The price elasticity of electricity demand when marginal incentives are very large*

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Abstract

Using unique data on Swedish households, we measure the price elasticity of electricity demand for households facing a mandatory non-linear distribution tariffs where households are charged based on their maximum consumption during a month, and where the marginal incentives are very large. We estimate the price elasticity using both 2SLS and bunching estimators, and we find that the price elasticity is smaller than what previous literature on electricity demand have found.

Furthermore, we illustrate why charging households based on maximum consumption during a month leads to weak incentives in the end of the month, and discuss alternative tariff designs.

Keywords: Demand flexibility, Non-linear pricing, Peak demand.
JEL classification: D12, Q41, Q48

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1 Introduction

In this paper, we measure the response of households to a non-linear distribution tariff where households are charged for the distribution of electricity based on their maximum consumption in any given month. Such distribution tariffs are commonly referred to as demand charges.[1] In this particular instance, the marginal incentives to reduce peak demand are very large, in the sense that the marginal price varies by several order of magnitude as the quantity increases infinitesimally: the highest per-unit price is more than 3 Euro, while the lowest price is less than 0.1 Euro. For comparison, in Sweden, the standard residential distribution tariff charges instead a constant price for every unit of consumption, typically coupled with a subscription fee; i.e., a two-part tariff.

Using a unique sample of Swedish households, faced with a mandatory demand charge, we measure the price elasticity of demand of electricity using both "conventional" two stage least squares (2SLS) and bunching estimators. We also explore whether households shift consumption from peak hours to off-peak hours, to what extent volontary acquisition of information affects price responsiveness, and how the response to prices vary during a month. Although our measurements differ slightly with the method used, we find that the price elasticity is smaller than that reported in the literature (e.g., Nesbakken (1999) and Reiss and White (2005)), that information has little effect on price responsiveness, and that the price elasticity is smaller in the end of the month. Finally, in the light of these results, alternative tariff designs and associated welfare effects are discussed.

1.1 Background

Although demand charges previously have been introduced in commercial and industrial rates in both Sweden and elsewhere (see, e.g., Borenstein et al., 2002; Hledik, 2014; Öhrlund et al., 2019), they have been rare in residential rate offerings. This is now changing, and demand charges at the residential level have recently been implemented in Sweden (Bartusch and Alvehag, 2014; Bartusch et al., 2011), Finland (Haapaniemi et al., 2017; Rautiainen et al., 2017) and Norway (Stokke et al., 2010). Further implementation of similar distribution tariffs are currently under consideration in the US (see Hledik (2014)) and elsewhere in Sweden.[2]

Demand charges have in some contexts been proposed as a way of distributing fixed costs among customers, based on their contribution to system peak load (Blank and Gegax (2014) and Rubin (2015). See also the discussion in Borenstein (2016)). However, the recent interest in demand charges, at least for the Swedish context, is linked to the discussions of how to reduce costly peak

[1] As pointed out by Taylor and Schwarz (1990), referring to the price of electricity distribution as a demand charge is somewhat confusing. This practice stems from industry terminology, in which "demand" is synonymous with "power".

[2] As far as we are aware, only three other distribution firms provide non-linear distribution tariffs as of 2019; Sala-Heby Energi (`https://sheab.se/`), Karlstads el och stadsnät (`https://karlstadsnat.se/Om-oss/`) and Jukkasjärvi Sockens Belysningsförening (`http://www.jbf.nu/`). However, for example Vattenfall, the largest electricity distributor in Sweden, with over 900 000 households as customers, are as of 2019 planning on implementing a similar tariff, see `https://www.nyteknik.se/energi/vattenfall-ska-infora-effekttariffer-trangselskatt-for-elkunder-6941047`

demand (Bartusch and Alvehag (2014), Bartusch et al. (2011), and THEMA (2019)). For this reason, demand charges in Sweden typically includes a time-varying component; in many cases, households are only charged for maximum consumption during system peak hours, whereas the price in off-peak hours often is zero.

The distribution firms' motivations for encouraging customers to reduce peak consumption are manifold. Most importantly, since the capacity of the distribution network is built to meet a given peak demand, this capacity remains unused most of the time. Furthermore, in addition to avoiding or postponing costly investments in the grid, a reduction in peak demand can also lead to cutting costs associated with subscriptions to the overlying grid, power losses, wheeling charges[3] and maintenance. To give a sense of magnitudes, distribution firms in Sweden typically have a fixed subscription of a given quantity of MW from the overlying grid, and pays approximately 15 to 30 Euro per kW for this subscription. If the distribution firm exceeds this limit, for example because of a shock to consumption to the customers, the distribution firm pays an additional fee of up to 50 Euro per kW exceeding the subscription (Pyrko (2005)). Regarding investment costs, the aggregate investments in distribution grids currently amounts to approximately eight million Euro per year, and are expected to increase in the coming years (IVA (2016)). Proponents of demand charges often claim that demand charges reflects this peak demand-driven nature of the cost structure of electricity distribution better than the typical two part tariff with a flat-rate volumetric price and a subscription fee (see the discussions in, for example, Bartusch et al. (2011), Faruqui and Aydin (2017), Nijhuis et al. (2017), and Schittekatte et al. (2018)).

1.2 Previous literature

In many cases, demand charges, like the pricing scheme studied in this paper, provides substantially larger marginal incentives compared to what is typically found in the electricity demand literature. Therefore, demand charges provide a unique opportunity for measuring households' price responsiveness to large price variation. However, the sparse previous attempts to estimate households' behavioral response to demand charges rely on evidence drawn from reduced-form regressions or purely descriptive analysis, and do not measure the response to the marginal incentives provided by the demand charge. Instead, they have focused on changes in the ratio of peak to off-peak consumption relative to some baseline (e.g., relative to the pre-tariff period). This approach ignores the fact that not all peak hours are associated with the higher price, but only the peak hours with the highest consumption during a month.

Bartusch and Alvehag (2014) and Bartusch et al. (2011), using data from Swedish households on demand charges, estimate changes in peak to off-peak consumption as the distribution firm replace a standard two-part tariff with a mandatory demand charge. Under this demand charge, households are charged based on the average of the five hours with highest consumption during a month, and pay between 2 and 8 Euro for this quantity (depending on season and fuse amp size). They find a reduction in households' peak to off-peak consumption of

[3]"Wheeling" is the transportation of electricity from within an electrical grid to a consumer outside the grid boundaries

2.5 percent, relative to the pre-tariff period where households faced a constant per-unit price of less than 0.04 Euro per kWh. In a similar spirit, Stokke et al. (2010) explore if Norwegian households faced with a voluntary demand charge reduce their peak consumption, and find a reduction in the peak to off-peak ratio of less than five percent, relative to the control group on a standard type of tariff.[4] Taylor and Schwarz (1986) find that households on demand charges decrease their maximum demand by eleven percent, relative to the control group, when faced with a demand charge of 5USD/kW[5]. Taylor and Schwarz (1990) illustrate that the response to the demand charge increase over time. Öhrlund et al. (2019) study the response of medium-sized commercial customers to a demand charge in Sweden, and find that a demand charge of approximately 10 Euro per kW leads to a reduction of peak consumption of up to 16 percent, relative to the pre-treatment consumption when customers faced a two-part tariff. See also Faruqui et al. (2017) for a meta-analysis of demand response to time-varying electricity tariffs in the US (drawing from the analysis of several small-scale pilot programs in the US between 2013 and 2017).

More generally, the literature reports that households' electricity demand is price inelastic in the short run. The range of estimated values is relatively large, however. In the US context, Ito (2014) finds the price elasticity to be between -0.03 to -0.1 for different model specifications. Similarly based on US data, Allcott (2011b) finds the price elasticity for households on hourly pricing to be -0.1, and Reiss and White (2005) estimate it to be -0.39. Alberini et al. (2019) estimate the response to a price shock in Ukraine, when electricity prices increased dramatically (up to 300 percent of the initial rates), and measure the price elasticities to be between -0.2 and -0.5. Nesbakken (1999) finds more elastic behavior for Norway, with estimated price elasticities as large as -0.66, and similarly, Filippini (2011) estimate the price elasticity for Swiss residential demand to be between -0.8 and -0.95. For the Swedish context, we have found surprisingly few estimates of the short-run price elasticity of electricity demand, Brännlund et al. (2007) provide a recent estimate the price elasticity of electricity around -0.24.[6]

1.3 Our contribution

This paper contributes to the existing literature on residential electricity demand in several ways: First, this paper is the first to estimate the price elasticity of electricity for Swedish households facing demand charges, explicitly accounting

[4] This demand charge is substantially more complicated than the demand charge studied in the current paper. In brief, the tariff includes an annual fixed fee of 75 Euro, a variable energy rate of 0.017 NOK/kWh, and a demand charge of 64 Euro/kW. The demand charge is settled and billed on a monthly basis in the winter months, December, January, and February for the highest registered hourly kilowatt consumption on working days between 7 a.m. and 4 p.m.. For the other months in the year, the average of the highest demand in each of the three winter months is billed. See Stokke et al. (2010) for details.

[5] The households were randomly assigned to either a demand charge tariff or a conventional two-part tariff. The demand charge tariff consisted of a fixed charge, a volumetric charge which was higher during peak than off-peak hours and a demand charge which was based on the highest peak hour during peak hours each month. The control group tariff consisted of them same fixed charge and a constant volumetric charge.

[6] In the long run, response may be substantially larger: for example, Krishnamurthy and Kriström (2015) find it to be as large as -0.7 for Sweden. Filippini (2011) estimate the long-run elasticity to be larger than one in absolute value.

for the non-linearity in the tariff. Specifically, we use two distinct empirical approaches to estimate the response to this distribution tariff: both an instrumental variables approach, where previous and future consumption are used to generate instrumental variables to account for the endogeneity of prices, and a bunching estimator, similar in spirit to Saez (2010) but modified to accommodate the unique characteristics of the distribution tariff and our data.[7]

Second, we also also illustrate that there are virtually no differences in price responsiveness across levels of frequency of usage of the firm's website, where households can access detailed information about their consumption. Finally, we also illustrate how charging based on the maximum consumption during a month leads to weak incentives in the end of the month, and how alternative tariff designs, based on quantiles, avoids this problem. Welfare implications of such alternative tariff designs are discussed. Our results provide insights which are both policy and business relevant, since many firms are considering implementation of such pricing schemes.

