

Residential end-use electricity demand and the implications for real time pricing in Sweden^{*}

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Abstract

Using a unique and highly detailed data set on energy consumption at the appliance-level for 200 Swedish households, seemingly unrelated regression (SUR)-based end-use specific load curves are estimated. The estimated load curves are then used to explore possible restrictions on load shifting (e.g. the office hours schedule) as well as the cost implications of different load shift patterns. The cost implications of shifting load from “expensive” to “cheap” hours, using the Nord pool spot prices as a proxy for a dynamic price, are computed to be very small; roughly 2-5% reduction in total daily cost from shifting load up to seven hours ahead, indicating small incentives for households (and retailers) to adopt dynamic pricing of electricity. Our results have important implications for Swedish energy policy, in particular for the Swedish government’s stated goal of real-time pricing.

JEL Codes: Q48, Q41, D12, C30

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1 Introduction

Driven by concerns involving, among others, capacity (and investment) constraints, environmental issues, and the need to balance intermittent renewable generation, there has been a renewed policy interest across the world in the efficient pricing of electricity. Given the specificities of the electricity market, the wholesale price of electricity varies substantially over the day; nonetheless, consumers have long been charged a fixed retail price. There is a long literature in economics arguing that the use of a price that better reflects the true cost of producing electricity on a more dynamic basis (e.g. an hourly price) will in theory give rise to substantial efficiency gains,¹ and a variety of “dynamic” or “real time” pricing (RTP) schemes have been proposed (but rarely implemented). These efficiency gains arise largely from a more efficient allocation of consumption, leading to a reduction in the need for costly peak capacity (see section 2 for details). Further, price-driven demand flexibility also has the potential to balance the variability of increased intermittent production, most notably wind (and solar) power.

However, evidence for the practicability of such a pricing scheme, and in particular the possibilities and incentives for households to respond to such pricing by shifting load from ‘expensive’ to ‘cheap’ hours, is rather scarce. Indeed, as documented in [Faruqui and Sergici \(2010\)](#), evidence is relatively mixed and depends upon a variety of factors. In general, the lack of relatively large samples of households on RTP schemes hampers evaluation of the demand reduction actually realized. Given that data on household behavior under RTP is scarce, one way of empirically exploring the practicability of RTP would be to compare the timing of current within-day electricity consumption (by households on non-dynamic-price contracts) with possible restrictions on substitutability, such as working hours and temperature variation.

These explorations are most useful with data at the appliance or end-use level, since substitutability will vary between appliances and end-uses; to illustrate, it might be easier to shift laundry within a day than to shift lighting, since use of lighting is to a

¹The literature on efficient pricing of electricity is vast; see, among the more recent studies, a survey in [Faruqui and Sergici \(2010\)](#), the study of [Allcott \(2011\)](#) (and references therein), and a slightly older review in [Aubin et al. \(1995\)](#). The readers are also directed to some of the simulation-based studies cited in section 2, including [Borenstein and Holland \(2005\)](#), [Borenstein \(2005\)](#) and [Kopsangas-Savolainen and Svento \(2012\)](#), among others.

large extent determined by available daylight. Further, estimates of current within-day consumption are necessary as a baseline for computing the cost savings of re-allocating load. Unfortunately, the data required for such analyses are rarely available and only a few studies (e.g., [Allcott \(2011\)](#); [Bartels and Fiebig \(2000, 1990\)](#); [Larsen and Nesbakken \(2004\)](#)) in the very large literature in economics on electricity demand have been able to illustrate how residential electricity end-use consumption varies within a day and how this information could be used for policy analysis, e.g. to understand substitution possibilities. Our analysis adds to this sparse literature, and considers the case of Sweden. Sweden introduced a law allowing consumers to have access to RTP, in the sense that consumers can choose to have hourly price contracts without having to pay for the necessary metering equipment. Sweden is, to our knowledge, among the few countries to have had such an explicit and country-wide possibility for RTP.

Our study contributes to the literature in two ways. First, using a unique, appliance-level direct metering data set, we are able to provide estimates of conditional load curves and understand the implications for substitutability of load across hours, a maintained assumption in the theoretical (and many empirical) studies estimating the benefits from RTP. Second, using the estimated load curves and wholesale price data, we are able to provide (an approximation to) estimates of benefits to the consumers. Our analysis, thus, is able to shed light on the extent to which various demand management strategies, particularly RTP, are likely to be effective. We note that, to our knowledge, ours is the first study providing such estimates for Sweden, and the results of our study should be of considerable relevance for Swedish energy policy, given the Swedish government’s strong thrust on RTP.

In more detail, our analysis uses data from a study commissioned by the Swedish Energy Agency, which metered household electricity consumption at the appliance-level at ten-minute intervals for 389 households, none of which were on RTP contracts. Data at this level of detail have rarely been available for most countries.² The appliance-

²To our knowledge, only one study has so far used the same data set as we do. [Widen et al. \(2009\)](#) develop a model for computation of daily electricity and hot-water demand profiles from time-use data using simple conversion schemes together with data on daylight and temperature. The model is shown to yield realistic reproductions of electricity demand for individual households and to generate load distributions which correspond very well to the available metering data.

specific nature of the metered data we use provides a unique opportunity to obtain better understanding of appliance- and end-use-specific consumption patterns. Prior approaches to estimating monthly appliance- (or end-use-) specific income elasticity used the approach of Conditional Demand Analysis (CDA), which suffered from many limitations, or a combination of metered data and CDA approaches.

Aggregating the ten-minute consumption data to hourly, we estimate end-use specific load curves (conditional on household characteristics) and analyze how these correlate to possible restrictions on substitutability of load within the day. That is, we do not explicitly explore substitutability of load, but rather analyze possible *restrictions* on substitutability. These restrictions, including working hours, outside temperature and (lack of) daylight might—independently of the type of (fixed- or variable rate) contract the household has chosen—impose significant limitations on any short-run attempt to shift load from “expensive” to “cheap” hours.

Finally, using the estimated load curves as the baseline, we examine the monetary incentives for households to shift load under an hourly pricing scheme based on average and maximum Nord pool spot prices, for average working days in February. The results presented here have important implications for Swedish energy policy, and in particular for the Swedish government’s stated goal of implementing RTP. The success of this pricing scheme depends heavily on demand response which, our results indicate, are likely to be small, absent substantial investments in new technology and a focus on it from the retailers. Both consumers and retailers appear to have little to gain from a potential switch to RTP—at least in the short run—based upon our simple cost shifting experiments.

