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Peak and off-peak demand for electricity: subsistence levels and price elasticities

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Abstract
In this paper, we explore subsistence levels and price elasticities for residential electricity demand in Sweden. Using a Stone-Geary functional form and unique Swedish data on residential electricity usage, we estimate demand Equations for peak and off-peak demand. We find that the subsistence levels are larger during peak than off-peak, and that there is a substantial variation in these subsistence levels across months. As a result, price responsiveness varies across hours and seasons. This has important policy implications, not the least with respect to effects of real time pricing, as it suggests that there are limits to households' price responsiveness.

Keywords: Dynamic price, Structural modeling, Stone Geary, Real time pricing

1. Introduction

The objective with this study is to estimate subsistence levels and price elasticities of residential electricity consumption for peak and off-peak demand. In particular, we illustrate how residential electricity demand can be described as consisting of two parts; a subsistence part and a

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supernumerary part, and where only the latter is responsive to changes in price and income. This feature of electricity demand may be an important explanation to the observations in previous empirical literature that electricity demand in Sweden and elsewhere is price inelastic (e.g., Andersson (1997), Damsgaard (2003), Brännlund (2007), Krishnamurthy and Kriström (2015), Labandeira et. al. (2017)). In addition, the paper provides structural estimates of conditional peak and off-peak price elasticities for Swedish households. Furthermore, we illustrate how subsistence levels and elasticities vary across the time of day and seasons.

Such estimates are of necessity if we want to analyze the effects of various policies and pricing schemes for electricity, and allows policy makers and other stake-holders to understand not only how aggregate electricity usage change in response to prices, but also how usage patterns within a day will change. This may, for example, be used to understand effects of dynamic pricing of electricity. As far as we are aware, there are only few such estimates provided in previous literature, and in particular, no previous estimates of subsistence levels nor peak and off-peak elasticities are available for the Nordic or the Swedish context.

2. Background and previous literature

The underlying motivation for studying this is that in Europe, and elsewhere in the world, electricity markets are being subject to major transformations that may cause considerable stress on electricity systems. These transformations may be explained by three key factors; (1) deregulation of electricity markets, (2) new technologies with respect to generation, distribution and use, and (3) substantial changes in the production mix as a result of energy and climate policy, as well as changes in relative production costs for different technologies. As a result, this may lead to more volatile prices and possibly to less secure electricity supply with more frequent power interruptions. These quite fundamental changes, in combination with a relative rigid demand side that is characterized by regular daily and seasonal use patterns, and with consumers that are not exposed to the momentarily marginal generation cost, have raised concern of security of supply related to resource adequacy. As a result of this concern, there is an ongoing discussion of whether energy-only markets, which are the most common market design, have to be complemented with some kind of capacity mechanism to ensure generation capacity in peak periods (Joskow, 2008a, 2008b, Newbery, 2016).

Related to this is also the discussion of demand management and demand flexibility, which in turn is closely related to the discussion of incentive mechanisms facing households. It is argued that incentives for demand flexibility are lacking as a result of the fact that most households in Sweden (and in many other electricity markets) face prices that are fixed over rather long periods, and therefore does not reflect the availability of electricity (Broberg and Persson, 2017, Broberg et. al. 2017). Because of this, hourly pricing of electricity has lately seen increased interest from policy makers (for the Swedish context, see, for example, Energimarknadsinspektionen, 2017).

Previous literature on dynamic pricing typically finds substantial welfare gains from introducing hourly pricing of electricity, which is assumed to incentivize households to shift consumption from peak to off-peak hours (Borenstein, 2006, Kopsakangas-Savolainen and Svento, 2012). However, these simulation studies are often assuming that i) households are price responsive, and ii) the price elasticity is constant across hours. However, these assumptions may be overly optimistic. Concerning price responsiveness, there are several factors that may contribute to the weak sensitivity of electricity consumption to price changes that are found in the empirical literature. This includes the fact that electricity is a necessity to modern life, and that some of the electricity usage should be thought of as subsistence consumption, and therefore is completely inelastic (Sanford and Savvides, 1983, and Poyer et. al.,1997). For example, households may need a minimum amount of electricity for heating, cooking and lighting, and therefore use this minimum amount irrespective of prices. Obviously, such subsistence levels may vary within a day, across months, and between households. For example, the subsistence level is expected to be higher during hours when household members are at home (peak hours) than during hours when they are not at home (off-peak hours). As a consequence, if a large share of total consumption is subsistence consumption, then the short-run effects of dynamic pricing (or other pricing policies) will not necessarily have any substantial effect on electricity consumption or load shifting between peak and off-peak. Rather, the effects of dynamic pricing may be realized in the long run, with peak prices providing incentives to invest in energy efficiency to reduce costly subsistence demand, i.e., energy conservation rather than load shifting.

For the supernumerary part of electricity demand, household's response to prices may very well vary within a day, and this may be true both for households on dynamic pricing contracts as well as for households on the more common type of contracts with prices varying by month or by year.

The intuition is the following; Electricity demand should be characterized as a derived demand, where households receive utility from services produced with electricity as an input. Specifically, households use electricity to heat their house when it is cold, cook dinner after work, light their home when it is dark, and watch TV to relax in the evening. Because the utilization of end-uses varies over the day, electricity usage will also vary. An increase of the electricity price will then likely lead to an adjustment of the utilization of appliances and end-uses, where some end-uses may be easier to adjust than others. For example, it may be easier for households to reduce stand-by consumption when they are away from home than it is to reduce the electricity used for essential services such as cooking dinner when they are home, or heat the house. On the other hand, when households are at work and away from home, they may have little possibilities to respond to any price variations, and may use little electricity to begin with, compared to when they are at home and use more electricity.

To summarize, the short-run response to monthly price variation most likely varies within a given day, where households start by reducing the electricity during hours when the marginal utility of electricity consumption is small, and/or the cost of adjustment is small. To that affect, one may view the analysis in this paper as estimates of how within-day load patterns differ across different price levels, which is of importance for understanding many price-driven policies in general.