The rest of the paper is structured as follows: in Section 2, we describe the specific pricing scheme in more detail, together with a description of the data used in this paper. Next, Section 3 details the empirical approaches for measuring the price elasticity for households faced with the demand charge tariff, and also explores to what extent price responsiveness is affected by voluntary acquisition of information. In Section 4, we explore how the response to prices varies throughout a month, and illustrate how charging households based on maximum consumption leads to less sharp incentives in the end of the month. Alternative tariff designs that avoids this potential problem are discussed. Finally, Section 5 concludes.

2 Electricity distribution and Sollentuna Energi

In Sweden, electricity is transported from power plants to all local and regional distribution networks via the national transmission grid. Our focus is on the local distribution networks that are operated by the distribution firms. There are approximately 170 distribution firms in Sweden and the trend favours fewer and larger companies (NordREG (2011))[8]. Each distribution firm has a monopoly over the distribution within its geographic region. Distribution firms are all regulated by the Swedish Energy Market Inspectorate through a firm-specific revenue cap, see the Swedish Electricity Act 1997:857 and NordREG (2011). Importantly for this paper, the revenue cap means that distribution firms are allowed to set their own prices and pricing schemes, as long as they adhere to the revenue cap. While there are many examples of firms that are both a distribution firm and a retailer (i.e., a firm that sells electricity, in contrast to the transport of electricity), these activities must be vertically separated under the Swedish Electricity Act, which in practice means that the two activities must be run as separate businesses (i.e., unbundling of generation, supply, and distribution of electricity).

[7]For example, the tariff introduces several and household- and time-specific kinks (as compared to, e.g., the context of labor supply, where there is typically one or few kinks), and that the data is recorded with some rounding of numbers (because of the precision of the metering equipment).

[8]At the end of the 1950s, there were more than 1500 firms, and in the early 1980s, the number had dropped to 380 companies (NordREG (2011))

Sollentuna Energi operates the distribution system in the municipality of Sollentuna, located approximately 20 kilometers north of Stockholm, and distributes electricity to approximately 8000 households living in villas and 12000 households living in flats. Since 2001, Sollentuna Energi charge their customers for distribution of electricity according to a demand charge distribution tariff, that works in the following way: between 7 a.m. and 7 p.m. during working days (hereinafter referred to as peak hours), customers are charged monthly for the distribution on the basis of the average of the three peak hours with highest consumption during a month. The distribution price for this quantity is approximately 9.4 euro[9] per kWh[10] during winter months (November to March) and 4.7 euro during the spring and summer months. For all other hours; i.e., between 7 p.m. and 7 a.m. during weekdays, and all hours during weekends and public holidays, distribution is free of charge. We refer to these hours as off-peak hours. The incentives are thus towards shifting consumption from day-time to night-time and from weekdays to weekends, and smoothing consumption during day-time.

A simple numerical example may clarify: Assume that the average of the three peak hours with highest consumption during a winter month is 4 kWh (for example, $(5+4+3)/3$). The household then pay $4 \times 9.4 = 37.6$ Euro in distribution cost for that month. In addition to this cost for distribution, households pay for the retail of electricity. Because retail of electricity is not regulated, households are free to choose between many different retailers.[11] The price variation across the different retailers is small, however, and the average retail price is approximately 0.06 Euro, i.e. fifty times smaller (See Statistics Sweden, `www.scb.se`).

The demand charge that Sollentuna Energi have implemented presents substantially larger marginal incentives than typically found elsewhere in the electricity market. Consider another simple numerical example: if the average of the three hours with highest consumption up until the last hour is 5 kWh, and a household consume 6 kWh in the last hour, the household's expenditure is approximately 50 euro ($(5+5+6)/3 * 9.4 \approx 50.13$). If, on the other hand, the household consume 5 kWh or less in the last hour, the household's expenditure is 47 euro ($(5+5+5)/3 * 9.4 = 47$). That is, the cost of the extra unit of consumption is more than 3 Euro. This should be compared to the per-unit retail price of approximately 0.06 Euro, and where the price variation is small: the highest price the majority of households in Sweden face (on standard linear type of tariffs) is approximately only twice as large as the lowest price. In the US context, e.g., Allcott (2011b) and Ito (2014), the highest price is approximately four times larger than the lowest price.

[9]Households are charged in SEK: one SEK is approximately 0.09 euro

[10]Although distribution of electricity is measured in kW, the metering equipment installed at the households only measure consumption by the hour. Therefore households are effectively being charged for kWh and not kW

[11]Previous literature suggest that most households choose the incumbent firm as retailer, few households switch retail contracts very frequently, and the the effect of price on retail choice is small (Vesterberg (2018) and Lanot and Vesterberg (2019))

2.1 Data and descriptive statistics

The data used in this paper consists of a random sample[12] of 1605 villas occupied by households who were customers of Sollentuna Energi as of September 2018 and that have a retail contract with Sollentuna Energi with prices varying by month (a so-called variable-price contract).[13] The source material has been anonymized and identification of households is not possible.

We focus on villas because they are most important from a policy perspective given their relatively large consumption (Energimarknadsinspektionen (2010)) and because many flats in Sweden have electricity expenditure included in their rent and this cost is therefore independent of the quantity they consume. Furthermore, we focus on households with variable-price contracts, both because they face monthly variation in the retail price, and because we lack retail price data on the households on fixed-price contracts (the retail price these households face is fixed over time and depends on the date when they signed their fixed-price contract, which we do not observe).

For each household in our sample, we observe the hourly electricity consumption in kWh from January 2015 to September 2018.[14] In addition to hourly consumption, the data also include information about retail price, and hourly temperature data for the municipality of Sollentuna is available from SMHI.[15] Unfortunately, the data lacks any information about household characteristics. While zip-code level census data is available from Statistics Sweden (`http://www.scb.se`), we note that variables such as income, household size and number of residents, that likely are determinants of electricity demand, have little variation over time (and especially at the zip-code level).

The households in the sample differ in the precision of their electricity meter. Most households (approximately 83 percent) have a meter that record consumption in kWh with a precision of a tenth of a kWh rounded down.[16] The remaining households have a meter with higher precision (one hundredth of a kWh). These differences in precision complicate the analysis. In particular rounding creates artificial bunching, which could be mistaken for a response to an incentive. Furthermore, the rounding of consumption means that the data is discrete, even though actual consumption in kWh is continuous. The data does not contain any information about the precision of the metering equipment

[12] We carry out the sampling using the `sample` command in Stata with a seed number generated by `https://www.random.org/`.

[13] Households in Sweden can typically choose between retail contracts with prices varying by month or with prices fixed for a year or longer (fixed-price contract). Among Sollentuna Energi's customers, approximately 80 percent have chosen a variable-price contract. Comparing with the Swedish population, approximately half of the households have a variable-price contract, and the remaining households have fixed-price contracts. The likely explanation to these discrepancies between the sample and the population is that Sollentuna Energi during the last years have promoted variable-price contracts over fixed-price contracts in a number of marketing campaigns.

[14] Because Sollentuna Energi introduced the tariff in 2001, some of the households in the sample may have had the demand charge tariff for many years. Unfortunately, our data is not informative about how long the households has been customers of Sollentuna Energi. See Taylor and Schwarz (1990) for a discussion of how the response to demand charges increases over time.

[15] See `http://opendata-download-metobs.smhi.se/explore/#`

[16] For example, a consumption of 1.19kWh will be measured as a consumption of 1.1kWh. The remainder of 0.09 is not recorded for this period since the household has not consumed 0.1kWh entirely (the remainder contributes to the measurement of consumption in the next period).

beyond the consumption actually recorded. We therefore classify households by the number of decimals of the smallest change in consumption between any two hours during a month. For simplicity, we focus our analysis on households with one decimal meters. This gives us a total sample size of of about 41.5 million observations. In Section 3, we detail how we in our empirical approach account for the discrete nature of the data.

Table 1: Summary statistics

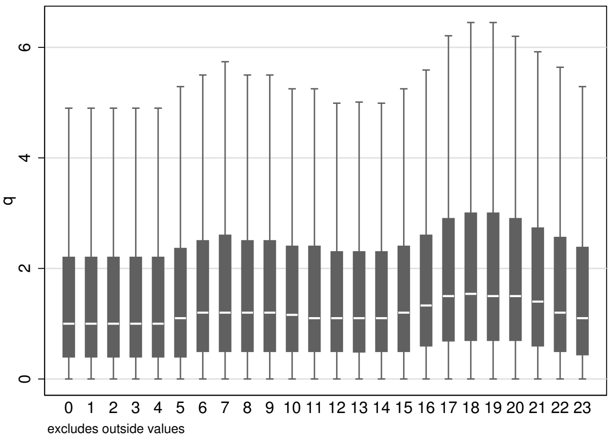
	Mean	Std. dev.	Median	Min	Max
Peak consumption, winter	2.460	1.805	2.2	0.1	18.6
Peak consumption, summer	1.134	1.070	0.8	0.1	17.1
Off-peak consumption, winter	2.435	1.814	2.2	0.1	21.9
Off-peak consumption, summer	1.169	1.127	0.8	0.1	20.3
m winter	4.677	2.622	4.414	0.044	14.319
m summer	3.013	1.872	2.647	0.022	16.060
Temperature, winter	1.550	4.339	1.7	-18.2	17.3
Temperature, summer	14.45	5.563	15	-0.4	29.3
Retail price, winter	0.054	0.007	0.051	0.043	0.072
Retail price, summer	0.055	0.016	0.05	0.031	0.107
Website logins	8.89	38.66	3	0	807

Note: i) Consumption of electricity is measured in kWh, temperature is measured in degrees celsius and retail price is measured in €/kWh. The statistics are calculated over individuals and periods (hours) ii) Peak hours are defined as hours between 7 a.m. and 7 p.m. iii) m is the average consumption of the three peak hours (7 a.m. to 7 p.m.) with highest consumption so far. iv) Website logins is the total number of logins to the firm's website between 2015 and 2018

Summary statistics for key variables observations are presented in Table 1. For electricity consumption in kWh (both peak and off-peak hours), we note that households consume substantially more electricity during winter than during summer, as expected. This is to a large extent driven by seasonal variation in temperature, but also availability of daylight.[17] We note that in summer months, off-peak consumption is slightly larger than peak consumption. While this seems counter-intuitive, it is because we define peak hours as the hours for which households potentially pay for distribution (i.e., 7 a.m. to 7 p.m.), rather than the hours with the highest consumption. For example, it is possible that consumption is the highest after 7 p.m., but because distribution is free of charge at that time, we refer to it as off-peak consumption. As illustrated in Figure 1 (for winter months), there is a distinct daily pattern with a small morning consumption peak and a larger evening peak, that stretches across both peak and off-peak hours. See Vesterberg and Krishnamurthy (2016) and Vesterberg

[17]For example, the city of Sollentuna has has approximately 9 hours of daylight in February, to be compared with approximately 18 hours of daylight in June.