The rest of this paper is structured as follows. A review of the different strands of literature relevant for our analyses is provided in section 2 followed, in section 3, by a brief description of the Swedish electricity market. Section 4 provides a description of the data used in this paper, together with a few summary statistics of key variables used in the analysis. Section 5 details the estimation of load curves, along with computations of the cost of servicing different end-uses and cost changes due to load shifts. Section 6 provides a discussion of the policy context of our analysis and concludes. Load curves

for the month of June and details regarding the goodness-of-fit measures for the SUR system used are relegated to Appendix A and Appendix B, respectively.

2 Related Literature

We turn now to a brief review of the literature on within-day and end-use-level electricity consumption. As emphasized earlier, a clear understanding of both price responsiveness and baseline consumption patterns are key inputs to any analysis of policies concerning dynamic pricing. In particular, the success of RTP depends upon consumers responding to hourly price variation by re-allocating consumption within a given day.³ However, as already noted, the literature on sub-annual appliance-level electricity demand –necessary for such analysis– is sparse, and especially rare are studies using hourly data. The CDA approach pioneered in Parti and Parti (1980) and refined in Bartels and Fiebig (2000, 1990); Fiebig et al. (1991) has been used as a way of overcoming the lack of appliance-level data. The idea in this approach is to combine data on total load with survey information on appliance holdings to estimate contribution from each appliance to total load, exploiting heterogeneity in household appliance portfolio.⁴ The estimated coefficients, interpretable as the the mean contribution of each appliance to total load, are then used to produce daily load curves for selected appliances.

Evidently, an obvious disadvantage of this method is an inability to estimate the load of appliances with high penetration rates such as TV, washing machine and lighting. Bartels and Fiebig (2000) partly solve this issue by combining survey data with real-time metering data, using a random coefficient model to allow for variation in appliance size and intensity of utilization between households. The mean response associated with each appliance is then estimated using data from both types of households, those

³Energy conservation is not the main policy goal of RTP and is also not something the retailers are likely to be supportive about; see section 3 for a brief overview of the retail electricity sector in Sweden. Further, households are likely to be less enthused by energy conservation than by re-allocation of consumption over time, which is also the main idea of RTP (reducing costs while not having to reduce total consumption). However, it might very well be the case that increased feedback through hourly electricity prices also will lead to energy conservation for Sweden (see e.g. Energimarknadsinspektionen (2010))

⁴In other words, households with a particular appliance are compared to similar households without the appliance in question and the difference in total load between these households is attributed to the appliance under consideration.

that were, and those that were not, directly metered. See also [Hsiao et al. \(1995\)](#) for a bayesian approach on combining metering data with conditional demand analysis. [Larsen and Nesbakken \(2004\)](#) compare the CDA approach with an engineering model, ERAD, whose inputs include engineering knowledge regarding technical and other features of housing stock, enabling estimation of energy demand for space heating. They compare the numerical results from these two approaches and provide a few recommendations regarding choice of end-use and what questions to implement in household surveys designed to disaggregate electricity consumption.

Before elaborating on how understanding within-day electricity consumption can assist in evaluating the scope for dynamic pricing, we briefly review some of the relevant literature on efficiency gains from RTP. We note that this literature is directly relevant for our analysis since substitution pattern across hours—the key aspect of our analysis—directly affects efficiency gains from RTP. A key aspect of RTP is that the benefits (“welfare gains”) are typically obtained from a more efficient allocation of consumption, where consumption is shifted from “expensive” to “cheap” hours, where “expensive” and “cheap” refer to system cost or spot market price. This then translates (in the long run) into re-allocation in capacity, with reductions in costly peak and mid-merit capacity. Naturally, the magnitude of the welfare gains depend upon the actual generation technology mix. These aspects are explored in several simulation-based studies.

[Borenstein and Holland \(2005\)](#) and [Borenstein \(2005\)](#), in the context of the U.S., simulate the long-run effects of residential RTP and find significant increase in consumer surplus (3 – 11%). The efficiency gains arise from reductions in capacity (both peak- and mid-merit capacity are reduced in favor of baseload) and not just from reduced generation, as in the short run, and with a very low price elasticity (of -0.025). [Kopsangas-Savolainen and Svento \(2012\)](#) reproduce these simulations for a Nordic market setting, imposing capacity restrictions on nuclear and hydro power (reflecting the limited scope for hydro and nuclear capacity expansion), and find that RTP reduces the need for peak and mid-merit capacity. As a further illustration, [Holland and Mansur \(2006\)](#) simulate the short-run effects of RTP, and find significant reduction in peak generation, but an overall increase in total generation for the U.S., with only a very modest

(0.24%) welfare gain resulting from this re-allocation.

In the context of Sweden, the Swedish Energy Market Inspectorate (EI),⁵ in a cost-benefit analysis of introduction of RTP in Sweden, estimates the social benefits to be substantial (varying between 1541 and 1989 million SEK, depending upon the share of households on RTP)⁶ and advocates introduction of RTP in Sweden, either on a voluntary or mandatory basis (Energimarknadsinspektionen, 2010). In the EI report it is assumed that a substantial share (40 percent) of all households will be on real time pricing by 2030, or roughly 60 000 new RTP contracts per year.⁷ However, the EI reports that during the first years of the RTP program in Sweden only about 8600 households had adopted this new pricing scheme (Energimarknadsinspektionen (2014)).⁸ Further, as detailed in section 3, demand flexibility might also play an increasingly important role as to balance the variability of wind power generation on a within-day basis. Hence, households will ideally not only respond to extreme price spikes but also to smaller but more frequent price variation (see Fritz et al. (2013)). Although there are technical issues to be solved, there exists substantial potential for using demand flexibility as an alternative to balancing generation.⁹

An important point to note is that all of the simulation-based studies cited above use a constant-elasticity hourly demand function, essentially assuming that household response to a price change is independent of time of the day and, further, that there is at least some substitutability between hours.¹⁰ The dependence of welfare computations

⁵The Swedish Energy Markets Inspectorate supervises the Swedish electricity market and is responsible for improvement of the functioning and efficiency of these markets. See <http://www.ei.se/en>

⁶The benefits largely arise from replacing peak capacity; specifically, the alternative cost of the peak capacity (defined as capacity used less than 40 hours per year) is estimated at about 5 SEK/kWh (roughly 0.56 €/kWh).

⁷This estimate is partly based on the idea that Swedish residential consumers in general are rather active on the electricity market. For example, between 2005 and 2010 the number of variable-price contracts (contracts with prices varying over months, as compared to longer-term contracts) has increased (from zero) to 30 percent of all contracts, indicating that many consumers are interested in flexible types of contracts.

⁸One explanation for this rather low figure is that as of spring 2014, only 68 (out of roughly 120) electricity retailers provided RTP contracts (according to a survey by the EI), and of these only a few had hourly prices on display (see Energimarknadsinspektionen (2014)). Most RTP contracts required the household to call the supplier for the current price information. This indicates that the incentives for the retailers to promote RTP are limited.