Empirical analysis of electricity demand has typically been using aggregate data to understand residential price responsiveness; see, for example, Fell et al. (2014). For the Nordic market, see, e.g., Andersson (1997), Damsgaard (2003), Brännlund (2007), and Krishnamurthy and Kriström (2015) for Sweden. In most of these and other studies, residential electricity demand is typically found to be inelastic. Previous literature on hourly residential demand is sparse, mostly explained by lack of data, but there are a few exceptions. Filipini (1995), using Swiss data on residential demand under time-varying prices, finds the price elasticity to be higher during off-peak than during peak. Allcott (2011) explores household's response to hourly prices in the US, and finds that household's response to real time pricing varies between hours, and that households are the most price elastic during peak hours. Furthermore, Bigerna and Bollino (2014) find price elasticities to vary across hours, with an estimated elasticity of -0.35 during night hours and -0.7 during day time. Knaut and Paulus (2016) finds demand response to be biggest during early morning hours and late evenings. See also, for example, Aubin (1995) and Faruqui and Sergici (2010).

Our paper adds to this previous literature in several ways. First, we are, as far as we are aware, the first to estimate subsistence levels of electricity consumption for peak and off-peak at the household level. Second, and as far as we are aware, we provide the first estimates of peak and off-peak demand response for households on non-dynamic pricing contracts. Not the least the latter is in our opinion an important contribution, because estimates based on small samples of households choosing real-time pricing contracts may suffer from selection bias if these households differ from the rest of the population. In contrast, our sample may be viewed as a random sample.

The rest of this paper is structured as following. In the next Section, we describe the economic model we use in this paper. Section 4 provides a description of the data used, as well as a description of the empirical approach. The empirical results are presented in Section 5, and Section 6 contains a discussion and concluding comments.

3. Economic model

Instead of aggregating the demand across hours to, e.g., monthly demand (as is typically the case in the previous literature), the approach here is to formulate separate demand functions for peak and off-peak. This allows parameters to differ across hours, which then provide a much more detailed exploration of electricity demand and price responsiveness over time (within a day).

The empirical model in this study departure from the reasonable assumption that households receive utility from the services that electricity produces, such as light and heat, as well as consumption of other goods. Concerning electricity, a household gets utility u from a service s that uses q kWh of electricity and the level of energy efficiency as inputs. For example, the production of a service s in an average peak and off-peak hour, t = 1, 2 (ignoring household index i for notational simplicity) can be described by a production function:

$$s = f(q_t, \kappa), \qquad (1)$$

where κ is the energy efficiency of appliances. We assume for simplicity that for each unit of electricity, the household can produce κ units of s. Normalizing $\kappa = 1$, we have $s_t = q_t$. Furthermore, we assume that households' utility is weakly separable, which in this case means that the household allocates a fixed budget for electricity per day to the peak and off-peak periods. The budget for electricity, in turn, given the separability assumption, is decided in a previous budgeting stage where the household allocate its income on electricity and other consumption goods. The resulting demand functions for peak and off-peak electricity can then be viewed as conditional demand and, as such, short-run demand functions. We argue that the separability assumption is a reasonable assumption and that the resulting demand function therefore may provide a reasonable picture of short-run demand.[3] Given this, and that utility can be represented by a Stone-Geary utility function, the household's optimization problem is:

$$\max_{q_1,q_2} U = (q_1-\gamma_1)^{\beta_1}(q_2-\gamma_2)^{\beta_2} \quad s.t. \;\; p_1q_1 + p_2q_2 = y \tag{2}$$

where q_1 and q_2 is electricity consumption in an average peak and off-peak hour, respectively, p_1 and p_2 are the corresponding prices, and y the total expenditure on electricity during a day. γ_1 and γ_2 are subsistence, or minimum, levels of consumption in each period, and β_1 and β_2 are preference parameters revealing the allocation between periods of the supernumerary ("left over") expenditure.

This particular utility function allows for non-constant price elasticities and it considers electricity consumption as consisting of two components: a fixed (in the short run) subsistence quantity that cannot be adjusted immediately after a price change, and a residual quantity that can adapt instantaneously. This specification, rarely used in studies related to electricity demand[4], has the advantage of being theory-compatible, intuitively appealing, as well as explicitly modelling a threshold below which electricity consumption is non-responsive to price changes. Specifically, the utility function in Equation (2) implies that households first satisfy the subsistence levels of

[3] Whether or not weak separability is an appropriate assumption is a pure empirical question that we don't test for in this study. However, multi-stage budgeting has been used in electricity demand estimation previously, see, e.g., Atkinson (1979), Caves and Christensen (1980) and Mountain and Lawson (1992).

[4] Sanford and Savvides (1983) and Poyer et. al. (1997) appears to be two exceptions. However, Stone-Geary functional forms has been used quite extensively in the empirical literature on water demand (see, among others, Dharmaratna and Harris, 2012)

consumption, and then allocate the remaining budget, the supernumerary expenditure, according to their preferences, conditional on prices and total expenditure.

Solving for q_1 and q_2 in Equation (2) gives us the peak and off-peak demand functions as:

$$q_t = \gamma_t + \frac{\beta_t}{p_t}(y - \gamma_t p_t - \gamma_\tau p_\tau), \quad t = 1,2 \quad \tau \neq t \tag{3}$$

where y is the expenditure on electricity in a given day.