Figure 1: Boxplot (with whiskers) of hourly consumption during winter months

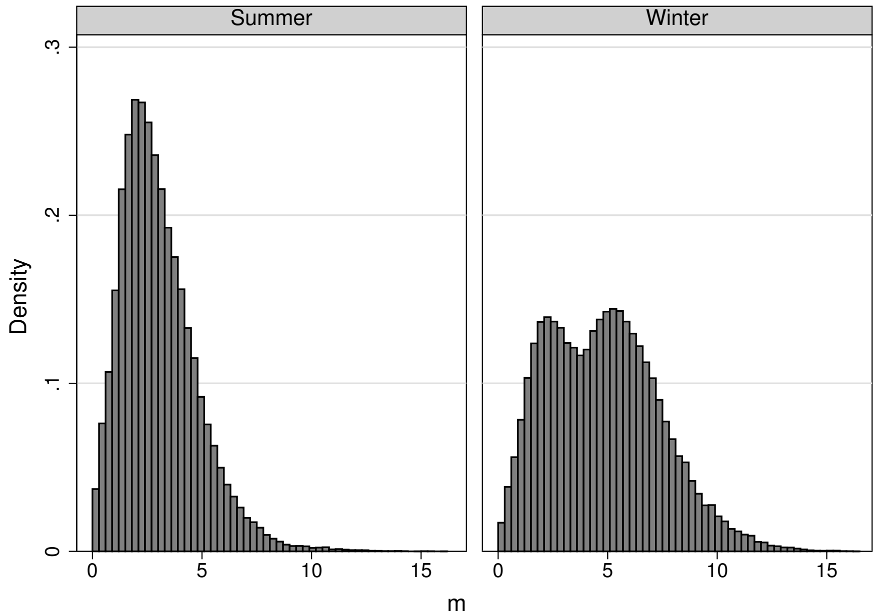


Note: i) The box plot illustrates consumption across hours for working days during winter months (November to March). That is, we look at all working days during winter and produce a box plot for each hour. ii) We have excluded outside values to make the box blot easier to read.

(2016) for detailed descriptions of electricity consumption patterns for Swedish households. We denote m as the average of the three peak hours with highest consumption: i.e., what the households are charged based upon, and for simplicity, we will refer to this quantity as the maximum consumption so far in the rest of this paper. We note that on average, m is relatively small; especially when comparing with maximum consumption. However, as with consumption, there is substantial variation in m; both across seasons and across households. The distributions of m for summer and winter, respectively, are shown in Figure 2. Evidently, the distribution of m for winter months is a mixture distribution with two peaks, and the intuition to this shape of the distribution is heterogeneity in heating systems. Specifically, for households with electric heating, electricity consumption during winter months is larger than for households with other sources of heating. Therefore, we deduce that the distribution for m is located further to the right for households with electric heating, whereas the distribution of m for households with mixed heating have a distribution located further to the left. Because heating is a small share of total consumption during summer, and households are relatively similar in other aspects, the summer distribution only has one peak.

The average retail price (for households on variable-price contracts, including taxes and other add-on costs) is approximately 0.06 Euro per kWh, and the standard variation, which is relatively small, reflects variation across months rather than across households because all households in the sample have Sollentuna Energi as retailer, and therefore face the same retail price. Finally, it is important to highlight that electricity amounts only to a small share of income for most households in Sweden. To give a sense of magnitude, the average monthly expenditure on electricity for our sample is approximately 95 Euro, which corresponds to less than five percent of the average monthly income (see `www.scb.se`).

Figure 2: Distribution of m for summer and winter



Note: i) The histograms of m for summer (April to October) and winter (November to March) are produced using all peak-hour (i.e., 7 a.m. to 7 p.m.) observations. ii) The two peaks in the distribution of m for winter months are explained by differences in heating system: some households have electric heating, and therefore a distribution of m with a larger mean, compared to households with other sources of heating.

Finally, we have access to data on the frequency of households' use of the distribution firm's website where they can acquire information about their own electricity consumption, which allows us to empirically explore how information affects price responsiveness, at least to some extent. We note that few households use the website very frequently, with the median number of logins between 2015 and 2018 equal to 3 (i.e., less than once a year). However, some households use it more frequently, in some cases more than 800 times since 2015.

3 Estimation of the price elasticity

3.1 Marginal incentives

Before outlining our empirical approaches, it is instructive to describe the marginal incentives faced by the customers of Sollentuna Energi in a more formal way. As before, m is the average of the three hours with the highest consumption so far, and let q be consumption in kWh in a given hour. To simplify, let us assume that the current period is the last peak hour in a given month. The budget constraint, which describes the affordable alternative bundles in terms of consumption expenditure, c_t and electricity consumption q_t given the current budget y, can then be described in the following fashion:

$$c_t + p_t q_t + \kappa(q_t - m_t)\mathbf{1}[q_t > m_t] = y - \kappa m_t \tag{1}$$

where p_t is the retail price and κ_t is the distribution price. Hence, if the quantity consumed in a given hour is larger than the maximum consumed so far, $q_t > m_t$, the budget constraint is:

$$c_t + (p_t + \kappa_t)q_t = y$$

while if $q_t \leq m_t$, the budget constraint becomes[18]:

$$c_t + p_t q_t = y - \kappa m_t$$

Therefore, if $q_t \leq m_t$, the marginal cost of consumption in a given period is p_t, while if $q_t > m$, the marginal cost is $p_t + \kappa_t$. In off-peak hours, the marginal cost is always equal to p. A budget constraint with these characteristics (together with indifference curves, explained in the next section) is illustrated in Figure 3.2.

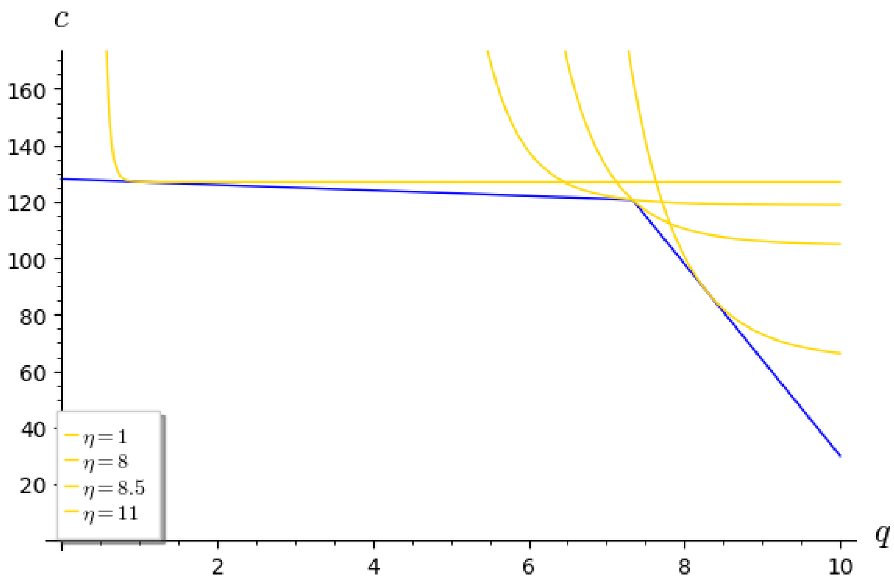
Note that although the tariff is common to all households in the grid area, the price in any given hour depends on the households individual consumption q relative to the maximum consumption so far m, which means that prices not only vary across hours, but also across households for any given hour: in hour t, some households face the marginal price of p, while for other households, the marginal price is $p + \kappa$.

3.2 Preferences and Demand

Following the literature on the elasticity of taxable income and labor supply (e.g., Saez, 2010), we assume that households preferences are described by the

[18]Note that the budget constraint during off-peak hours would take the same form

Figure 3: Budget constraint and indifference curves



Note: The budget constraint is drawn for prices $p = 1$, $\kappa = 33$ and $y = 400$. The indifference curves are drawn assuming an iso-elastic utility function with $\alpha = 0.08$ and for different values of η (shocks to consumption) assuming these shocks follow a gamma distribution (η is increasing from left to right).

following utility function:

$$U(c, q, \eta) = c + \frac{\eta}{1 - 1/\alpha} \left(\frac{q}{\eta}\right)^{1-1/\alpha} \tag{2}$$

where η plays the role of a random preference shifter with $\eta > 0$. We think of η as idiosyncratic to each household and period.

Importantly for our empirical approach, the marshallian demand for electricity if the household faces a linear budget constraint with unit price p, takes the simple log linear form:

$$\ln q = -\alpha \ln p + \ln \eta, \tag{3}$$

and the parameter α is naturally interpreted as the elasticity of the demand for electricity with respect to its price. Furthermore, from this expression, we observe that this simple model of demand allows for the quantities to respond to prices and to randomness through η. As we illustrate in Figure 3.2, a larger value of η yields a steeper indifference curve (i.e., meaning that, keeping utility constant, the household requires a larger increase in its expenditure in other consumption to compensate for a reduction in electricity consumed when η is large, compared to the amount it would need when η is smaller). Hence, when a shock is large and positive, the model suggests that the substitution effect is smaller.

Finally, note that the indirect utility, i.e., the welfare obtained when the household expresses its optimal demand behaviour given a unit price for electricity p and some budget y, satisfies the expression:

$$V(p,y) = y + \frac{\eta}{\alpha - 1} p^{1-\alpha}. \tag{4}$$

We require α to be positive, and from our reading of the previous literature on electricity demand, we expect α to be small and less than one. Given this restriction, we observe that the utility function is increasing and concave in the quantity of electricity while the indirect utility function is decreasing and strictly convex in the price p.