⁹Fritz et al. (2013) emphasize the need for sufficient monetary incentives to compensate households for loss of comfort, and point out that the current relatively small price variation within a given day will likely not yield sufficient potential cost savings for households.

¹⁰If demand was completely inelastic for all hours, households would not shift any load at all.

upon assumptions regarding consumer willingness, and ability, to shift consumption across hours provides a strong motivation for understanding current consumption behavior across hours. The key results of these simulation-based approaches, of some slight increase in total demand— indicating that consumers shift load from peak hours to off-peak hours—, can then be explained by this assumption. However, one of the few recent empirical studies evaluating an actual RTP scheme in Chicago, Allcott (2011), finds that the RTP scheme considered does not lead to load shifting. Rather, the response to the pricing scheme is by energy conservation through reduction in load during peak hours, but with no increase in consumption during off-peak hours, contrary to the simulation results cited above that indicate a slight increase in total consumption.

Further, Allcott (2011) notes that even if households on RTP are fairly price elastic, the gains are rather small; the estimated increase in consumer surplus amounts to about \$10 per year or approximately two percent of annual household electricity expenditure.¹¹ The very small benefits of, and therefore incentives to adopt, RTP for any individual household might imply that consumers are less likely to respond to RTP in the hypothesized way – by shifting load from peak to off-peak. There might also be reason to believe that there are short-run restrictions on the households possibility to respond, further strengthening this effect. For example, working hours, outside temperature etc. might impose restrictions on the substitutability of load within a given day, the combination of which can explain the results in Allcott (2011).¹²

There is some experimental literature on how households respond to dynamic pricing schemes in Sweden. For example, in a small-scale experiment, Swedish Elforsk Market Design and a few local retailers in southern Sweden¹³ analyze the short-run household response to staged price spikes in the interval of 3 to 10 SEK/kWh (Lindskoug (2006)).

¹¹In fact, Allcott goes as far as suggesting that even if residential RTP might be theoretically sound, it might “*provide an important real-world example of situation where this is not currently welfare-enhancing*” (p.839, emphasis added).

¹²Borenstein (2005) briefly discusses these issues in his sensitivity analysis, where he allow elasticity to vary with the demand level, first with elasticity increasing in demand levels and subsequently the opposite. For the latter case, he finds that the efficiency gains are “*much smaller than in the case in which demand is more elastic at peak times*” and also smaller than with constant elasticity (p.14, emphasis added).

¹³Skånska Energi and Vallentuna Energi were the two local utilities involved in the experiment. Elforsk is a Swedish electricity research institute financed by the Swedish electricity industry and the Swedish TSO, Svenska Kraftnät.

The resulting load reduction was found to be rather large, up to 50% at hours with price spikes, with households using mixed heating (i.e. electric heating combined with other sources of heating, for example wood stove) succeeding in reducing total load the most.¹⁴ Given that such large price spikes are very unusual in Sweden (see e.g. Hellström et al. (2012) and the Nord pool February spot price in fig. 6), it is not clear how relevant these results are for more moderate (and frequent) price variations typically considered in dynamic pricing analyses. Factors such as the magnitude of the price shocks and the fact that households self-selected into these experiments render the external validity of these findings questionable.

To summarize, the key points of the literature regarding RTP are that, while simulation results—assuming low-to-moderate but fixed-across-hours price elasticity—indicate modest welfare gains from RTP (along with moderate increase in total load), the limited empirical evidence accumulated indicates minimal welfare gains from RTP (along with possible energy conservation). In particular, for Sweden, projections of voluntary adoption rates of RTP, based on limited evidence, appear rather optimistic. Further, a major determinant of the magnitude of welfare gains from RTP is the (generally assumed) elasticity of substitution across hours, an exploration of which is the goal of our analysis.

3 The Swedish electricity market

The deregulation of the hitherto highly regulated Swedish electricity market in 1996, following the example of other European countries, introduced competition between electricity supplying companies, with distribution a state monopoly. This period also marked the beginning of market integration with the other Nordic countries (Finland, Norway, Denmark) and the Baltic states via a common spot market, the “Nord Pool Spot”. Following this deregulation, market price today is determined by demand and supply on the Nord Pool power exchange, located in Oslo, Norway. The day-ahead market, Elspot, is the main venue for trading electricity in the Nordic region, with 75%

¹⁴Interestingly, the load reduction from increasing prices to 10 sek/kWh was found not to be significantly greater than for prices of 3 SEK/kWh.

of total electric supply in the Nordic countries traded here. Contracts are concluded between the approximately 370 sellers and buyers for delivery of power the following day, and market price is determined based upon the supply and demand of electricity on that day. Further, there exist a intra-day market, Elbas, to cover potential imbalances occurring between the closing of Elspot at noon and delivery the next day. In 2014, maximum system price was 1.45 SEK/kWh (in December) and average price was 0.27 SEK/kWh (source: <http://www.svenskenergi.se>).¹⁵

The bulk of electricity produced in Sweden is from hydro and nuclear sources, constituting 45 and 43 percent of total production, respectively (figures for 2014, from SvK). The remaining production is from thermal (co-generation) plants and windpower, together with some smaller sources of peak capacity.¹⁶ This peak capacity, loosely defined (following e.g. [Kopsangas-Savolainen and Svento \(2012\)](#)) to be the technology with highest marginal cost (and hence least utilization), consists of gas turbines and oil fired condensing power plants, with approximately 3000 MW of installed capacity.¹⁷ It is anticipated that the reserve capacity needed will likely increase in the future due to substantial expansion of intermittent (e.g. wind power) generation in Sweden ([Energimarknadsinspektionen \(2010\)](#)). Currently, hydro power is used in Sweden both as baseload and as balancing load (to balance the variability of wind power generation, in particular). However, there is an ongoing debate on whether hydro power alone will be sufficient in balancing the (anticipated and on-going) expansion of wind power generation. Here, demand flexibility could play an important role in providing alternative means of balancing system load, as emphasized by Elforsk ([Fritz et al. \(2013\)](#)).

Turning to the demand side, Sweden has a high—among the ten highest—electricity intensity per capita, at roughly 14000 kWh for 2014 (source: <http://www.svenskenergi.se/Elfakta/Elanvandning/>). This is explained both by cold win-

¹⁵1 SEK (Swedish Krona) was approximately 0.12 € or 0.15\$ in Feb 2014.

¹⁶Shortages and blackouts are not an issue in Sweden due to large (surplus) capacity in hydro-power; peak capacity is therefore relatively small.

