure (USD)	315.37	365.92	297.57	223.70
Number of people	5.02	4.49	4.82	4.66
Number of rooms	3.64	3.04	2.82	2.75
Appliance ownership				
Fridge	0.84	0.69	0.40	0.27
Washing machine	0.23	0.18	0.06	0.06
Fan	0.65	0.56	0.54	0.63
Air conditioner	0.03	0.01	0.00	0.00
Computer	0.06	0.00	0.01	0.02
Television	0.83	0.72	0.61	0.57

Note: The table shows summary characteristics of switching households by the quartile of their change in consumer surplus from metering. The results in the bottom two blocks are only shown for 469 switching households that have matched census data; however, the assignment to quartiles is based on the full sample.

Figure 1: Consumption and welfare effects of metering

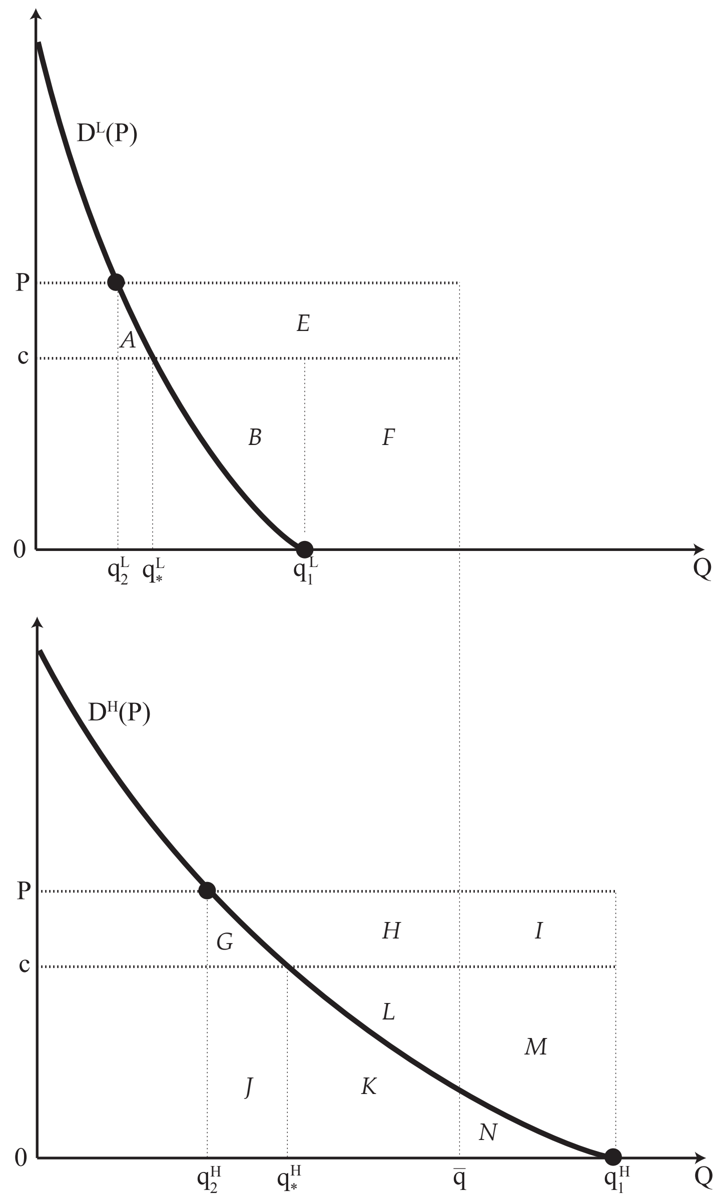
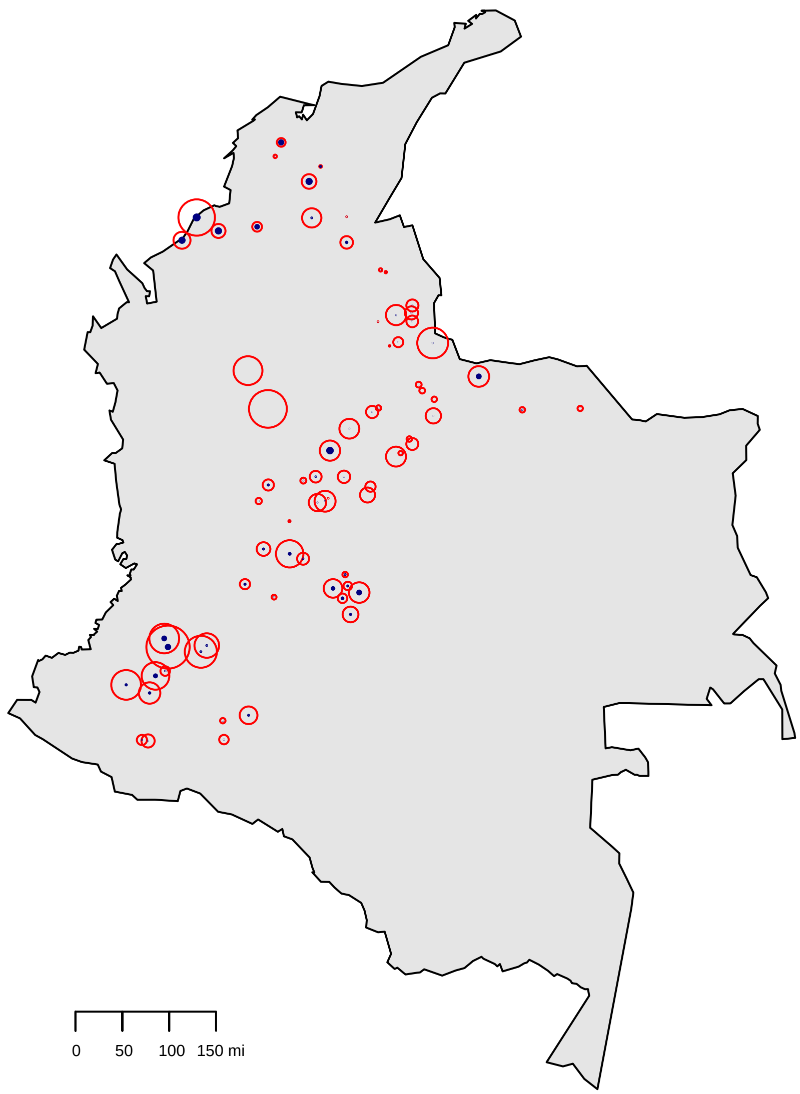