In response to the piece-wise linear budget constraint defined in Equation 1, the demand behaviour is more complicated. Everything else constant, we can define three regions over the range of possible values of η: firstly whenever $\eta < mp^{\alpha}$, i.e. *η small enough*, corresponds to the range of values of η such that the demand is less than m and, at the margin, the price is p; second, when $\eta \geq m(p+\kappa)^{\alpha}$, *eta large enough*, corresponds to the range of values of η such that the demand is larger than m, that is, such that the relevant price at the margin is $p+\kappa$. Finally, if η is located instead in the interval $mp^{\alpha} \leq \eta < m(p+\kappa)^{\alpha}$, the demand is exactly m. The existence of this last regime suggests that we should observe some bunching (i.e., an accumulation of observations, or a local mode in the distribution of the quantity demanded) at or around m.

We can provide an expression for the quantity demanded, q^*, which summarises the response to the piece-wise linear budget constraint:

$$\begin{aligned} q^* = & C_-(m,p)\eta p^{-\alpha} + C_+(m,p+\kappa)\eta(p+\kappa)^{-\alpha} + \\ & \big(1 - C_-(m,p) - C_+(m,p+\kappa)\big)m, \end{aligned} \tag{5}$$

where $C_-(m,p) = \mathbf{1}\{\eta : \eta < mp^{\alpha}\}$ and $C_+(m,p+\kappa) = \mathbf{1}\{\eta : \eta \geq m(p+\kappa)^{\alpha}\}$ indicate the marginal incentive that describes the demand behaviour.

Given the budget constraint in Equation 1 and the functional restriction on the utility as in Equation 4, and in particular the absence of income effects on the demand for electricity, the indirect utility function when the price schedule is non-linear, given m and η, is defined as:

$$\begin{aligned} & W(m,y,\eta) = C_-(m,p)V(p, y - \kappa m) + \\ & C_+(m,p+\kappa)V(p+\kappa, y) + \\ & \big(1 - C_-(m,p) - C_+(m,p+\kappa)\big)U(y - (p+\kappa)m, m) \end{aligned} \tag{6}$$

3.3 Regression approach

Our empirical analysis takes the log-linear specification we discuss in the previous section as its starting point. Specifically, consider the reduced-form demand equation

$$\ln(q_t) = \beta_0 + \beta_1 \ln(r_t) + \beta_2 \mathbf{x}_t + \epsilon_t \tag{7}$$

where $\mathbf{x}_t$ is a vector of control variables (e.g., temperature and time and household fixed effects), and where

$$r_t = \mathbf{1}[q_t > m_t]\kappa_t + p_t \tag{8}$$

so that

$$\ln(q_t) = \beta_0 + \beta_1 \ln(\kappa_t + p_t) + \beta_2 \mathbf{x}_t + \epsilon_t \tag{9}$$

if $q_t > m_t$ and

$$\ln(q_t) = \beta_0 + \beta_1 \ln(p_t) + \beta_2 \mathbf{x}_t + \epsilon_t \tag{10}$$

if $q_t \leq m_t$.

We understand any estimate of β_1 as an estimate of the structural parameter α, the elasticity of demand. The analysis we present in the previous section suggest that this is the key parameter needed to complete a welfare analysis (i.e., a comparison of welfare in response to changes to the marginal incentives).

Because of the non-linear distribution tariff, the per-unit cost r_t of electricity in a given peak hour depends on q_t (and m_t), therefore it is endogenous.[19] In our regression approach, we solve this by using as an instrumental variable the (predicted) probability $\mathbb{P}[q > m]$ if consumption q_t was equal to the consumption in the month before or the next month (i.e., the same hour of the day and the same day of the month in the previous or next month)[20], which we denote by $q_{t-\tau}$ and $q_{t+\tau}$, respectively. For robustness/sensitivity analysis, we also estimate a model where lags and leads of both q and m are used to estimate the probability $\mathbb{P}[q_t > m_t]$, which is then used to generate the instrumental variable. Similar instrumental variables approaches has frequently been used in the context of taxable income and labor supply, see Auten and Carroll (1999), Carroll (1998), and Gruber and Saez (2002). The parameters in Equation 10 are estimated using 2SLS following the empirical strategy described in Wooldridge (2010), see Appendix B for details.

Parameter estimates and estimation statistics are presented in Table 2. We find that the F-value for the first stage is very large which indicates that our instrumental variables have substantial explanatory power, and additional tests for weak instruments, such as the Anderson-Rubin Wald test and the Stock-Wright LM statistic also rejects the null hypothesis of weak instruments. The price elasticity in the second stage is estimated precisely to be -0.16. We note that this estimate is in the lower range of the estimates in previous literature, and indicate that households' electricity consumption is inelastic; possibly more so than previously thought. Furthermore, we note that the results are very similar across the two alternative instruments, and that the negative effect of temperature is expected and similar across specifications. We return to a more detailed discussion of the implications of the result in Section 5, and turn next to our other empirical approach, where we use a bunching estimator to measure the price elasticity.

[19]Both p_t and κ_t can be assumed to be exogenous to the individual household. For example, both Nesbakken (1999) and Krishnamurthy and Kriström (2015) assume the retail price to be exogenous to the individual household for the Nordic context. Specifically, in the Swedish setting, the marginal energy price is exogenous to the individual household, and does not vary with quantity consumed, as would be the case if households faced, e.g., increasing block-rate pricing or other non-linear pricing schemes. Similarly, κ_t only vary by season and not by level of consumption.

[20]For example, to instrument for the per-unit cost in month 2, day 25 and hour 16, we use q in month 1, day 25 and hour 16, and q in month 3, day 25 and hour 16 to compute the per-unit costs, which are subsequently used to generate the instruments.

Table 2: First and second-stage results, 2SLS

	q, W		q and m,W	
	Coef.	Std. err.	Coef.	Std. err.
First stage				
$\mathbb{P}[q_t > m_t] \| q_{t-\tau}, q_{t+\tau}$	0.308	0.000		
$\mathbb{P}[q_t > m_t] \| q_{t-\tau}, m_{t-\tau}, q_{t+\tau}, m_{t+\tau}$			0.312	0.000
Temperature (celsius)	-0.001	0.000	-0.002	0.000
HH FE	Yes		Yes	
Time FE	Yes		Yes	
F-value	3.3e+06		9.2e+05	
Second stage				
ln(price)	-0.160	0.000	-0.177	0.001
Temperature (celsius)	-0.033	0.000	-0.033	0.000
HH FE	Yes		Yes	
Time FE	Yes		Yes	
N	41,448,211		41,448,211	
Anderson-Rubin Wald test:	F(1,41446503)=47165.31		F(2,41446501)=22390.63	
Stock-Wright LM statistic:	Chi-sq(1)=47113.60		Chi-sq(2)= 67065.92	

Note: i) $\mathbb{P}[q_t > m_t] | q_{t-\tau}, q_{t+\tau}$ refers to the probability of $q > m$ given the consumption in the month before, $q_{t-\tau}$, and the next month, $q_{t+\tau}$. $\mathbb{P}[q_t > m_t] | q_{t-\tau}, m_{t-\tau}, q_{t+\tau}, m_{t+\tau}$ refers to the probability of $q > m$ given the consumption in the month before, $q_{t-\tau}$, and the next month $q_{t+\tau}$, and given the value of m in the previous month, $m_{t-\tau}$, and next month, $m_{t+\tau}$. ii) All specifications are estimated using the Stata command `ivreghdfe` using the `absorb` option and the approach detailed in Wooldridge (2010). Estimation time approximately 20 min. iii) Weak instrument test of joint significance of endogenous regressors in main equation (Ho: $\beta = 0$ and orthogonality conditions are valid):
a) Anderson-Rubin Wald test: F(1,41446503)=47165.31
b) Stock-Wright LM statistic: Chi-sq(1)=47113.60

3.4 Bunching approach

Bunching estimators have gained popularity, both in the context of nonlinear pricing of electricity demand (e.g., Ito, 2014) but most notably in the context of the estimation of the elasticity of taxable income (see Kleven, 2016 for a review). Applications of this approach has also been used to study prescription drug insurance (Einav et al., 2017), fuel economy policy (Sallee and Slemrod, 2012), mortgages (DeFusco and Paciorek, 2017), cell phones (Grubb and Osborne, 2015), broadband (Nevo et al., 2016), among other contexts.

In our context, the bunching approach focuses on the proportion of households who accumulate exactly at m. In a different context but using an identical framework, Saez (2010) shows how it is possible to deduce an estimate of the elasticity of demand from the accumulation at m (which is easily observed) relative to the density of observations 'around' and not far from m, given the model outlined earlier.

Our analysis follows a similar approach and starts from the expression for the quantity demanded, q^*, in Equation (5). From this expression, we deduce an expression for the derivative of its expected value given m, i.e., $\mathbb{E}[q^*|m]$, relative to m:

$$\frac{d\,\mathbb{E}[q|m]}{dm} = \overset{+}{\mathbb{P}} - \overset{-}{\mathbb{P}}, \tag{11}$$

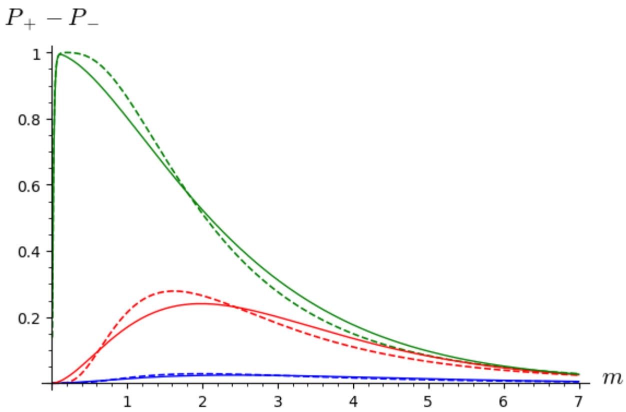
where $\mathbb{P}^+ \equiv \mathbb{P}[\eta < m(p+\kappa)^\alpha]$ and $\mathbb{P}^- \equiv \mathbb{P}[\eta < mp^\alpha]$. This quantity therefore tells us about the increase in the quantity demanded as the maximum consumption so far, m, changes. This increase is exactly equal to $\mathbb{P}^+ - \mathbb{P}^-$ which measures the amount of observations which "bunch" at m exactly.

Hence, the elasticity of the expected optimal quantity given m relative to m is equal to $\left(\mathbb{P}^+ - \mathbb{P}^-\right) m/\,\mathbb{E}[q|m]$. Thanks to the result given in Equation (11), this elasticity depends only on observable quantities. That is, given m, we are in principle able to measure from the data the difference $\mathbb{P}^+ - \mathbb{P}^-$ as well as the conditional mean $\mathbb{E}[q|m]$. Furthermore, given our modeling assumptions, this elasticity is determined by the price elasticity of demand α, the key parameter of interest.