¹⁷Svenska Kraftnät (SvK), the governmental Transmission System Operator (TSO), is responsible for managing the balancing capacity and strategic reserve, and can procure up to 1500 MW in peak capacity (from Swedish producers). Note however that generation from these technologies is quite small, and during the last ten years production has varied between 0.2 - 1.5 percent (300 – 2000 GWh) of total annual production (http://www.scb.se/Pages/TableAndChart_24270.aspx). The Swedish Parliament has decreed that the capacity reserve shall be phased out by the 15 March 2020 and replaced by market-driven capacity and/or demand flexibility.

ters and an energy intensive industry. The residential sector accounts for roughly 23 percent of total consumption. Disaggregated information about residential demand is sparse, but Statistics Sweden assumes that a “representative” household with electric heating consumes approximately 20000 kWh per year. As of 2013, about 40 percent of all households were on fixed rate contracts with yearly or longer contract durations while about 30 percent were on variable rate contracts. The general trend is that households are switching from so-called default contracts to variable rate contracts.¹⁸ For the previous nine years (2005 – 2014), the average fixed rate price was 0.49 SEK/kWh while the variable contract price was 0.45 SEK/kWh (with a variance of 0.019 SEK/kWh).

Concerning energy and climate policy, Sweden has set out rather ambitious climate policy targets following the EU Climate and Energy Package (the 20-20-20 target), stipulating, among other things, 20 percent increase in energy efficiency and 50 percent share of renewable sources in total energy consumption by 2020 (relative to 2009).¹⁹ The Swedish Energy Agency has been commissioned by the Swedish government to both detail what this target implies for Sweden (concerning the specific energy efficiency target over the stipulated period) and to present a plan of how to reach the target. It is argued that a Swedish implementation of real time pricing, and a more efficient energy market in general, will assist in reaching this goal (see e.g. [Energimarknadsinspektionen \(2010\)](#)).

4 Data and summary statistics

The data used in this paper originate from a metering project commissioned by the Swedish Energy Agency between 2005 and 2008. The purpose of this project 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 all major appliances. We provide a brief overview of the survey here, and refer the readers to

¹⁸All households have the opportunity to choose a preferred contract type and energy provider (“retailer”); those households which do not make an active choice are assigned a default contract where prices typically are fixed on an annual basis.

¹⁹The EU 20-20-20 target is defined to have 20 percent of renewable energy, 20 percent more energy efficiency and a reduction in emissions of 20 percent, by 2020.

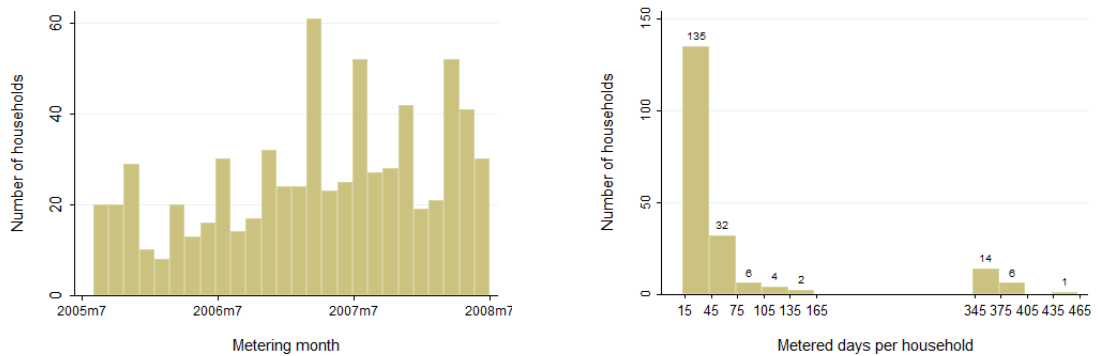
the Energy Agency’s report ([Zimmermann \(2009\)](#)) for more details. Roughly 150 different appliances were metered, with each household having a maximum of 46 appliances metered at a time. In addition, each household had individual meters recording both outdoor and indoor temperature; consumption and temperature data were recorded at ten-minute intervals. 200 of the homes metered were detached houses, and the remaining 189, flats. We focus exclusively on detached houses, since they have a substantially higher level of consumption and are typically more important in Sweden from a policy perspective.

A majority of the households were located in the Mälardalen region, with only 25 households each located in northern and southern Sweden.²⁰ The project was carried out between 2005 to 2008 and each household was metered for between 15 days and 16 months. Figures [1a](#) and [1b](#) illustrate the time distribution of metered households. Figure [1a](#) illustrates the months (and years) households were metered in; as is evident, roughly 10-20 households per month were metered during 2005 and 2006, and 20-30 households per month during 2007 and early 2008. From fig. [1b](#), which illustrates how many days household were metered for, it is evident that a majority of the households were metered between one or three months, and a few households metered for three to six months, and fewer still for between 12 and 16 months.

In addition to the metering data, survey data was collected on household characteristics such as (monthly) income, number and age of inhabitants, living area size, main heating system, building year and year of refurbishment. For some appliances, information on brand and model is also available. The lack of household level price and contract data precludes an analysis of price responsiveness. Table [1](#) provides summary statistics for household characteristics by heating source. Household income is reported in intervals, but following e.g. [Stewart \(1983\)](#) we use interval regression to generate a continuous income variable.²¹ Motivated by policy, which is broadly centered around

²⁰The Energy Agency is situated in Mälardalen, so convenience is a possible explanation for this geographical focus. Since this is a very small geographical region, the variation in temperature is likely small; however, variation in other household characteristics is substantial. Overall, the rather narrow geographic spread of the sample tends to weaken the external validity of the quantitative results. Nonetheless, provided households in the rest of Sweden have patterns of behavior which are not very dissimilar, we anticipate the qualitative results to broadly hold.

²¹Our results do not change when the original income variable, in intervals, was used. The continuous



(a) Monthly household metering
Metering began in August 2005 (2005m8) and ended in July 2008 (2008m7).

(b) Total metered days.
Days of metering do not correspond to a full calendar month.

Figure 1: *Distribution of metered data.*

end-use categories, we focus on four key end-uses into which the individual appliances are aggregated: space heating (including water heating), kitchen (all kitchen appliances), lighting, and residual (appliances that do not fall into any of the previous three categories)

Household size (number of persons) varies between 1 and 6, with a mean of slightly above 3, and living area (m^2) has a mean value of 136. Building year, which varies between 1926 and 2007, with a mean year of 1970, is expected to have a substantial effect on heating consumption, with old houses being expected to be more “leaky” and hence have higher heating load. Finally, between 10 and 46 appliances were metered for each household with a mean of 25, covering all main appliances.²² We find only moderate differences in household characteristics between households with different heating systems, with notable differences restricted to appliances (larger number of appliances metered for electrically-heated households) and income (slightly higher income for households with mixed heating). Overall, households with mixed heating tend to have slightly higher income, to be slightly larger in size (both in m^2 and number of inhabitants) and slightly older than electrically heated homes. Nonetheless, the differences between these two types of households are rather moderate. This feature motivates the relatively sim-

variable was retained in the interest of interpretability.