Figure 2: Locations and sizes of sample counties



Notes: The open circles correspond to the locations and number of connections for each of the counties in the sample. The size of filled interior circles corresponds to the number of connections that switch from unmetered to metered status over the sample period.

Figure 3: Billed quantity estimation results before and after metering

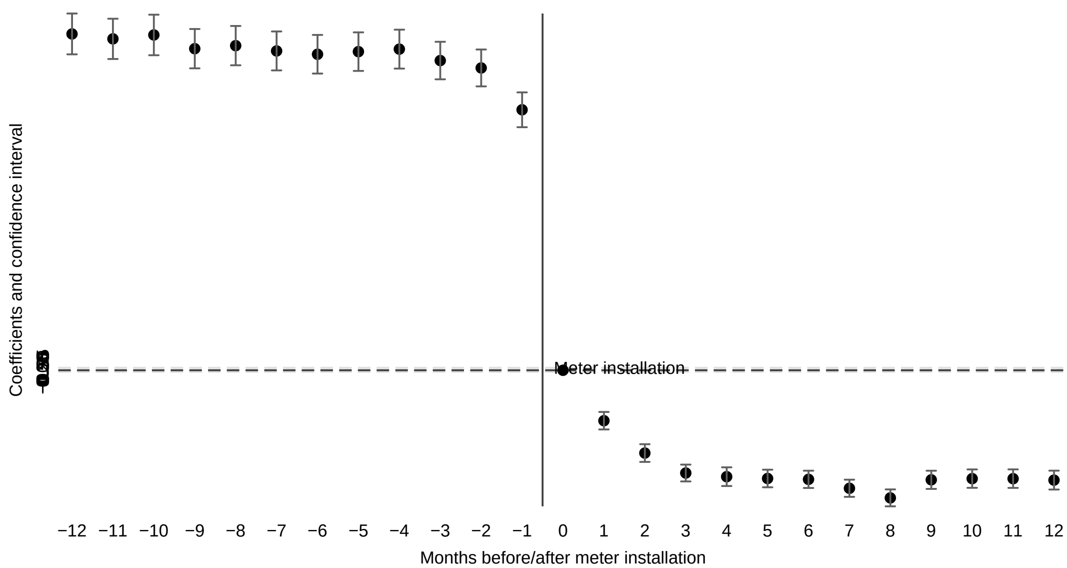


Figure 4: Metered quantity estimation results after metering

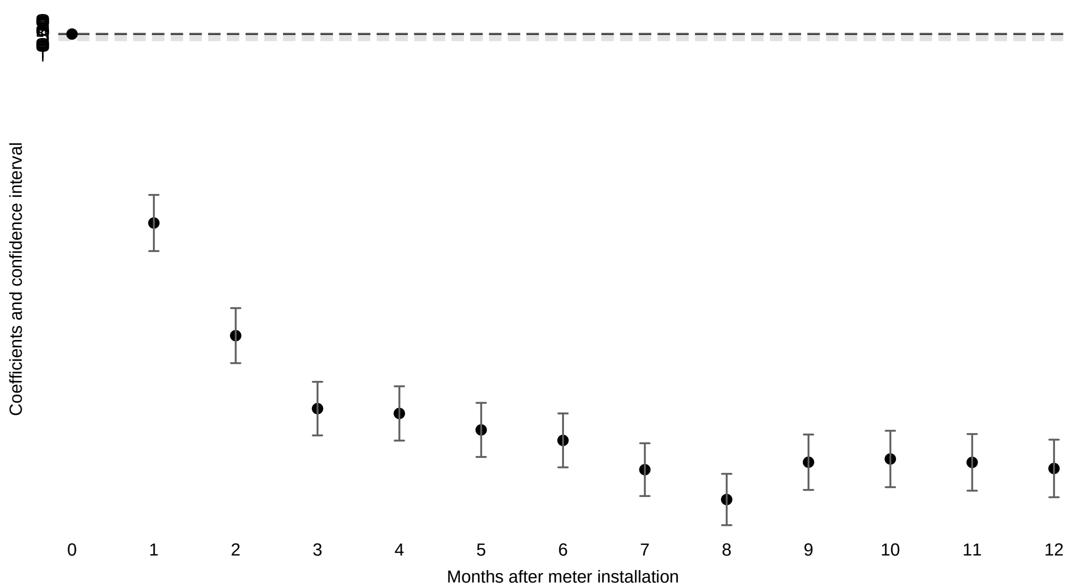


Figure 5: History of wholesale and retail electricity prices during sample period