Figure 4 illustrates the relationship between m and the difference $\mathbb{P}^+ - \mathbb{P}^-$ for different values of α, given some numerical assumptions, and for different distributional assumptions for η (we find that both the log-normal and the gamma distributions fit the data reasonably well, see Figure 5). In particular, we observe that small values of $\mathbb{P}^+ - \mathbb{P}^-$ correspond to small values of α, all else equal.

Our empirical approach can thus be summarized as follows: First, we find the range of m across households, and we focus on specific values: for example, the median, the first and the third quartiles of distribution of m. Next, around these values, we calculate the proportion of households consuming exactly or very nearly m, i.e., we estimate $\mathbb{P}^+ - \mathbb{P}^-$. Then, for estimates of the parameters in the distributions of η, and for given values of p and $p+\kappa$, we find the value of α which is consistent with the observed values of $\mathbb{P}^+ - \mathbb{P}^-$ for the m chosen (i.e., for a given value of α, we minimize the difference between the theoretical $\mathbb{P}^+ - \mathbb{P}^-$ and its empirical equivalent).

Saez (2010) approach to the estimation the elasticity of taxable income provides an approximation to this final step. Saez (2010) proposes to approximate



Note: From top to bottom, green line for $\alpha = 1$, red for $\alpha = 0.1$ and blue for $\alpha = 0.01$. The dashed line correspond to the calculations assuming log-normality for the distribution of the shock, while the continuous line corresponds to the calculation with a Gamma distribution. The two distributions have identical expectation and variance.

Figure 4: $\mathbb{P}^+ - \mathbb{P}^-$ for different values of m, given α.

$\mathbb{P}^+ - \mathbb{P}^-$ by a trapezoidal rule. Following exactly the steps of his derivation, we obtain:

$$2\{\overset{+}{\mathbb{P}} - \overset{-}{\mathbb{P}}\} \approx \left\{\left(\frac{p+\kappa}{p}\right)^{\alpha} - 1\right\}\left\{h_-(m) + h_+(m)\left(\frac{p}{p+\kappa}\right)^{\alpha}\right\}, \tag{12}$$

where the quantities $\mathbb{P}^+ - \mathbb{P}^-$, $h_-(m)$ and $h_+(m)$ (the density of the observed quantity on either side of m) can all be estimated from the data. The expression above yields a quadratic equation with $\left(\frac{p+\kappa}{p}\right)^{\alpha}$ as the unknown. Given a solution to this quadratic equation, an estimate of α is easily obtained since the ratio $\frac{p+\kappa}{p}$ is known.

3.5 Adapting the bunching approach to the aggregation over a small range of values of m

In our context, m plays the role of the kink. However, in contrast with the empirical applications in public finance where there is typically one or few kinks, we observe a large number of potential kinks. In this section, we wish to show that the estimation procedures based on the bunching approach can be adapted at little cost, at least under the assumption that the elasticity of demand is constant across households, or alternatively, does not vary within small intervals for m.

Consider a given period t. Assume that we observe that the quantity of the maximum so far is distributed according to the density function (the probability density function if it is discrete) $\lambda(m)$ over a range of values for m. In our case, this would describe the distribution of m around a particular quantile of the distribution of m.

We observe that the approximation by Saez as described in Equation (12) can be modified in a simple fashion to account for this empirical context. Denote by $\mathbb{P}^+(m) - \mathbb{P}^-(m)$ the probability to observe electricity consumption exactly at m (or very close to it), in the distribution of consumption given m. Similarly, denote $h_-(m|m)$ and $h_+(m|m)$ the densities to the left and the right of m of the density function for q_t given m.

Consider a range between $\underline{m}$ and $\overline{m}$ for the value of m of interest. Assume that the elasticity is independent of m over that range. Equation (12) is satisfied approximately for all m in the range $[\underline{m}, \overline{m}]$, and therefore it is satisfied approximately on average:

$$2\int_{\underline{m}}^{\overline{m}} \left\{ \overset{+}{\mathbb{P}}(m) - \overset{-}{\mathbb{P}}(m) \right\} \lambda(m) dm \approx \left\{ \left(\frac{p+\kappa}{p} \right)^{\alpha} - 1 \right\} \cdot \\ \left\{ \int_{\underline{m}}^{\overline{m}} h_-(m|m)\lambda(m)dm + \int_{\underline{m}}^{\overline{m}} h_+(m|m)\lambda(m)dm \left(\frac{p}{p+\kappa} \right)^{\alpha} \right\} \tag{13}$$

which has the same form exactly as the original approximation. The inputs into the calculations are no longer the probability to bunch at m exactly or the densities around m, but their average over the distribution of m in the particular range.

In a similar spirit, assuming once more that an estimate of $\lambda(m)$ over the range $[\underline{m}, \overline{m}]$, the density of the maximum at the start of a given period, is available, we can calculate the theoretical quantity on the RHS ("the size of the bunch"):

$$\int_{\underline{m}}^{\overline{m}} \left\{ \overset{+}{\mathbb{P}}(m) - \overset{-}{\mathbb{P}}(m) \right\} \lambda(m) dm, \tag{14}$$

and calculate theoretically (all else given) how this varies with α, assuming once more that it is constant over the range $[\underline{m}, \overline{m}]$.

Its empirical equivalent can be obtained (assuming a discrete distribution for the values of m in the relevant range) as:

$$\sum_{k=1}^{K} \hat{p}(m_k) \frac{1}{N_k} \sum_{i=1}^{N_k} \mathbf{1}[q_i = m_k, m = m_k], \tag{15}$$

where N_k denotes the number of observations (of quantities consumed) where $m = m_k$ exactly, and $\hat{p}(m_k)$ is the proportion of observations (out of the whole sample) such that $m = m_k$ exactly. In this particular case, we would use, for example, $\hat{p}(m_k) = N_k/N$. The expression above then simplifies to:

$$\frac{1}{N} \sum_{k=1}^{r} \sum_{i=1}^{N_k} \mathbf{1}[q_i = m_k, m = m_k], \tag{16}$$

which can be easily evaluated with the data at hand.

3.6 Bunching results

The bunching approach to the measurement of the effect of incentives on behaviour is appealing to researchers since the effect(s) of incentives leave a simple visual tell tale: the data bunches in ex-ante determined locations; the kink(s). In our case, however, this is not as obvious, for several reasons. First, the kink varies both across households and across time, meaning that there are few observations of consumption for each value of m. This is different from the context of, e.g., taxable income, where there typically are many observations and few kinks.[21] Secondly, the data is discrete because of the precision of the metering equipment which may create artificial bunching at the rounded numbers. Thirdly, the price elasticity is expected to be small (based both on our reading of the previous literature, and on the regression results presented earlier), implying little bunching at the kinks.

In Figure 5, we present histograms for q for all peak hours within a month, conditional on different values of m. Because few households have exactly the same level of m, we consider all the values of m within a small interval centered around the value given in the table (plus or minus 0.2 kWh). Evidently, there is no obvious/clear bunching at the kinks m.[22] In general, we have analyzed the data in many different dimensions, and find no conclusive graphical evidence of any bunching in general. This suggest little price responsiveness, and is expected given the regression results presented earlier.

We next present the estimation results using the bunching approaches outlined above. $\left(\mathbb{P}^{+} - \mathbb{P}^{-}\right)$ is estimated as the proportion of observations of q within the interval $m \pm 0.2$, and similarly for the Saez approach, the densities h_{+} and h_{-} are estimated using an interval width of $\delta = 0.2$ (i.e., $m \pm 0.2$, see Saez (2010) for details). We have also tested other widths of these intervals, and results are very similar. Because we are pooling observations for many months when we estimate the elasticity using the bunching approach, we use the average retail price over all months. The parameters in the log normal and gamma distributions are estimated by maximum likelihood.

First, Figure 5 illustrates the density of the data for given values of m, together with the fitted conditional (on the value of m) log-normal and gamma distributions. Evidently, while both distributions fits the data relatively well, the gamma distribution provides a better description of the distribution of the right tail. Next, in Table 3, we present results for the two different bunching approaches outlined in Section 3.4. Price elasticities are estimated separately for a range of values of m (approximately from the 25^{th} to the 75^{th} percentiles of m, in increments of 0.5 kWh). The price elasticity parameter α is precisely estimated in all specifications, with a bootstrapped standard error of less than 0.001 for the gamma and the log-normal model, and less than 0.01 for the Saez model (bootstrapped standard errors with 1000 replications. For brevity, these standard errors are not displayed in the tables but are available upon request).

The measured response to prices is small, with the estimated price elasticity ranging from 0.012 to 0.126. Importantly, we note that the estimates presented here in general are smaller than what has been found in some of the previous

[21]Because there are many different levels of m, and therefore many different kinks, it would be useful to do some normalization to fit all observations in the same histogram. For example, if dividing q by m, one could look for bunching at $q/m = 1$. However, computing this ratio for rounded number creates artificial bunching at integers for the data used in this paper.

[22]By zooming in around the kink, there is actually some indications of bunching at the kink for some specific hours. For example, the lower left panel of Figure 9 in Appendix C, illustrating the distribution of q for $m = 5$, possibly reveals some bunching. On the other hand, for other values of m (as illustrated in the other panels in that figure), there is no obvious bunching.