²²We note that no information is available in the survey regarding the criteria used to choose the number of appliances metered in each household. A plausible assumption is that these are in proportion to the number of energy consuming appliances owned, but we note that for our analysis, it is not critical that this assumption holds.

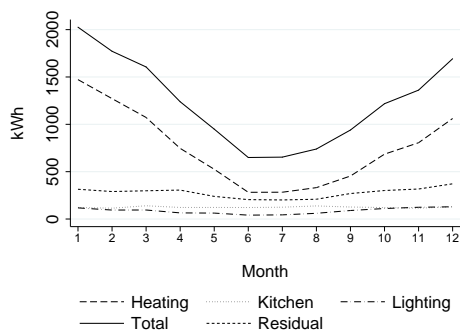
Table 1: Summary statistics for households by heating source.

	Mixed heating	Electric heating	All heating systems	p-value
<u>Household characteristics</u>				
Household income (SEK)	42210.5 (6796.764)	40760.5 (8023.424)	41292.4 (7628.566)	0.000
Household size (persons)	3.5 (1.067)	3.1 (1.147)	3.3 (1.129)	0.000
Living area (m^2)	139.6 (49.625)	134.2 (28.586)	136.4 (38.601)	0.000
Building Year	1966.5 (20.433)	1970.9 (24.071)	1969.3 (22.916)	0.000
Number of appliances	21.628 (4.190)	28.238 (5.562)	25.295 (5.419)	0.000
<u>Monthly consumption (kWh)</u>				
Total	1039.866 (651.869)	1392.303 (812.638)	1224.253 (759.881)	0.000
Heating (incl. water heating)	518.361 (627.024)	948.027 (671.768)	743.153 (684.377)	0.000
Kitchen	118.658 (39.712)	132.104 (53.828)	125.693 (48.019)	0.014
Lighting	81.081 (42.317)	86.614 (56.702)	83.976 (50.352)	0.341
Residual	321.689 (226.469)	225.474 (230.715)	271.351 (233.340)	0.000
Number of households	264	135	399	

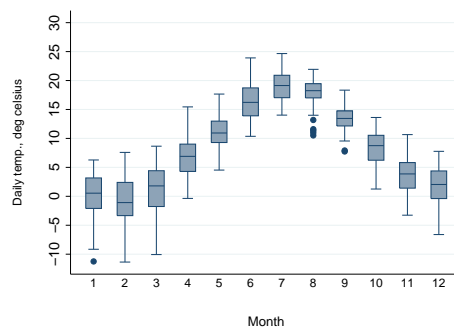
Notes: Sample mean reported, with standard deviation in parenthesis. Note that mixed heating refers to households which used some form of electric heating (e.g. portable heaters) but wherein the major source of heating was not electric. The column “p-value” refers to the p-value on the Welch (t-) test of equality of mean (for relevant characteristic) across households with mixed and electric heating.

ple load curve estimation framework, with load curves for houses which are electrically heated differing from those on mixed heating by only an intercept; see section 5.

The monthly average for a household with electric heating corresponds to an annual load (multiplying the average monthly load by 12) of roughly 17000 kWh, slightly less than the 20000 kWh assumed by Statistics Sweden for the reference household, as already mentioned. Also evident from table 1 is the substantial difference in load between households with different heating systems, in terms of both total and heating load. However, households are rather homogenous in terms of kitchen and lighting consumption, irrespective of heating system. Naturally, residential electricity consumption is subject to seasonal variation; as is evident, during warm summer months even households with electric heating only have very small heating consumption. This seasonal pattern is illustrated in fig. 2a, where we present average monthly consumption by end-use over the studied period (2005-2008), from which a distinct winter peak, with more than the double the monthly summer load, is evident. As winters in Sweden are both dark and



(a) Monthly electric consumption by end-use.



(b) Daily outdoor temperature by month.

Figure 2: *Monthly end-use load and outdoor temperature.*

cold (see fig. 2b), this pattern is anticipated.

5 The Load curves

5.1 Estimation Framework

For the load curve estimation we consider a subsample of the full data set, consisting of all working days in February (of all years). Given that heating is the end-use with by far the largest load, the choice of February is motivated by the fact that this is usually the coldest month (see fig. 2b). We also compare the results from this month with consumption for working days in June, June being the warmest (non-vacation) month; these figures are presented in Appendix A.

Following Bartels and Fiebig (2000, 1990), we also use a Seemingly Unrelated Regression (SUR) framework for estimation of the end-use load curves, conditional on household-specific characteristics, with a total of 24 hourly equations for each end-use. Note that conditioning on household-specific variables can serve many purposes, including allowing for a formal interpretation of the “average household”, for counter-factual policy simulation (e.g. Bartels and Fiebig (1996)), and for providing a basis for understanding the determinants of hourly demand, including demand elasticities (a task undertaken for this dataset in a companion paper). Unlike in Bartels and Fiebig (2000), a majority of the appliances are metered in our sample and, as a result, there is no scope for combining metered and unmetered data. This considerably simplifies our estimation

framework, which we present next.²³

The actual equation estimated, for a given end-use and for hour t , is

$$\bar{Y}_{i,t} = b_t + \delta_t^y + \beta_t X_{i,t} + v_{i,t}, \quad i = 1, 2, \dots, H, \quad (1)$$

where $\bar{Y}_{i,t} = \frac{\sum_{d=1}^D Y_{i,t}^d}{D}$ is the mean daily load for hour t and household $i = 1, \dots, H$, with D the number of relevant days, $X_{i,t}$ are the control variables and δ_t^y denotes a year dummy accounting for year-specific effects (if any) on daily consumption (year indices are suppressed on X and Y).²⁴ In other words, one SUR system of equations are estimated for each of the K end-uses, where the equations correspond to hours and observations to household load for that hour. Essentially, this formulation allows us to focus on variability across households, and leads to an interpretation of equation (1) as modeling the consumption of household i on an *average* February day. Thus, the percentiles of (predicted or actual) consumption, based upon equation (1), refer to those of the relevant household on an average February day, an interpretation which facilitates our subsequent discussions regarding household behavior.