Following, e.g., Pollack and Wales (1981), Martinez-Espineira and Nauges (2004) and Gaudin et. al. (2001), we allow the subsistence levels of consumption to vary across households by assuming a linear relationship between γ and a vector $\mathbf{z}$ of observable household characteristics, i.e.,

$$\gamma_t = \alpha_t + \delta_t \mathbf{z}_t, \quad t = 1,2 \tag{4}$$

Finally, we note that for the case of Sweden (and most other electricity markets), the vast majority of households faces electricity contracts where prices are fixed across hours. Given this, the demand for electricity can be written as:

$$\begin{aligned} q_t &= (\alpha_t + \delta_t \mathbf{z}_t) - \beta_t(\alpha_t + \delta_t \mathbf{z}_t) - \beta_t(\alpha_\tau + \delta_\tau \mathbf{z}_t) + \frac{\beta_t}{p_t} y \\ &= \zeta_t + \mu_t \mathbf{z}_t + \frac{\beta_t}{p_t} y, \quad t = 1,2 \quad \tau \neq t \end{aligned} \tag{5}$$

where

$$\zeta_t = \alpha_t - \beta_t \alpha_t - \beta_t \alpha_\tau$$
$$\mu_t = \delta_t - \beta_t \delta_t - \beta_t \delta_\tau$$

The fact that prices are constant across the peak and off-peak period introduces an identification problem. Specifically, the structural parameters in Equation (5) cannot be identified when the restriction of adding-up of budget shares is imposed (i.e., $\beta_1 + \beta_2 = 1$). Further, if only one Equation (e.g., peak demand) is to be estimated, some assumptions has to be made regarding the subsistence level in the other time-period (off-peak demand). We solve this problem by assuming that some of the parameters of the system of Equations are the same in both peak and off-peak time periods. In particular, we assume that some of the elements in μ are identical in both peak and off-peak, and others are set to zero for off-peak. It is then sufficient to estimate the demand Equation for peak demand and subsequently computing the off-peak subsistence level from a subset of the estimated parameters from the peak demand Equation.

Given the demand functions in Equation (3), the price and expenditure elasticities are: [5]

$$e_{tt}^{p} = \frac{-\beta_t\left[1-\left(\sum_{j=1}^{2} p_j\gamma_j - p_t\gamma_t\right)/y\right]}{S_t}, \quad t=1,2$$

$$e_t^{y} = \frac{\beta_t}{S_t}, \quad t=1,2 \tag{6}$$

$$S_t = \frac{p_t q_t}{y}$$

In particular, note that the specification of the subsistence parameters in Equation (4) provides a theoretically consistent and intuitive way of allowing for price elasticities to depend on household characteristics. Further, note that the elasticities are negative and non-constant. In particular, an increase in the own-price implies that the price elasticity decreases (in absolute value), as shown in Equation (7). Similarly, if the subsistence levels increase, the own-price elasticity goes towards zero as demonstrated in Equation (8).

$$\frac{\partial e_{tt}^{p}}{\partial p_t} = \frac{(\beta-1)\beta\gamma_t(\gamma_j p_j - y)}{(\gamma_j\beta p_j + \beta\gamma_t p_t - \beta y - \gamma_t p_t)^2} \geq 0, \quad t=1,2, \quad j\neq t \tag{7}$$

$$\frac{\partial e_{tt}^{p}}{\partial \gamma_t} = \frac{(\beta-1)\beta p_t(\gamma_j p_j - y)}{(\gamma_j\beta p_j + \beta\gamma_t p_t - \beta y - \gamma_t p_t)^2} \geq 0, \quad t=1,2, \quad j\neq t \tag{8}$$

[5] Note that this expenditure elasticity refers to the change in quantity consumed as the share of income spent on electricity changes.

4. Data

The unique data we are using for estimating the parameters in Equation (5) originates from a metering project commissioned by the Swedish Energy Agency between 2005 and 2008. We provide a brief overview of the data here, and refer the reader to the Energy Agency's report (Zimmermann, 2014) and previous research in Vesterberg and Krishnamurthy (2016) and Vesterberg (2016) for further details. The Energy Agency's purpose of gathering this data was to increase the quality of data on residential electricity consumption, and to assess the potential for energy conservation and increasing energy efficiency. In total, 389 households, sampled by Statistics Sweden, had metering equipment installed on most electrical appliances in the household, which metered electricity usage at the ten-minute level. Here we aggregate the data into average peak and off-peak hours, where peak hours are defined as 4 pm to 9 pm (electricity usage is expected to be high when households typically are home after work) and off-peak as the remaining hours (electricity usage is expected to be small when households are at work, or at sleep). Swedish breakfast is by tradition cold, so electricity usage is expected to be relative low during morning hours. Therefore, morning hours are also classified as off-peak hours. See Vesterberg and Krishnamurthy (2016) for a detailed description of how residential electricity demand varies within a day.

Two hundred of the metered homes were detached houses, and the remaining 189 were flats. We focus exclusively on detached houses during working days in this study, as these households typically are the most interesting from a policy perspective. Each household was metered for between 15 days and 16 months, with a majority of the households observed for one month. Because prices are constant within a month, this means that the price responsiveness is identified across households (i.e., no within-household price variation for most households), and we are therefore unable to control for household-level fixed effects. In addition to the metering data, data was collected on household characteristics such as (monthly) household income, number of household members, size of living area, household type, and main heating system. Further, each household had individual meters recording both outdoor and indoor temperature.

Descriptive statistics of the metering data used in the estimation is described in Table 1. In general, there are no fundamental differences between the sample and the population (see Statistics Sweden, www.scb.se).

Table 1. Descriptive statistics of metering data.

Variable	**Mean**	**Std. Dev.**
Peak usage (kWh/hour)	1.90	1.28
Off-peak usage (kWh/hour)	1.50	1.07
Number of persons	3.28	1.08
Living area (m^2)	135.96	38.13
Electric heating (share)	0.60	0.49
Temperature (outdoor, °C)	8.53	7.32
Household income (SEK/month)	38799	11694

While the metering data is very detailed in terms of electricity usage and household characteristics, it unfortunately lacks any information about contract choice or household-level prices per kWh.[6] In the Swedish population, roughly 40 percent of the households have a so-called variable-price contract, with prices varying by month. Another 40 percent have a fixed-price contract, where the price is fixed for a year or longer. Most of the remaining households have a so-called default contract, which households automatically are assigned to if the household do not make an active choice of contract. Less than one percent of the Swedish households have hourly pricing of electricity (see Statistics Sweden, www.scb.se).