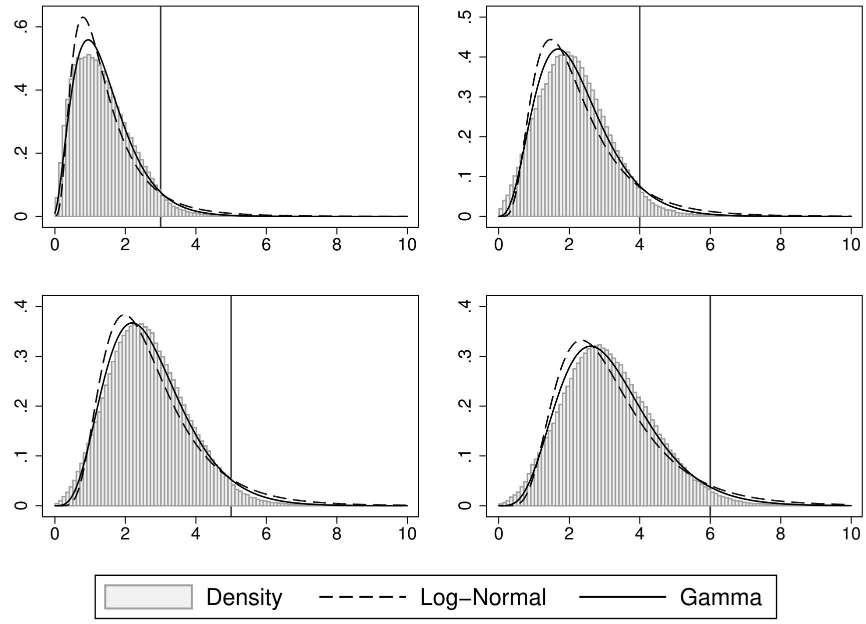


Figure 5: Conditional Density of electricity consumption data for different values of m (3, 4, 5 and 6, indicated by the vertical lines) and fitted log-normal and gamma distributions

Note: i) Histograms of consumption are generated using all observations for which m is equal to 3, 4, 5 and 6, respectively. The values of m are indicated by the vertical lines. ii) Because few households have exactly the same level of m, we here consider m as a small interval; $m\pm0.2$. iii) We assume that the density of the data for given values of m can be described by either a log-normal or a gamma distributions. We estimate the parameters for these distributions using maximum likelihood. The fitted conditional (on the value of m) log-normal and gamma density functions are illustrated using the dashed and solid curves.

Table 3: Bunching results

m	$\mathbb{P}^+ - \mathbb{P}^-$	LN α	G α	Saez α	N
3	0.037	0.037	0.037	0.126	410,360
3.5	0.035	0.028	0.028	0.128	380,598
4	0.032	0.023	0.023	0.127	380,337
4.5	0.027	0.019	0.020	0.076	391,991
5	0.022	0.017	0.018	0.078	411,821
5.5	0.017	0.013	0.014	0.075	416,268
6	0.014	0.012	0.013	0.078	384,183

Note: i) All parameter values are estimated using the pooled peak-hour (7 a.m. to 7 p.m.) observations for different values of m. ii) Because few households have exactly the same level of m, we here consider all values within a small interval centered around m; $m \pm 0.2$kWh. iii) LN α refers to the bunching estimator when η is assumed to follow a log-normal distribution iv) G α refers to the bunching estimator when η is assumed to follow a gamma distribution. v) Saez α refers to the "non-parametric" bunching estimator describe by Saez.

literature (Filippini (2011), Nesbakken (1999), and Reiss and White (2005)). In general, we find the estimates from the Saez-type of estimator to be slightly larger than the other bunching estimators, and while it is difficult to understand precisely why this is the case, we note that comparisons between IV regressions and bunching estimators in other contexts have found similar patterns (e.g., Aronsson et al. (2017), in the context of labor supply). Interestingly, we observe that the elasticity is smaller for large values of m. Several explanations can account for this fact: firstly, households with high electricity consumption (those who would exhibit large values for m) may care less about the price (i.e., a selection effect), or alternatively, these households are more likely to have installed electric heating (or other appliances that use a lot of electricity) and have fewer possibilities to adjust their electricity consumption to the price. Lijesen (2007) finds similar results for the US context.

3.7 Voluntary acquisition of information

A key assumption in most of the empirical literature on both electricity demand and consumer behavior in general is that individuals have perfect information about their optimization problem. Recently, this assumption of perfect information has been challenged, both in the literature on public finance (e.g., Chetty et al., 2009) and in the literature on electricity demand (e.g., Allcott, 2011a, Ito, 2014, Sexton, 2015 and Kažukauskas and Broberg, 2016).[23]

To explore the effect of voluntary acquisition of information about consumption on price responsiveness, we estimate the price elasticity using a split-sample approach for both the regression approach and the bunching approach.[24] Specifically, we estimate the price elasticity separately for households above and below the $75th$ percentile of number of logins (we have also tried using, for example, the median, and the $90th$ percentile, and results are qualitatively similar. Results from these specifications are available upon request).

We find that the correlation between information and price responsiveness is small; for the regression approach, households that use the website frequently (number of logins above the $75th$ percentile) have an estimated price elasticity of -0.196, while households that use the website less (i.e., their number of logins are below the $75th$ percentile) have an estimated price elasticity of -0.148. These results are robust to different percentiles of website use. Similarly, we find little to no effect of information on price responsiveness using the bunching approach, and alternative empirical explorations indicate similar results.[25] This

[23]However, it is important to point out that even if households lack perfect information about their consumption, the tariff may still indicate to households that peak demand is expensive, and this information may be enough to affect households' consumption. In particular, if customers know how to avoid the simultaneous use of electricity-intensive appliances, this may lead to a substantial reduction in maximum demand even without detailed information about, e.g., maximum consumption so far. For example, in the evaluation of a similar pricing scheme (Bartusch et al., 2011), eight out of ten households (N=232) were aware of and understood their tariff, that they were being charged for peak demand, and had adapted their energy related behavior to the demand-based tariff.

[24]For the regression approach, an interaction term between the log of price and the number of logins would also be an option, but because number of logins likely is endogenous (depends on consumption), we choose the much simpler split-sample approach. Also, this approach allow us to also use the bunching approach to test the role of information on price responsiveness.

[25]For example, we also estimate a logit model with the outcome variable equal to one if the household's last login happened in a given hour and zero otherwise, and the explanatory

is in line with, for example, Alberini et al. (2019), who find no evidence that households who are attentive about their consumption levels, their bills, or the tariffs are more responsive to the price changes.

3.8 Peak to off-peak load shifting

Households can respond to the tariff incentives not only by keeping consumption below the maximum so far, but also by shifting consumption from peak hours to off-peak hours. The previous literature exploring this issue finds little or no load shifting of this kind. For example, Bartusch et al. (2011) and Bartusch and Alvehag (2014) find that the change in the consumption peak to off-peak ratio relative to the pre-tariff period is approximately 2.5 percent, to be compared with the change in the price differential between peak and off-peak hours relative to the pre-tariff period, which was approximately 160 percent. While these authors do not report any elasticity, their findings implies a small elasticity of the peak to off-peak consumption with respect to the peak to off-peak price differential of $-2.5/160 = -0.017$. The implied elasticity for the results presented in Stokke et al. (2010) are of similar magnitude (-0.009). Furthermore, the evidence for load shifting under other types of pricing schemes, e.g., real-time pricing, also appears to be weak (e.g., Allcott (2011b)), and in the cases where cross-price elasticities are significant, they are often found to be relatively modest (e.g., Filippini (2011). Obviously, households are not able to shift their electricity consumption load freely, and many consumption patterns are the result of rigidities elsewhere, e.g., working hours, dinner time, and daily habits in general (Vesterberg and Krishnamurthy (2016)).

To explore shifting of consumption from peak to off-peak hours under the Sollentuna Energi tariff, we compare consumption before and after the beginning and end of the peak periods (i.e., before and after 7 a.m. and 7 p.m.). If households respond to the tariff incentives by shifting load from peak to off-peak hours, we should observe a discrete jump in electricity consumption as we cross the threshold between one period and the next. Because other factors than the relative price between peak and off-peak may influence the difference in consumption, we make use of the change in the distribution price between winter and summer. Since peak consumption is substantially more expensive during winter months (November to March), we expect the increase in consumption from 6 p.m. to 7 p.m. to be larger in winter months than in summer months (e.g., larger in March than in April). Similarly, we expect the decrease in consumption from 6 a.m. to 7 a.m. to be larger during winter months than during summer months.

Table 4 presents the results from a t-test for consumption in 7 p.m. minus the consumption in 6 p.m. ($q_{19} - q_{18}$), by season (winter vs. summer, March vs. April and October vs. November). We do not find any evidence that households shift more consumption from peak to off-peak hours in winter months than in summer months, and this is true both when comparing winter and summer months, and when comparing March to April. Similarly, Table 5 illustrates the corresponding t-tests but for consumption in 7 a.m. minus consumption in 6

variables being the absolute difference between consumption q in that hour and the maximum consumption so far m, and hour fixed effects. The results show no significant effect of being close to the maximum consumption so far on the probability of logging in to the website.

a.m. ($q_7 - q_6$). Again, we do not find any evidence that households shift more consumption when the incentives for doing this are larger.

Table 4: T-test, $q_{19} - q_{18}$, by season

Time-period	Obs	Mean	Std. Err.	[95% Conf.	Interval]
Summer	1,292,830	0.007	0.0007	0.0055	0.0084
Winter	860,760	-0.0122	0.0010	-0.0143	-0.0101
diff		-0.0192	0.0012	-0.0217	-0.0167
Time-period	Obs	Mean	Std. Err.	[95% Conf.	Interval]
March	199,881	0.0415	0.0022	0.0371	0.0459
April	186,679	0.0779	0.0021	0.0736	0.0822
diff		0.0363	0.0031	0.0302	0.0425
Time-period	Obs	Mean	Std. Err.	[95% Conf.	Interval]
October	150,245	-0.0692	0.0023	-0.0738	-0.0646
November	142,990	-0.0271	0.0026	-0.0322	-0.0220
diff		0.0421	0.0035	0.0352	0.0489

Note: i) Difference in $q_{19} - q_{18}$ between months, i.e., the difference in difference.

Table 5: T-test, $q_7 - q_6$, by season

Time-period	Obs	Mean	Std. Err.	[95% Conf.	Interval]
Summer	1,292,823	-0.0361	0.0006	-0.0375	-0.0348
Winter	860,681	0.1566	0.0009	0.1547	0.1585
diff		0.1928	0.0011	0.1905	0.1950
Time-period	Obs	Mean	Std. Err.	[95% Conf.	Interval]
March	199,843	0.0712	0.0021	0.0672	0.0752
April	186,672	-0.1301	0.0021	-0.1342	-0.1258
diff		-0.2012	0.0030	-0.2071	-0.1955
Time-period	Obs	Mean	Std. Err.	[95% Conf.	Interval]
October	150,245	-0.0401	0.0022	-0.0444	-0.0356
November	142,990	0.1824	0.0023	0.1778	0.1870
diff		0.2225	0.0032	0.2161	0.2288

Note: i) Difference in $q_7 - q_6$ between months, i.e., the difference in difference.