The complete list of control variables are: living area (m^2), income (in SEK), and number of inhabitants. In addition, we include outdoor temperature, building year and an indicator of electric heating for the heating end-use. The motivation for inclusion of the independent variables is as follows: as heating is by far the largest component of total load, outdoor temperature is expected to significantly affect electricity consumption; a similar argument can be made for the inclusion of building year and living area, as old (and presumably more leaky) houses, and larger houses, consume more electricity

²³It is worth pointing out that the reason the framework in [Bartels and Fiebig \(2000\)](#) is relatively involved is the heteroscedasticity induced by the presence of non-metered appliances/end-uses. This leads to the use of a more involved, non-standard approach (an iterative, two-stage approach) to deal with the issue of additive heteroscedasticity. Since all end uses—and almost all appliances—are metered in our case, we can use the standard SUR framework with hours as equations (as pointed out in [Bartels and Fiebig \(2000, p.54\)](#)).

²⁴More formally, the SUR system above can be written in the usual form for the k^{th} end-use as

$$\mathbf{y}_t^k = \mathbf{X}_t \boldsymbol{\Gamma}_t^k + \mathbf{v}_t^k, \quad (2)$$

where $\mathbf{y}_t^k = [\bar{Y}_{1,t}^k, \bar{Y}_{2,t}^k, \dots, \bar{Y}_{H,t}^k]^T$ is a vector of size $H \times 1$, \mathbf{X}_t is of size $H \times M_t$, with H the number of households (40 in our case) and M_t the number of covariates for the t^{th} hour, $\boldsymbol{\Gamma}_t^k = [b_t^k, \delta_{y,t}^k, \beta_t^k]$, an $M_t \times 1$ vector of coefficients, and $t = 1, 2, \dots, 24$ the number of equations.

for space heating. Of course, whether the household has only electric heating or mixed heating should also affect (heating) consumption. We also include number of inhabitants and income, as this is likely positively correlated with both the number of appliances possessed and their efficiency.

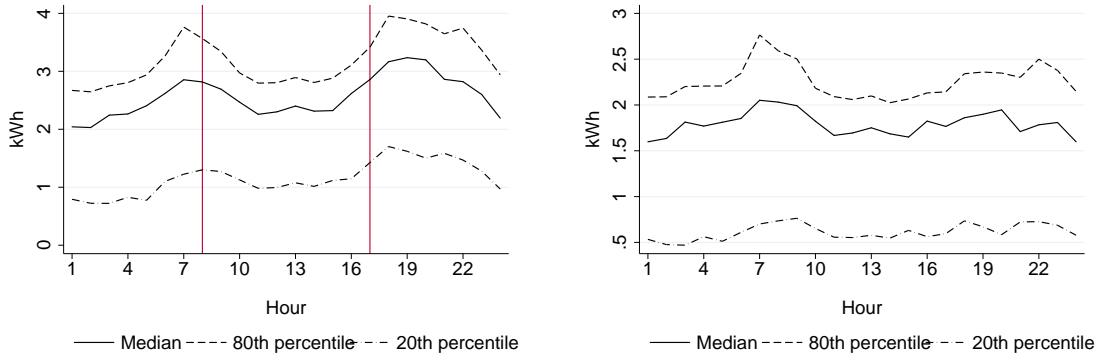
The SUR framework is motivated by the observation that it is very likely that unobserved determinants of household behavior are common to all hours and joint estimation across hours is likely to yield efficiency gains. In addition, the variation of outdoor temperature across hours (i.e. equations) implies that our SUR framework is not equivalent to equation-by-equation OLS (since one of the X s varies across equations). We estimate eq. (1) and use the median predicted value to produce end-use specific load curves. In addition, we also produce load curves for the 20th and 80th percentile consumption (i.e. percentiles of \widehat{Y}_i) to illustrate household heterogeneity in terms of hourly load. We define total load for hour t as the sum of the predicted values of the K end-uses in that hour, i.e. $\widehat{Y}_{i,t}^{total} = \sum_k^K \left(\widehat{Y}_{i,t}^k \right)$.²⁵

5.2 Estimated Load Curves

We now turn to the estimation results; we illustrate daily load curves for working days in February in the main text, and note that corresponding load curves for working days in June are to be found in Appendix A. We note that the estimated coefficients from the SUR system are not reported but are available upon request. The SUR framework set up above passes many standard goodness of fit tests, and are detailed in table B.1, Appendix B.

Total load is displayed in fig. 3a, illustrating the median consumption together with the 20th and 80th percentile consumption. Note the rather large, and expected, difference between the median and the 20th and 80th percentile, driven to a large extent by differences in heating load. We elaborate more on this below, when we discuss the

²⁵We note that metered total load differs from the computed (as sum of end-use) total by a small amount. Estimating the total load curve using metered, rather than estimated, total load makes only a very modest difference to the load curve; the level of peak load is lower with metered than with estimated total load. Note also that since metered total load for hour t is simply the sum of all metered end-use loads for that hour, when estimating the metered total hourly load, one of the end-use loads must be estimated as residual.



(a) Total consumption by hour. Typical working hours—assumed to be 8 AM to 5PM—are indicated by the vertical red lines.

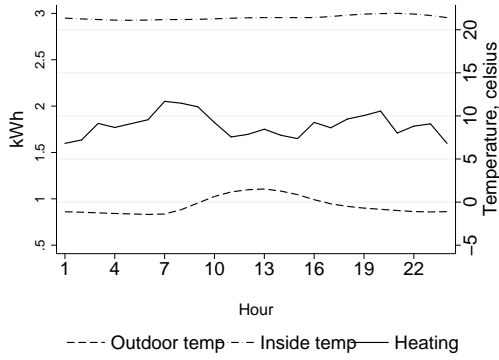
(b) Heating consumption by hour.

Figure 3: Total and heating load curves for an average February working day.

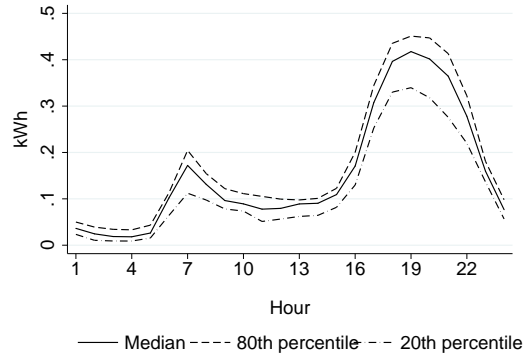
load curve for heating (see fig. 3b). As anticipated, there are two distinct and intuitive peaks, the first at approximately 6 am when the household wakes up and the second, at about 5 pm when the household returns home from work. It is clear that the two peaks correspond roughly to working hours (typically 8 am – 5 pm in Sweden), illustrated by the two vertical lines.