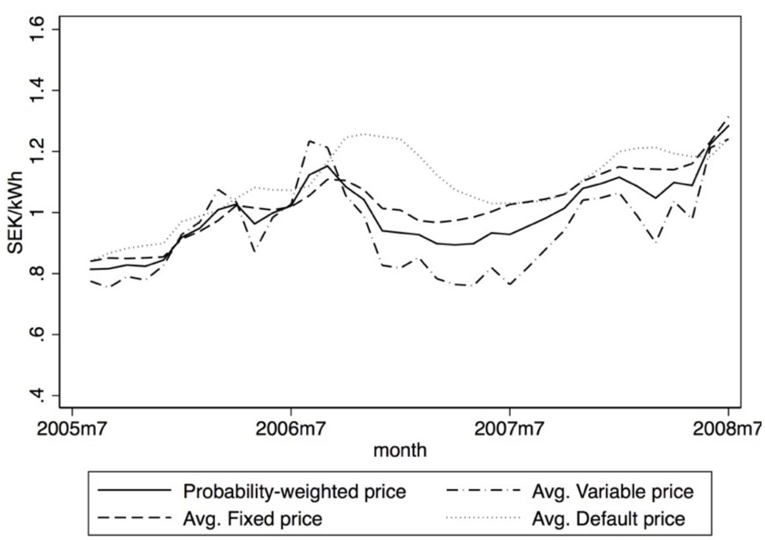
To solve the problem with missing household level price data, we use other information sources to estimate a probability weighted price for each individual household in the sample. This approach can be described as follows. Given that households can be on different contracts, the price in a given month for household *i* can be expressed as (omitting peak and off-peak indices for notational simplicity):

$$p_i = a_i p_i^{fix} + b_i p_i^{var} + c_i p_i^{def} \quad , \tag{9}$$

where p^{var} is the variable price, p^{fix} is the fixed price and p^{def} is the default price, and where *a*, *b* and *c* are indicator variables. That is, *a*, *b*, *c* = 1 if the household have a fixed price, variable price,

[6] This problem of unobserved prices is not unique to our data, but is relatively common in, for example, survey data, or data that is not collected by economists. Our methodological approach to solve this issue may therefore be relevant for other studies as well.

and default contract, respectively, and zero otherwise. The first step in our approach is then to estimate the indicator variables in Equation (9), (a, b, c), by using information from a Swedish survey (Broberg and Persson, 2015) that includes the same household characteristics as the metering data, but that in addition includes contract choice (details are provided in Appendix A). In the second step, we replace each of the prices in Equation (9) by average prices by contract type and household type, available from public data (see Statistics Sweden, www.scb.se). The resulting household specific price can then be thought of as a probability-weighted average price.[7] The average price development over time for each type of contract and the probability-weighted price for electrically heated villas are displayed in Figure 1. As can be seen, all prices are highly correlated, and the fixed price series have the lowest variance, as expected. Furthermore, it can be seen that probability-weighted price mimics the other prices well, on average. In particular, it should be noted that the prices for each type of contract are highly correlated over time (see Figure 1), which means that non-perfect information about contract type for each household should not bias the results to any larger extent.



Figur 1. Price variation across months for variable-price contracts, fixed-price contracts and the probability-weighted price for electrically heated villas.

[7] As far as we are aware, average prices over the entire population (i.e., average over all contract types) are unavailable from public data and elsewhere. Further, even if information about such price was available, we would have no variation across households.

5. Estimation and Results

The demand Equations for peak and off-peak are estimated using the least-square estimator. The vector **z** in Equation (5) includes the following variables for peak subsistence: Number of persons, size of living area, temperature, heating system (1 = electric heating, zero otherwise), an interaction term between heating system and temperature, and monthly dummies. Adding-up is imposed, and off-peak subsistence is estimated using the parameter estimates from peak subsistence but setting the coefficient for number of persons equal to zero (because people typically are away from home during these hours). Parameter estimates and associated standard errors are provided in Appendix B, Table B1, and the results are summarized below. In general, most parameters are precisely estimated and have the expected sign.

The estimates of the monthly subsistence levels for peak (γ_1) and off-peak (γ_2) are presented in Table 1. The columns marked "All" include all households, "Electric heating" refers to households with electric heating, and "Mixed heating" to households with non-electric heating[8]. Evidently, the subsistence levels are larger in peak than in off-peak, and also larger during winter months (e.g., November to March) than summer months (where they are insignificantly different from zero for most months), which is expected. To get a sense of magnitudes, the average peak subsistence during February, 1.11 kWh, is roughly half of the average usage per hour, and corresponds to using the oven for 30 minutes, or running the dish washer for 40 minutes (Broberg et. al. 2017). This can be compared with, e.g., June, when the peak subsistence level is insignificantly different from zero, and the average hourly peak demand is roughly 1.2 kWh.

Furthermore, it can be noted that subsistence levels are considerably larger for households with electric heating than for households with mixed heating, which is expected. In particular, households with electric heating require more electricity for a given indoor temperature, which intuitively relates to subsistence levels. Households with mixed heating, on the other hand, may substitute electric heating for other sources of heating, and therefore relies less on electricity to meet heating needs.

[8] Although these households do not have electric heating as their main heating source, they may still have some smaller electrically-powered heating sources. By comparison, households with electric heating has this as their only heating source.

Table 2. Subsistence levels for peak and off-peak, evaluated at the mean of data for each month. Standard errors in parenthesis are calculated by the delta method.