4 Dynamics of response and alternative tariff designs

Because households only pays for distribution during peak hours when consumption is larger than the maximum consumption so far (i.e., hours for which $q > m$), it is relevant to illustrate how often and when such event takes place,

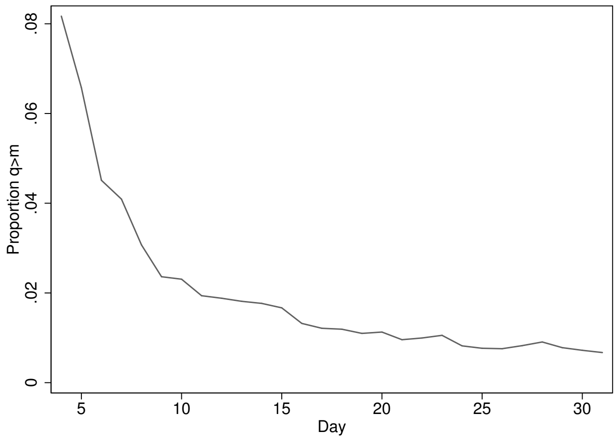


Figure 6: When during a month does $q > m$ happens?

and whether this affects households' response to the tariff. Specifically, because m can only increase or remain the same during a month, the probability $\mathbb{P}[q > m]$ can only decrease or remain the same. If this probability is smaller at the end of the month, this would suggest that the marginal incentives becomes less sharp. Figure 6 illustrates the proportion of hours for which $q > m$ for the sample at hand. Evidently, the proportion of hours with $q > m$ is relatively large, 8 percent, at the beginning of the month, but then decreases rapidly and is much smaller during the second half of the month, i.e., between 2 and 1 percent (i.e., $\approx \frac{3}{252}$).

This suggests that we should expect households to be less price responsive in the second half of the month. To explore this possibility empirically , we estimate our models again for only for the second half of the months, where estimates of the price elasticity for the latter part of the month are expected to be smaller compared to the estimates for all hours. The results are presented in Table 6 for the regression approach and in Table 7 for the bunching approach. For both these models, we find the price elasticity to be smaller for the second half of the month, compared to the results presented in Section 3.3.

Whether this means that the current tariff is sub-optimally designed, and what the optimal pricing of the distribution of electricity would be, is beyond the scope of this paper. In particular, that analysis would require detailed information about the firm's cost structure. However, it seems likely that the firm would want the incentives to apply uniformly throughout the month, and that, assuming that peak demand is costly, the firm not only wants to reduce the global peak but peak demand more generally. For any pricing scheme based on the maximum consumption, m will necessarily increase with the number of peak time periods and the proportion of hours with $q > m$ will decrease monotonously throughout the month.

To avoid this feature, firms could instead charge households based on some quantile of the distribution of a household peak time consumption instead of the maximum. Intuitively, if m is some quantile; say, the 95^{th} percentile, the proportion of hours with $q > m$ will not decrease as much over time, which in

Table 6: First and second-stage results, 2SLS, end of month (day> 15)

	q, W		q and m,W	
	Coef.	Std. err.	Coef.	Std. err.
First stage				
$\mathbb{P}[q_t > m_t]\|q_{t-\tau}, q_{t+\tau}$	0.337	0.000		
$\mathbb{P}[q_t > m_t]\|q_{t-\tau}, m_{t-\tau}, q_{t+\tau}, m_{t+\tau}$			0.342	0.000
Temperature (celsius)	-0.001	0.000	-0.002	0.000
F-value	3.5e+05		3.6e+05	
Second stage				
ln(price)	-0.032	0.000	-0.066	0.001
Temperature (celsius)	-0.033	0.000	-0.033	0.000
HH FE	Yes		Yes	
Time FE	Yes		Yes	
N	21,449,635		21,449,635	
Anderson-Rubin Wald test:	F(1,20771032)=19135.73		F(2,20771031)=11930.67	
Stock-Wright LM statistic:	Chi-sq(1)=19119.64		Chi-sq(2)= 23835.86	

Note: i) $\mathbb{P}[q_t > m_t]|q_{t-\tau}, q_{t+\tau}$ refers to the probability of $q > m$ given the consumption in the month before, $q_{t-\tau}$, and the next month, $q_{t+\tau}$. $\mathbb{P}[q_t > m_t]|q_{t-\tau}, m_{t-\tau}, q_{t+\tau}, m_{t+\tau}$ refers to the probability of $q > m$ given the consumption in the month before, $q_{t-\tau}$, and the next month $q_{t+\tau}$, and given the value of m in the previous month, $m_{t-\tau}$, and next month, $m_{t+\tau}$. ii) All specifications are estimated using the Stata command `ivreghdfe` using the `absorb` option and the approach detailed in Wooldridge (2010). Estimation time approximately 20 min. iii) Anderson-Rubin Wald test and Stock-Wright LM statistic refers to weak instrument test of joint significance of endogenous regressors in main equation (Ho: $\beta = 0$ and orthogonality conditions are valid)

Table 7: Bunching results, end of month (day> 15)

m	$\mathbb{P}^+ - \mathbb{P}^-$	Ln α	G α	Saez α	N
3	0.012	0.021	0.032	0.108	202,164
3.5	0.012	0.016	0.022	0.119	174,199
4	0.012	0.013	0.017	0.125	163,365
4.5	0.011	0.012	0.016	0.073	178,446
5	0.010	0.012	-0.010	0.077	202,613
5.5	0.008	0.009	0.011	0.068	213,936
6	0.007	0.008	0.010	0.071	212,344

Note: i) Ln α refers to the bunching estimator when η is assumed to follow a log-normal distribution ii) G α refers to the bunching estimator when η is assumed to follow a gamma distribution iii) Saez α refers to the Saez-type of bunching estimator

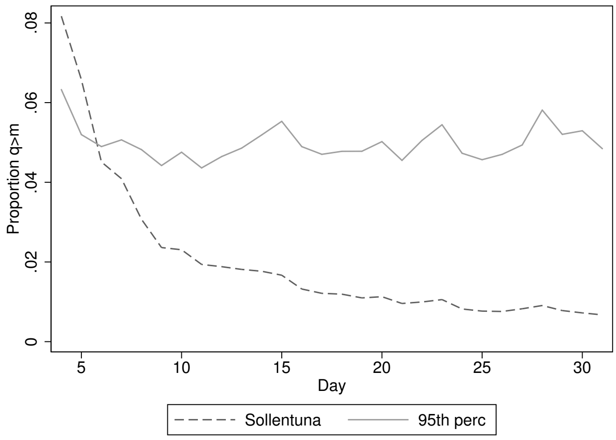


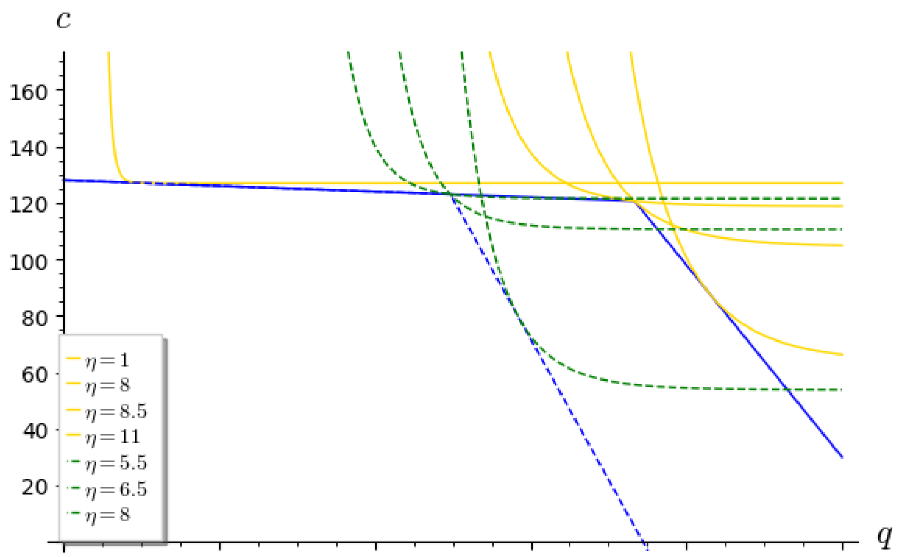
Figure 7: Comparison between the Sollentuna (maximum) tariff and an alternative tariff based on the 95th percentile.

turn implies that the marginal incentives for the households remain relatively constant throughout the month. This is illustrated in Figure 7 for our sample, where we compare the proportion of hours with $q > m$ for the Sollentuna tariff and a hypothetical tariff where m is set (approximately[26]) to the 95^{th} percentile of the hourly peak consumption during the month instead of the average of the three hours with highest consumption. Evidently, for the 95^{th} percentile tariff, the probability that the incentive bites is almost constant after day 5, so that the marginal incentives exist even at the end of the month. Results are similar for other percentiles.[27]

For a given level of κ, the 95^{th} percentile will leave the firm with smaller revenues, because the household is paying for a smaller quantity: the 95^{th} percentile instead of the max. However, it seems likely that the firm would wish to keep its revenue fixed. Hence, it will increase κ to compensate for charging based on a smaller quantity (i.e., the 95^{th} percentile is smaller than the max). Whether or not the firm increase κ, the tariff based on the 95^{th} percentile will result in a dead weight loss for the household, relative to the tariff based on the maximum, because the household is forced to consume less electricity, all else equal. This is illustrated in Figure 8, where we compare the Sollentuna tariff to the 95^{th} percentile. We have used the same parameter values as in Figure 3.2, but have have increased κ slightly (from 3 Euro to 4.5 Euro) to keep expenditure fixed across the two tariffs. Evidently, the 95^{th} percentile tariff

[26]This is only approximate, since the actual procedure which determines m in each period adapts to the actual household consumption. We use the simple adaptive scheme: $m_t = m_{t-1} + \left\{19\mathbf{1}[q_t > m_{t-1}] - \mathbf{1}[q_t <= m_{t-1}]\right\} \frac{1}{\texttt{scale}(t)}$ where t indicates the position of the peak hour, $\texttt{scale}(t)$ is a known function which depends on t only. To generate the figure, we use $\texttt{scale}(t) = 2.5t$. This simple adaptive scheme is markovian like the procedure which determine the maximum consumption so far. Feldman and Shavitt (2007) study a similar approach to calculate the median in more detail.

[27]Of course, even with this alternative design, households' price responsiveness may still vary during a month. For example, the cost of responding (e.g., in terms of effort) may vary throughout a month, or it may be easier to keep track of consumption in the beginning of the month.