In fig. 3b we illustrate the estimated load curve for heating. Sizeable differences between households are evident, with the median heating load roughly three times the 20th percentile load. As noted above, this is mainly due to differences in heating systems. Households with mixed heating have the possibility to reduce electricity consumption substantially by substituting electric heating with, e.g., a wood stove or district heating. However, even if the 20th percentile consumption is relatively small compared to the median, it is nonetheless large compared to that of lighting or kitchen (roughly 0.5 kWh throughout the day, comparable in magnitude to peak lighting or kitchen load for the 80th percentile household, see fig. 4b and fig. 5a). Hence, the heating load curves not only illustrate household heterogeneity but also just how large space heating is (in terms of kWh) relative to other end-uses. A distinct morning peak (and to a lesser extent an evening peak) for the heating load curve are also evident from fig. 3b (for all levels of consumption, although it is less pronounced for the 20th percentile).

Turning to fig. 4a, we illustrate the median heating load together with the average



(a) Heating consumption by hour. Also illustrated are mean outdoor and indoor temperatures, both metered for each household.



(b) Lighting consumption by hour.

Figure 4: Heating and lighting load curves for an average February working day.

outdoor and indoor temperatures. The heating load curve appears (approximately) to be a mirror-image of outdoor temperature, as can be anticipated. Interestingly, although there is a decrease in heating load during the mid-day, this does not lead to a corresponding reduction in indoor temperature. As residents usually are away from home during mid-day (and therefore should not be concerned with a specific indoor temperature), this suggests that there is potential for energy conservation by reducing heating consumption without reducing the utility derived from it (i.e. without reducing indoor temperature during periods when householders are at home).

The load curve for lighting is displayed in fig. 4b. Here households appear to be rather homogenous in their consumption, with both the 80th and 20th percentile close to the median. There is a smaller peak during the morning, and a larger one between 4 pm and 10 pm, corresponding respectively to sunrise and the evening post-sunset period. Furthermore, lighting load is higher during the evening, likely since there are more activities at home during this time (compared to the morning). Also worth noting is that the load is close to zero late at night, implying only limited stand-by usage. Compared to the heating load, we note that lighting load is rather small in absolute terms. Note that the metering campaign was commissioned before the EU phase-out of incandescent bulbs in favour of more energy-efficient lights. This, we surmise, is likely to have led to a (parallel to the one here) shift of the lighting load curve downwards i.e. we anticipate that the shape of the load curve has remained roughly the same after this

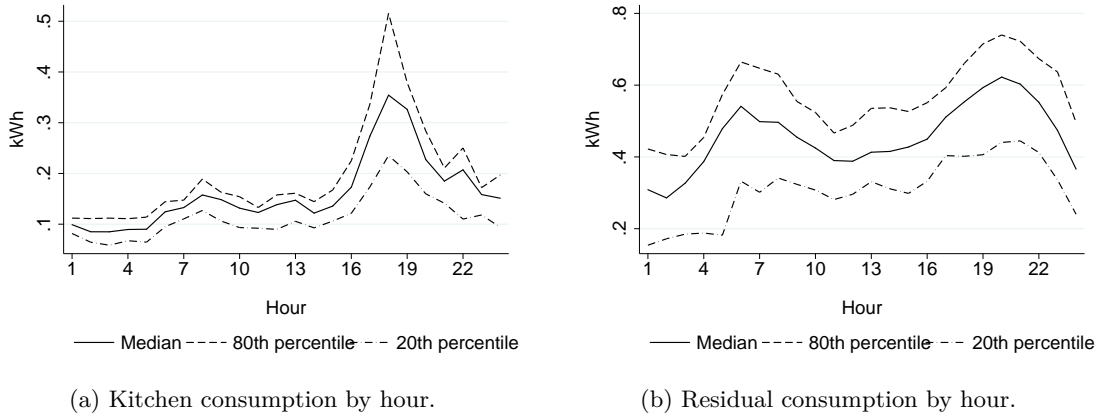


Figure 5: Kitchen and residual load curves for an average February working day.

policy measure.

The load curve for the kitchen end-use is displayed in fig. 5a. Households appear to be rather homogeneous in terms of kitchen electricity use, since the percentiles are close together. At first sight, it might also seem strange that there is no morning peak. However, Swedish breakfast is by tradition cold, and even if some electricity is used for making coffee etc. this load is small compared to the more cooking-intensive dinner. There is a distinct dinner peak between 4 pm and 8 pm, as anticipated. Clearly, some people end their working day early since the dinner peak starts at roughly 4 pm, one explanation being that some householders are retired or are working part time (this is the case for lighting as well). The magnitude of the kitchen load is comparable to that of lighting, and is rather small in comparison to heating. Finally, we illustrate the load curve for residual electricity consumption in fig. 5b. Since this category contains many different end-uses such as TV, computers, etc, it is difficult to interpret the shape. However, we note that this curve also has a morning and an afternoon peak, occurring roughly at the same time as the other end-uses.

Note that certain individual appliances such as laundry that are “easily shifted” appear, at a first glance, interesting from a RTP perspective, as already discussed. For example, with modern washing machines it is relatively straight-forward to program start of laundry at a given time, e.g. when spot prices are low. However, laundry and similar appliances consume very small amounts of electricity compared to the end-

uses displayed above (laundry load is only one percent of total February load for the average household), and a shift of these loads is likely insufficient if the goal is to shift a substantial amount of total load. Finally, note that the load curves illustrated here are for a given technology, and that advances in technology may alter the observed patterns in the load curve.

5.3 Cost savings from load shifting

We turn now to computing the cost of servicing each end-use and to understand how these would change if the average household shifted total load. From either the policy maker or the consumer perspective, this is an important factor to understand. Before turning to this task, however, we first briefly explore the patterns in the Nord pool spot price upon which our cost shift analyses are based. Note that we only consider the spot price for working days in February and also that the price is applicable for all demand, not just residential. In that sense, the price curve not only show the scope for price-induced load shifts but also gives a picture of the system peak. Finally, observe that the Nord pool spot price, as the wholesale price, is likely to form a base for retail price in any dynamic pricing scheme.

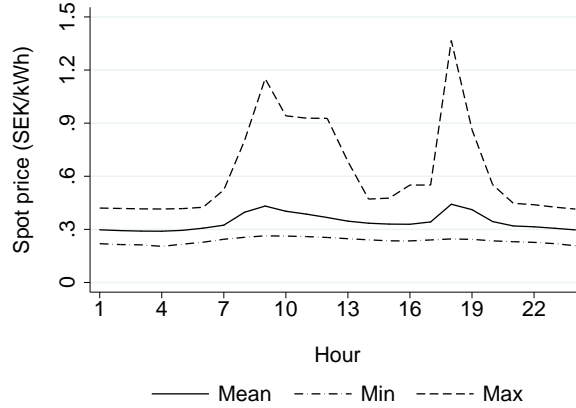


Figure 6: Hourly Nord pool spot prices (price area three in Sweden) for February (2006-2008).