	All		Electric heating		Mixed heating	
Month	*Peak* (γ_1)	*Off-peak* (γ_2)	*Peak* (γ_1)	*Off-peak* (γ_2)	*Peak* (γ_1)	*Off-peak* (γ_2)
1 (Jan)	1.08 (0.12)	0.45 (0.05)	1.51 (0.13)	0.70 (0.06)	0.62 (0.12)	0.19 (0.05)
2	1.11 (0.12)	0.47 (0.05	1.59 (0.14)	0.74 (0.06)	0.59 (0.11)	0.18 (0.05)
3	0.98 (0.12)	0.40 (0.05)	1.26 (0.14)	0.55 (0.06)	0.56 (0.11)	0.16 (0.05)
4	0.73 (0.13)	0.26 (0.06)	0.91 (0.14)	0.37 (0.06)	0.43 (0.12)	0.09 (0.06)
5	0.54 (0.15)	0.15 (0.07)	0.64 (0.15)	0.21 (0.07)	0.36 (0.15)	0.04 (0.07)
6	0.22 (0.17)	-0.02 (0.08)	0.22 (0.17)	-0.01 (0.08)	0.23 (0.18)	-0.03 (0.09)
7	0.09 (0.18)	-0.09 (0.09)	0.05 (0.18)	-0.11 (0.09)	0.17 (0.19)	-0.06 (-0.10)
8	0.11 (0.18)	-0.08 (0.09)	0.07 (0.18)	-0.10 (0.09)	0.19 (0.19)	-0.05 (0.10)
9	0.41 (0.15)	0.09 (0.07)	0.48 (0.16)	0.13 (0.08)	0.30 (0.16)	0.02 (0.08)
10	0.67 (0.14)	0.23 (0.06)	0.84 (0.14)	0.33 (0.07)	0.42 (0.14)	0.09 (0.06)
11	0.85 (0.12)	0.34 (0.05	1.19 (0.13)	0.53 (0.06)	0.52 (0.12)	0.14 (0.05)
12 (Dec)	1.01 (0.12)	0.41 (0.05)	1.33 (0.13)	0.60 (0.06)	0.61 (0.12)	0.18 (0.05)

Concerning heterogeneity over households, Figures 2 to 4 show the distribution of peak and off-peak subsistence levels across the households in the sample. Figure 2 is for the whole sample, Figure 3 is the distribution for households with electricity heating, and Figure 4 for households with mixed heating.

Several interesting results are revealed from these Figures: First, the distribution for both peak and off-peak hours are slightly skewed to the right for households with mixed heating, but less so for households with electric heating. This may be explained by larger heterogeneity in heating sources among households with mixed heating (which may include electric heating in addition to, for example, a wood stove). Second, there appears to be a wider distribution in peak subsistence than in off-peak subsistence. The likely explanation is that there is larger heterogeneity in peak demand than in off-peak demand, for example in cooking and lighting.

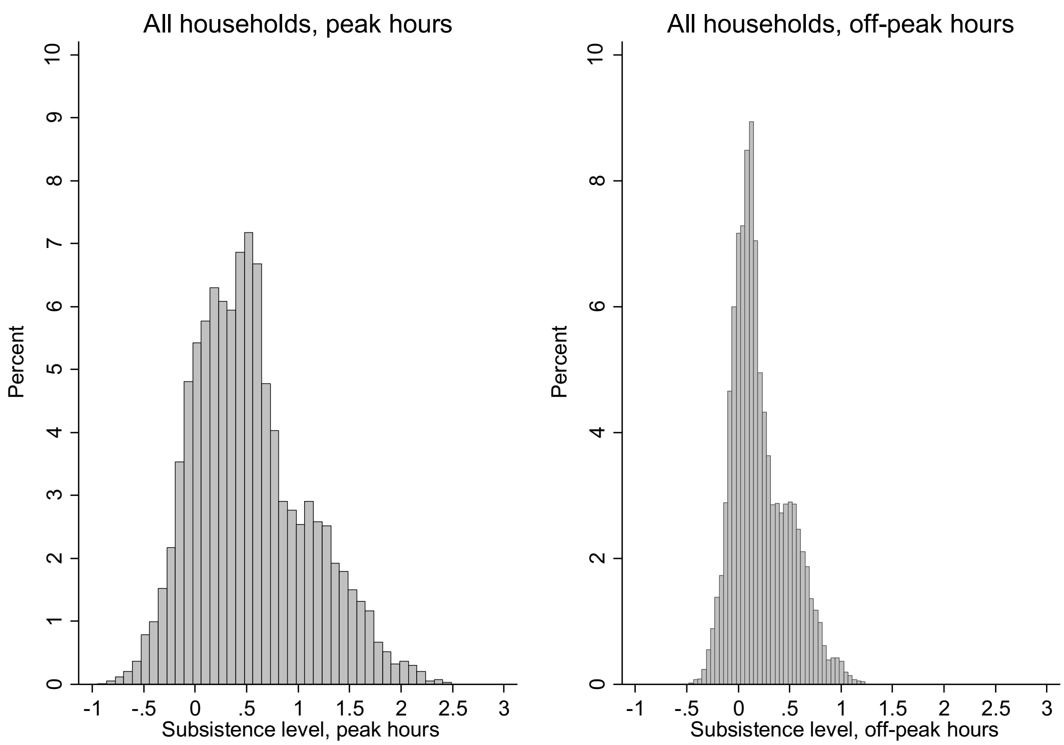


Figure 2. Distribution of subsistence levels, all households.