Note: The budget constraint for the Sollentuna tariff (solid line) and the indifference curves are drawn as in Figure 3.2. The budget constraint for the 95th percentile tariff is drawn for prices $p = 1$, $\kappa = 49$ and $y = 400$.

Figure 8: Budget constraint and indifference curves

leads to a welfare loss (as is illustrated by the green indifference curves) for the household, compared to the Sollentuna tariff, because the budget set is smaller. The exception to this is if households are faced with very small shocks to consumption; small enough shocks for the tangency point to be to the left of the kink. However, such small shocks are very unlikely, according to our estimates of the distribution of shocks.

5 Conclusions

In this paper, we measure households' response to demand charges for distribution of electricity. Using unique Swedish data on hourly consumption for households faced with a mandatory demand charge tariff, we estimate the price elasticity of electricity using two separate empirical approaches; an instrumental variables approach and a bunching approach. We claim that this data is useful for identifying this price elasticity, i) because of the very large marginal incentives households face, ii) because there is no self-selection into the tariff, and iii) because of the non-linearities in the tariff that allows us to use a bunching approach to estimate the price elasticity. The results from either empirical approaches illustrates that electricity demand is inelastic, more so that the previous literature suggests, and this is despite the large marginal incentives households face. As far as we are aware, this is the first paper to measure the price elasticity for households on such demand charges, and the paper contributes to the developing literature on non-linear distribution pricing by extending previous descriptive analysis with a more formal analysis of consumer behavior. From the firms' perspective, the fact that price responsiveness is small means that implementation of demand charges are unlikely to lead to large changes in peak demand. On the other hand, it may be the case that even small changes to peak demand reduces firms' cost. This is an obvious suggestion for further research.

Next, we also evaluate whether information available to households affects this price responsiveness. Specifically, we use data on frequency of usage of the firm's website, where households can access detailed information about their electricity consumption. We find no effect of such information. Policy makers have recently stressed the importance of information in order to elicit more demand response, for example through regulations on mandatory provision of information. Our results indicate that such efforts have little effect on behavior.

Finally, we illustrate that charging based on the maximum consumption during peak period does not guarantee that incentives apply uniformly during peak hours, because the maximum consumption will be relatively large towards the end of the month and therefore less likely to be exceeded, which in turn means that households can care less about exceeding this threshold. This leads to weaker incentives towards the end of the month. An alternative approach is to charge based on percentiles of peak hour consumption. This result should be of interest both to firms that already implement demand charges, but also to firms currently considering implementation of similar pricing schemes.

From a policy perspective, the results presented in this paper are important, especially given the recent interest in demand flexibility, where households adjust their electricity consumption to the availability of electricity. Our results are in line with some of the recent literature on this topic (e.g., Allcott (2011b)), illustrating that households are inelastic in the short run, with a price elasticity close to zero. Most importantly, we illustrate that the response to prices is small, even when households are faced with very large marginal incentives (as could be the case in the future, with electricity retail prices that are more variable as the share of intermittent generation increases). While the response may be larger in the long run, our results indicate that alternatives to non linear pricing rules of the kind we study here are needed in order to reduce peak demand.

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Appendix A Data

The data used in this paper originates from the customer database of the Swedish distribution firm Sollentuna Energi (see `www.seom.se`). The source material has been anonymized and identification of households is not possible. This dataset is owned by Sollentuna Energi, and Sollentuna Energi has released the data to us under many conditions: The database shall be used solely for research, exclusively and solely by us, and with an explicit instruction regarding not sharing the database with any third party without permission from Sollentuna Energi. We have signed an undertaking to this effect prior to obtaining the data. As a result, we are unable to provide the dataset to other researchers. For further information, please contact the authors.

Appendix B Regression details

As explained in, for example, Heckman (1978) and Wooldridge (2010), there are no special considerations in estimating Equation 10 by 2SLS when the endogenous variable is binary. However, Wooldridge (2010) show that using a three-stage approach improves efficiency (Chap. 24.1, pp 937 in 2nd ed.). First, a logit model is estimated for the probability $\mathbb{P}[q > m]$ using the lead and the lag of q (i.e., $q_{t-\tau}$ and $q_{t+\tau}$) as regressors in addition to the other exogenous variables. We can then use the predicted probabilities from this model to replace $\mathbf{1}[q_t > m_t]$ in Equation 8 to get

$$\hat{r_t} = \mathbb{P}[q_t > m_t]\kappa_t + p_t \tag{17}$$

which then can be used as an instrumental variable for the endogenous price in a 2SLS model.[28] The 2SLS standard errors are asymptotically valid (Wooldridge, 2010).

Appendix C Bunching histograms

[28]Obviously, when estimating the logit model on the full data (that is, both peak and off-peak hours), the hour fixed effect for off-peak hours will predict the outcome perfectly (because households always only pay p in these hours), and these observations will be dropped from the estimation. For off-peak hours, we therefore manually set $\hat{r} = p$ (remember that the endogeneity is introduced by q, and that p, in line with previous literature, can be assumed to be exogenous to the individual household). In essence, this only reflects the fact that the pricing scheme only is non-linear, and hence endogenous, during peak hours. Alternatively, we can estimate the 2SLS model only for peak hours, and we find that results are similar.

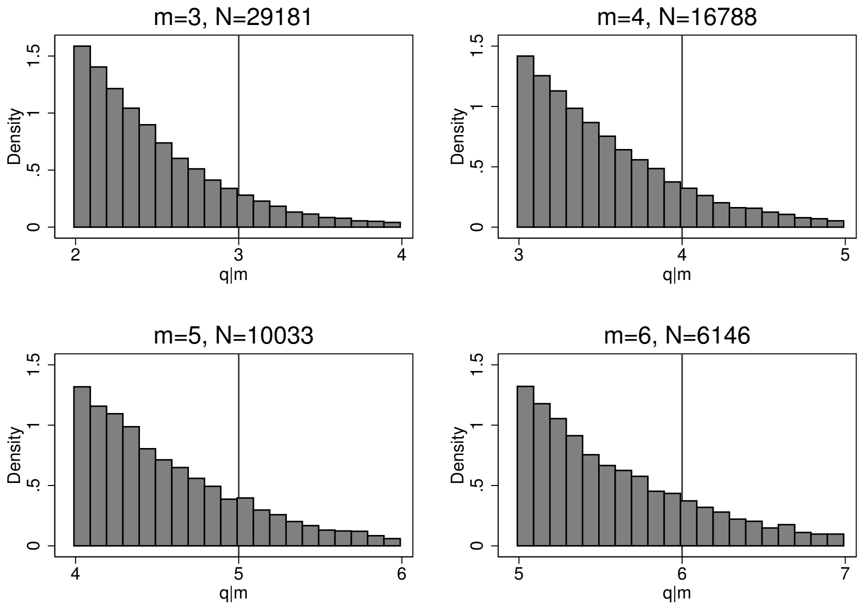

Figure 9: Zoomed-in distribution of q, conditional on m, end of month, evening hours

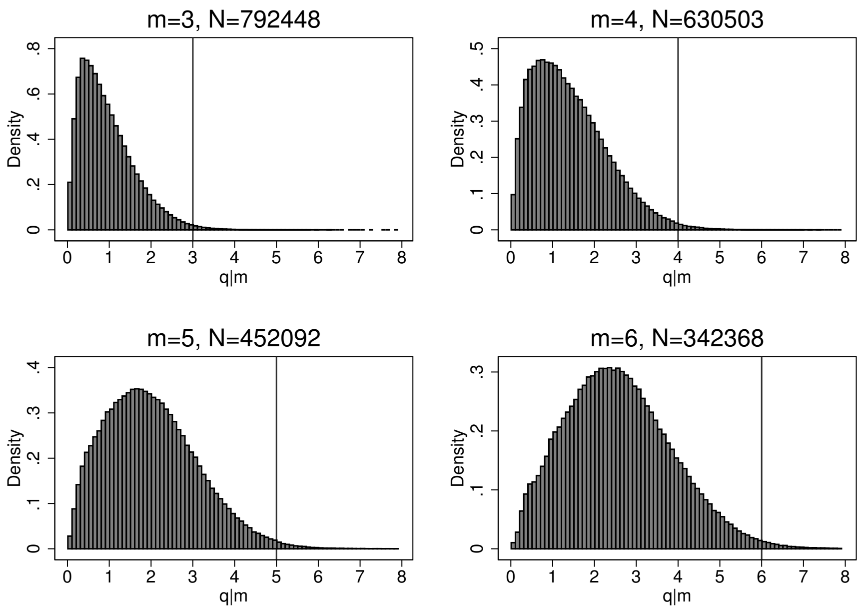

Figure 10: Distribution of q, conditional on m, end of month

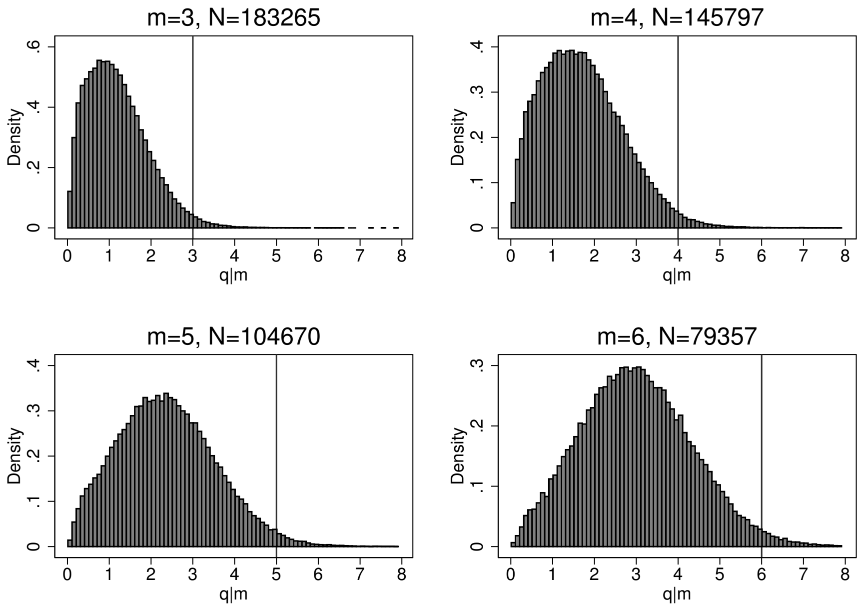

Figure 11: Distribution of q, conditional on m, end of month, evening hours