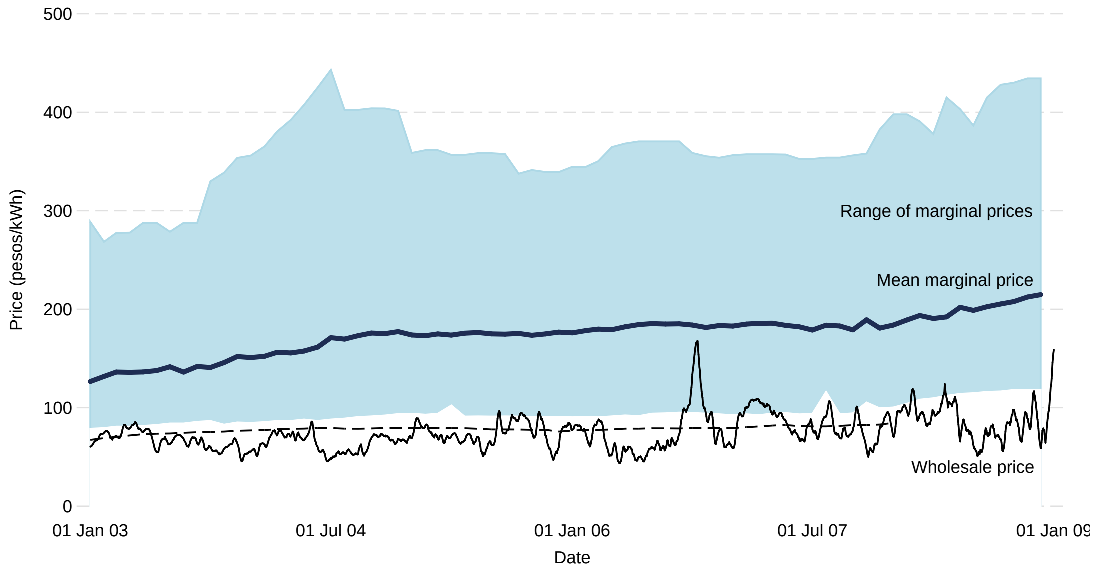
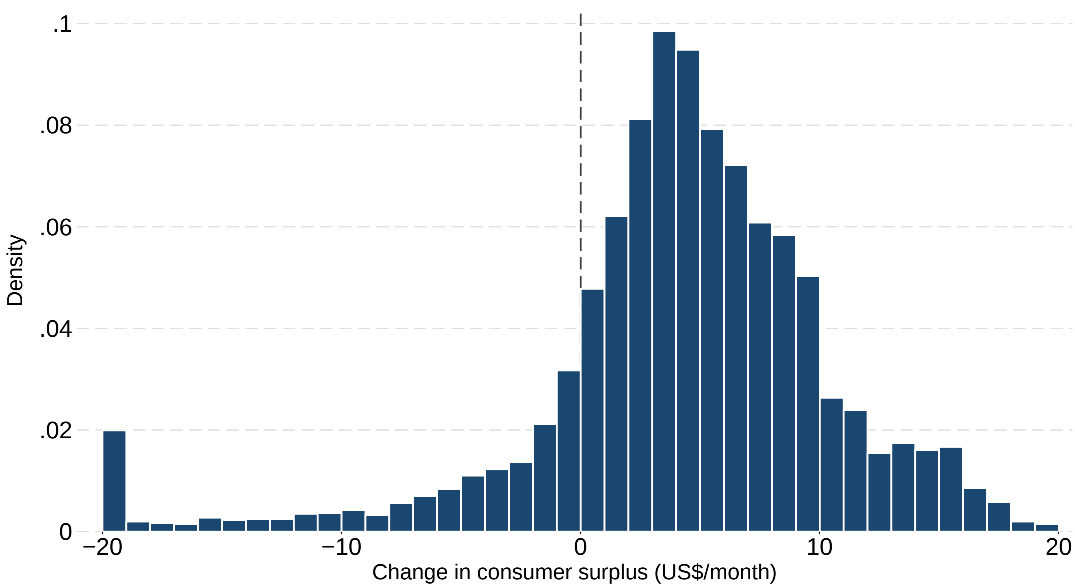


Figure 6: Distribution of changes in consumer surplus due to metering



Appendix: Estimation of Marginal Emissions Factors

A second approach is to follow the economics literature in estimating the marginal emissions factor econometrically.[24] I follow the approach of Graff Zivin et al. (2012) and estimate equation (7.1).

$$e_{thm} = \theta_h Q_{thm} + \gamma_{hm} + \varepsilon_{thm} \tag{7.1}$$

In this equation e_{thm} is the total emissions of carbon dioxide in hour-of-sample t, hour-of-day h, and month-of-sample m. Q_{thm} is the total system generation in hour-of-sample t. γ_{hm} are hour-of-day by month-of-sample fixed effects. This equation provides hour-of-day marginal emissions factors θ_h, estimated using within-month variation in load during hour-of-day h.

Unfortunately there are no continuous emissions monitoring data available for Colombia to calculate e_{thm}. Instead, I calculate emissions using daily unit-level fuel consumption, allocated across the hours of each day based on hourly generation. Emissions factors for each fuel are from UPME (Unidad de Planeación Minero Energética).[25] I then aggregate across all thermal plants to obtain carbon dioxide emissions for each hour from 2006 to 2011.

Figure 7 shows the estimated marginal emissions factors by hour of the day, as well as the average emissions factor (calculated by dividing total carbon dioxide emissions in each hour by total generation). These are lower than the estimates of marginal emissions factors used for carbon credit calculations. In part, this reflects the use of hydro to respond to hour-by-hour changes in load. If there is a constraint on hydro availability then this would effectively defer thermal emissions to subsequent periods, which would not be captured in the above estimates. Alternatively, the difference between the two estimates could be because operating, fuel, or transmission constraints limit the ability of thermal plants to respond to changes in system load.

[24] Cullen (2012), Novan (2011) and Kaffine et al. (2013) use plausibly exogenous variation in wind generation to estimate the marginal emissions reductions from wind generation in Texas.

[25] The source for the data is the spreadsheet "Factores de emisión para combustibles en Colombia". I use coal data for the Cerrejón middle field and natural gas data for the Guajira field.

Figure 7: Average and estimated marginal emissions factors for generation in Colombia