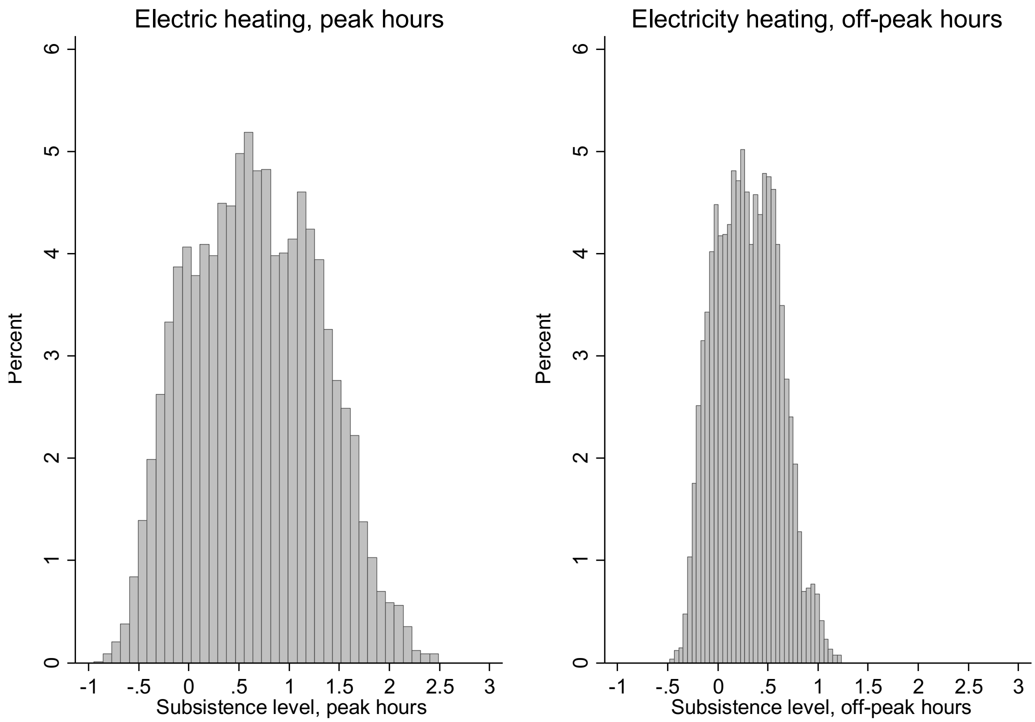


Figure 3. Distribution of subsistence levels, households with electric heating.

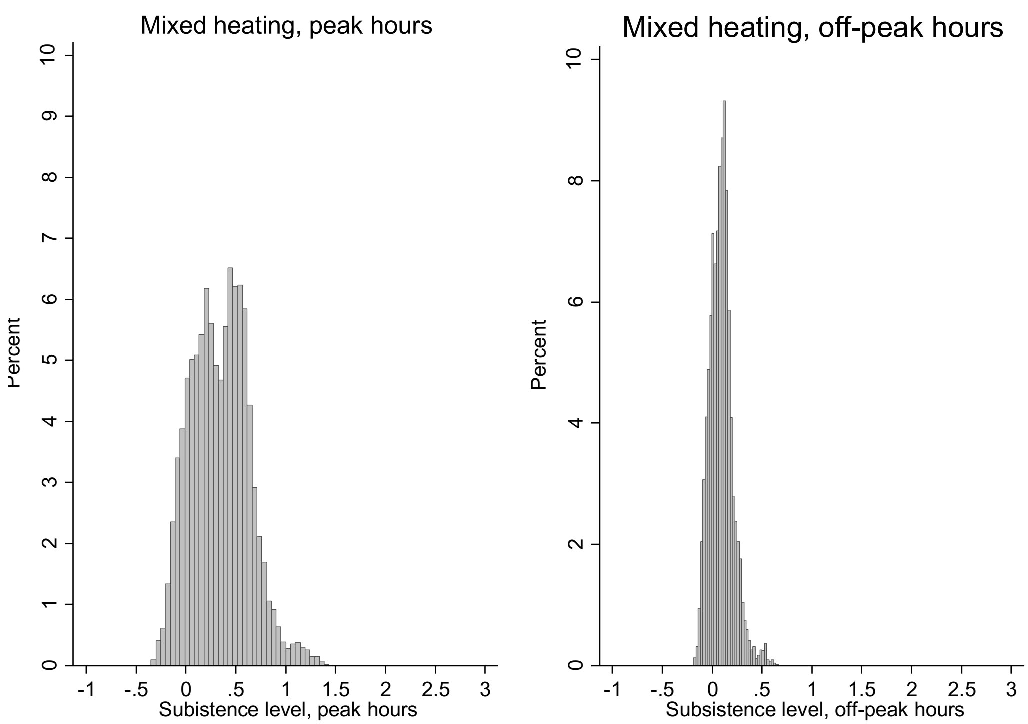


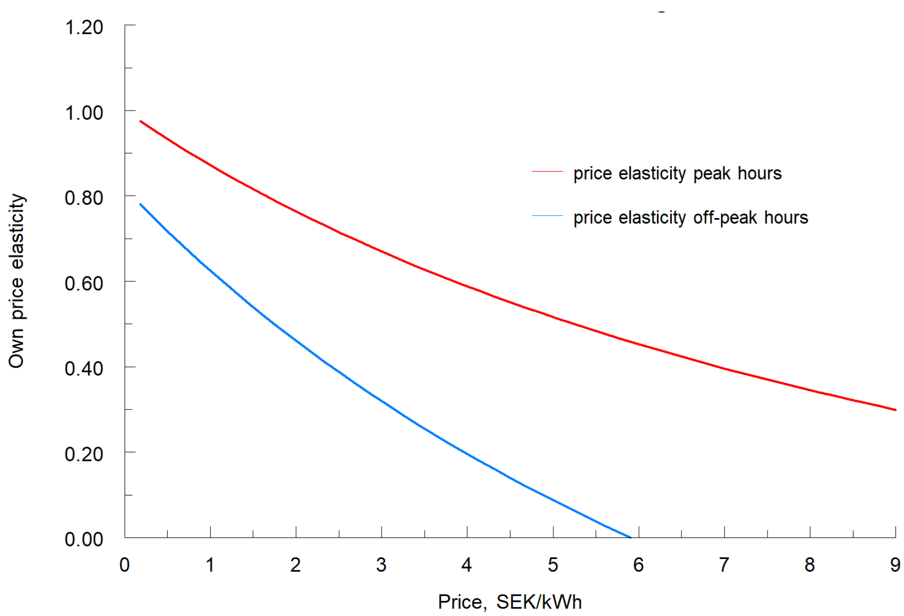
Figure 4. Distribution of subsistence levels, households with mixed heating.

The estimated price and income elasticities for peak and off-peak, respectively, are presented in Table 3. Starting with the elasticities for an average household in Table 3, we find price elasticities to be negative, and with point estimates ranging between -0.8 and -1.2. While these estimates are larger in absolute values than many previous estimates from reduced-form specifications, they are comparable in magnitudes to previous structural estimates (see, for example, Filipini, 1995). Further, we note that the elasticities for an average household are higher in absolute value during peak hours than during off-peak hours for almost all months, but that the differences are small. A plausible explanation to this is that even though households are away from home or at sleep during off-peak hours, and therefore cannot influence their electricity usage as much as when they are at home, households may adjust their off-peak consumption by, for example, turning off stand-by consumption. Further, we find rather similar elasticities across months, as well as across household types concerning heating system. Income elasticities are all positive and roughly equal to one, and only differs between peak and off-peak during winter months (although differences in general are very small).

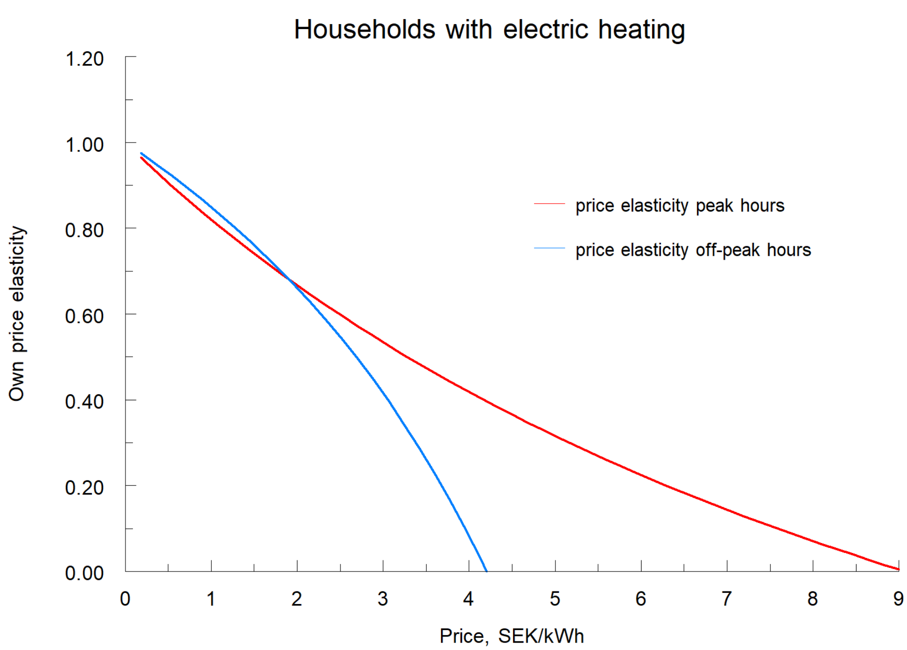
Table 1. Price and income elasticities (Standard errors in parenthesis).

	All households				**Electric heating**				**Mixed heating**			
Month	*Peak price*	*Off-peak price*	*Peak income*	*Off-peak income*	*Peak price*	*Off-peak price*	*Peak income*	*Off-peak income*	*Peak price*	*Off-peak price*	*Peak income*	*Off-peak income*
1	-0.89	-0.79	0.98	0.98	-0.90	-0.75	1.01	0.99	-0.89	-0.87	0.94	1.06
	(-0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)
2	-0.89	-0.86	0.97	0.97	-0.89	-0.86	0.99	0.98	-0.89	-0.86	0.95	1.06
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)
3	-0.94	-0.84	1.01	1.01	-0.94	-0.84	1.03	0.97	-0.94	-0.85	0.99	1.03
	(0.02)	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)
4	-0.95	-0.86	1.03	1.03	-0.95	-0.86	1.06	0.94	-0.95	-0.86	0.99	1.04
	(0.02)	(0.02)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)
5	-0.96	-0.84	0.98	0.98	-0.95	-0.83	0.99	1.00	-0.96	-0.84	0.98	1.01
	(0.03)	(0.03)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)	(0.04)	(0.04)	(0.00)	(0.00)
6	-0.98	-0.90	0.97	0.97	-0.97	-0.90	0.97	1.04	-0.98	-0.90	0.96	1.05
	(0.04)	(0.04)	(0.00)	(0.00)	(0.04)	(0.04)	(0.00)	(0.00)	(0.05)	(0.06)	(0.00)	(0.00)
7	-0.99	-0.94	0.97	0.97	-0.98	-0.94	0.98	1.02	-0.99	-0.94	0.95	1.06
	(0.05	(0.05)	(0.00)	(0.00)	(0.05)	(0.05	(0.00)	(0.00)	(0.06)	(0.07)	(0.00)	(0.00)
8	-0.95	-0.91	0.94	0.94	-0.94	-0.96	0.96	1.02	-0.95	-0.96	0.92	1.09
	(0.05	(0.05)	(0.00)	(0.00)	(0.04)	(0.05)	(0.00)	(0.00)	(0.05)	(0.06)	(0.00)	(0.00)
9	-0.93	-0.89	0.96	0.96	-0.94	-0.90	0.96	1.07	-0.95	-0.91	0.96	1.07
	(0.03)	(0.04)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)	(0.04)	(0.04)	(0.00)	(0.00)
10	-0.92	-0.89	0.96	0.96	-0.92	-0.89	0.97	1.06	-0.92	-0.89	0.96	1.05
	(0.02)	(0.02)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)
11	-0.90	-0.91	0.97	0.97	-0.90	-0.91	1.00	1.04	-0.90	-0.92	0.94	1.09
	(0.02)	(0.02)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)
12	-0.92	-0.87	0.99	1.02	-0.92	-0.88	1.01	1.01	-0.92	-0.88	0.97	1.06
	(0.01)	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)

The elasticities presented in Table 1 are evaluated for an average household and at the average price. As discussed previously, the elasticities derived from the Stone-Geary demand functions are non-constant, as can be seen in Equations (7) and (8). An illustration of how the own-price elasticities (in absolute value) vary across price levels, i.e., along the demand curves, is provided in Figures 5 and 6.



Figur 5: Price elasticities in absolute value across price levels, mixed heating



Figur 6: Price elasticities in absolute value, electric heating

Figures 5 and 6 reveals that the more we move up along the demand curve, the less responsive will the (average) household be to a price change. The reason, as discussed, is that as we move up along the demand curve the closer we get to the subsistence level, leaving less room for demand response. One immediate conclusion is then that if this change in demand response is not considered, we may overstate the overstate the effects of for example dynamic pricing.

5. Discussion and Conclusions

To design effective policies and pricing mechanisms, there is a need to understand residential electricity demand. In this paper, we provide novel insights to how households use electricity, and in particular, how subsistence levels and the responsiveness to prices vary between peak and off-peak hours. This have important implications for the scope for dynamic pricing, and suggest that previous results on welfare gains from real-time pricing are based on unrealistic assumptions about price responsiveness.

In more detail, using a structural empirical approach, we estimate the magnitude and variation of subsistence levels of household electricity use. The results reveal that the subsistence level is considerably higher during peak hours, and that it varies, both for peak and off-peak hours, considerably over the year. The average subsistence level for a household with electric heating in peak hours during the winter is approximately 1.6 kWh in January, but essentially zero in July. The interpretation of this is that the average household will respond to price changes in January as long as the electricity use is higher than 1.6 kWh, but not respond to a price increase when electricity use is at this level. In July, on the other hand, electricity use will respond to a price increase all the way down to zero use, reflecting that electricity is less of a necessity during the warm and light period of the year. It should be stressed that the subsistence levels vary significantly between households, as indicated in Figures 2 to 4.

Concerning the average price elasticities, the results show that they are fairly stable over the year, but that they differ between peak and off-peak hours. The price elasticity during peak hours is slightly above 1 (in absolute value), and slightly below 1 in off-peak hours. However, it should be noted these are the elasticities for an "average household" facing an average price. It should also be stressed that the elasticities are conditioned on a given daily budget for electricity, which means that it measures how households reallocate this given budget between peak and off-peak consumption. Concerning the income (expenditure) elasticities, the results reveal minor differences, both between months and between peak and off-peak hours. The elasticities are close to 1, which means that an increase in the budget for electricity with one percent will lead to an increase of electricity use in both peak and off-peak hours with approximately 1 percent.

To summarize, there is substantial variation in electricity demand within a day and for different periods of the year, which cannot be explained by price variation, but rather by differences in basic needs. For example, an increase in electricity price during peak hours in the winter will have an effect on electricity use, but that this effect will decrease substantially with a further price increase. As the price is reaching very high levels the effect on electricity use will go towards zero.

From a policy perspective, the results presented in this paper are something that should be taken into account both when designing and evaluating policies. For example, this may have important implications for the introduction of real time pricing in Sweden. The reason being the rather high subsistence levels for periods in time (over day and over year) in which we would expect the price to be high, i.e., during peak hours. In particular, the relatively large subsistence levels suggest that at least some of the response to hourly prices may be in the long run; through investments in energy efficiency in order to reduce subsistence levels, and not only through short-run load shifting as is typically envisioned in studies on real time pricing. Whether this leads to comparable welfare gains, as is typically found in previous literature is outside the scope of the current paper, but an obvious suggestion for future research.

Similarly, the finding that subsistence levels vary substantially across months also have important policy implications. Typically, demand response will be more valuable to the grid during winter months when demand is high and capacity is operating close to its maximum. However, the findings in this paper suggest that there will be relatively more response in summer months, when subsistence and price levels are low or even zero, compared to winter months. Again, this may have large implications for the hypothetical welfare gains from introducing dynamic pricing. Finally, the finding that price elasticities vary within a day and to some extent also across months is an important result, and suggest, for example, that the constant-across-time elasticities frequently assumed in simulation studies on dynamic pricing of electricity may be an overly simplified assumption.

Finally, the implications of the results presented in this paper is of course not limited to the introduction of dynamic pricing of electricity, but rather for all pricing policies for the electricity market, including energy taxes. Further, the subsistence levels may have implications for market efficiency. For example, if the subsistence level is large relative to total consumption, it may be easier for retailers to exercise market power, since households are unable or unwilling to respond to price changes. This is especially true if it is costly for households to switch retailer. To the extent this have implications for the Swedish context may also be an interesting extension for future research.

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Appendix A.

Details about the estimation of contract probabilities

The data used for estimation of determinants of contract choice consist of Swedish survey data collected via an internet panel, consisting of approximately 90,000 randomly recruited Swedes. The questionnaire was sent out to roughly 5900 people from this panel, and 918 of them responded within a week. In order to get a sample representative for the Swedish population the selection procedure considered a number of socio-economic factors, including age, gender, and geographic location. For a detailed description of this data, see Broberg and Persson (2015). In using this data for our purpose we have excluded households with missing observations on key variables and outliers, e.g., where number of persons living in the household is suspiciously large. This leaves us with a total sample size of 686 respondents in total from the survey data. Descriptive statistics of this data can be found in Table A1.

Tabell A1. Descriptive statistics.

	Mean	Std. Dev.
Household income (monthly)	42618	23668
Number of persons	2.16	1.1
Living Area	119	48.9
Electric heating (share)	0.49	
Mixed heating (share)	0.51	

Tabell A2: Parameter estimates, multinomial logit.

	Variable-price contract		Default contract	
	Parameter estimate	Standard error	Parameter estimate	Standard error
Household income	0.00	0.00	0.00	0.00
Number of persons	0.04	0.09	0.55	0.21
Living area	-0.06	0.00	-0.01	0.01
Mixed heating (1=yes)	0.33	0.25	1.47	1.87
Constant	-0.37	0.63	-17.09	18.75

Using this data, we estimate a multinomial logit model with contract choice (fixed-price contract, variable-price contract or default contract, with fixed-price contract as the reference) as dependent variable, and living area size, number of persons in the household, household type, household income and zip-code as independent variables. Estimation results is found in Table A2. Finally, we use the estimated parameters to make out-of-sample prediction on contract choice for the metering data.

Appendix B.

Parameter estimates for demand Equations

Tabell B1. Parameter estimates, demand Equations.

Variable	Parameter estimates	Std. Error
Living area	0.002	0.001
Temperature	-0.023	0.008
Temperature x Elec. heating	-0.056	0.006
Electric heating	0.924	0.072
Constant	0.027	0.035
Number of persons	0.070	0.005
February	0.007	0.029
March	-0.173	0.028
April	-0.282	0.030
May	-0.182	0.033
June	-0.179	0.038
July	-0.248	0.042
August	-0.189	0.043
September	-0.064	0.036
October	0.022	0.031
November	0.081	0.029
December	-0.012	0.029
β	0.552	0.001
Log-likelihood		-1822,400
Adj. R-squared		0,953
BIC		1907,980