Two price peaks are evident from fig. 6, in which the mean, minimum and maximum hourly spot prices are plotted; one at roughly 9 am and another at about 5 pm, with maximum price peak being more pronounced. Comparing the spot price to the esti-

mated load curves, it is evident that these two price peaks coincide with the household demand peak. Further, when residential demand is low during the early morning, and late at night, the system price is also rather low. This consumption pattern has two important implications: first, it is in line with the hypothesized behavior of “excessive” consumption during periods of high (system/spot) price and second, it indicates that there are potential cost savings from shifting consumption to off-peak hours. However, as the variation in the average spot price is rather small, the potential cost savings are a priori expected to be limited, *on average*.

To estimate the cost of servicing each end-use, we match the estimated load curves with the corresponding spot prices, using the average/maximum spot price (over 2005-2008) for working days in February (see equations 3 and 4). Since we use spot prices rather than retail prices, these costs could either be interpreted as the retailer’s cost, or as a proxy for household cost when on RTP.²⁶ Further, the EI estimates that roughly 50 percent of the variation in wholesale prices translates to variation in retail prices (Energimarknadsinspektionen (2006)). This then implies that the price curve for RTP contracts is flatter than that of the corresponding spot price. We denote the mean spot price for hour t by \bar{p}^t and the predicted hourly load for end-use k as \hat{Y}_k^t . To obtain the cost C_k^t of servicing end-use k in hour t , we simply multiply the predicted hourly load with the mean spot price for that hour:

$$C_k^t = \hat{Y}_k^t \bar{p}^t, \quad t = 1, \dots, 24, \quad k = 1, \dots, 4. \quad (3)$$

The daily cost of servicing end-use k is then the sum of the 24 hourly costs,

$$C_k^d = \sum_{t=1}^{24} \hat{Y}_k^t \bar{p}^t = \sum_{t=1}^{24} C_k^t, \quad (4)$$

computed separately for the median and the 20th and 80th percentiles. The total daily cost is defined as the sum of the daily end-use specific costs.

²⁶It is a proxy since the households also pay taxes, transmission fees and a mark up. Note however, that, except for the VAT, other fees tend to be fixed costs. A 25% VAT is charged on the total electricity price, including transmission fees. We choose to ignore this cost in the calculations, but note that the calculated cost savings below, for this reason, are slightly downward biased. However, this should not substantively affect the qualitative results of the experiment.

Table 2: Daily cost (in SEK) of servicing different end-uses for an average February working day.

End-use	Median household	80 th percentile household	20 th percentile household
Using average spot price			
Heating	14.787	18.591	5.098
Lighting	1.331	1.537	1.028
Kitchen	1.365	1.660	0.955
Residual	3.785	4.694	2.585
Total	21.269	26.483	9.668
Using maximum spot price			
Heating	27.204	34.093	9.474
Lighting	2.559	2.945	1.995
Kitchen	2.637	3.241	1.834
Residual	6.968	8.609	4.823
Total	39.367	48.888	18.127

Notes: Cost calculations based on load curves for average February working days matched with average and maximum February daily spot prices.

Table 2 illustrates the cost of servicing each end-use for the median household during an average February working day. Evidently, heating is by far the most expensive end-use, being the largest load. For the other end-uses, even if the timing of demand (being part of peak demand) coincides with high spot prices, cost is nonetheless small relative to the cost of heating.

We turn next to evaluating how these costs change when we shift a particular end-use load from expensive hours to cheap hours; the interpretation of cost changes is as before. The conceptually most simple way of shifting the load curve is to move the whole curve a few hours ahead in time, while keeping the shape of the load curve intact, similar to the approach used in [Bartels and Fiebig \(2000\)](#) (although they only shift the load for one appliance; pool pump).²⁷ This implies that evening hours now turn up as morning hours. We shift the total load curve in this way one to seven hours ahead and compute the cost change in percentage of daily total costs. When load is shifted seven hours ahead, the demand peaks occur at the hours with the lowest prices. Note that by doing this we keep the total daily load *constant*, and are only re-allocating consumption across hours, consistent with the constant-elasticity-across-hours assumptions in evaluations of RTP benefits in [Borenstein \(2005\)](#); [Kopsangas-Savolainen and Svento \(2012\)](#). We carry

²⁷Note that we only carry out this experiment for within-day load shifting, not for across-day shifting. For all of these end-uses except for laundry, the substitutability of load across days (for example from a working day to the weekend) is limited. For example, it would not make any sense to shift space heating or lighting from one day to another, since that would imply one very cold and dark, albeit cheap, day.

out this experiment for the median household, using average price, but test how the cost changes differ for households at the 80th and 20th percentile of consumption, as well as the implications of using more extreme prices such as the maximum February price.

Table 3: Cost reductions due to load shift (as % of daily total cost)

Hours shifted	Median household	80 th percentile household	20 th percentile household
Using average spot price			
1h	0.003	-0.15	0.42
3h	0.77	0.768	2.29
5h	1.58	1.82	3.96
7h	2.15	2.44	4.80
Using maximum spot price			
1h	0.18	-0.32	1.59
3h	1.98	2.00	6.21
5h	3.74	4.55	10.10
7h	5.56	6.55	12.50

Notes: Cost savings calculations based on load curves for average February working days matched with average and maximum February spot prices.

It is evident from table 3 that the cost decreases overall are surprisingly small, and this holds for all three type of households although the cost savings in percentage are largest for households with low consumption.²⁸ Even if we shift the whole load curve seven hours ahead, the daily cost decreases by only 2.15 percent, or roughly 0.38 SEK for the median household at average prices. The cost savings are, as expected, larger for maximum prices, but are still relatively small; only 5.56 percentage or 1.05 SEK. Further, if we shift the load additional hours ahead, cost actually increases. Of course, the cost savings would have been even smaller had the household only shifted a part of the load, e.g. heating. It is important to bear in mind that these are the cost changes for an average February working day (using the load curve and prices for an average February working day and average February prices). Hence, for some days the cost reductions are possibly larger while for other days, cost reductions are likely lower. In particular, while the potential cost savings increase with price variation, if households

²⁸At first glance, this might suggest that households with lower consumption levels are more likely to respond to price variation. However, it is not clear whether households care about cost savings in relative (percentage) or absolute terms. Further, note that the costs associated with for example necessary metering equipment are same for all households, and such costs are not evidently not included in the above calculations. Therefore, it is not certain that policy makers should interpret this result as an argument for promoting RTP to households with low(er) consumption levels.

are unable to respond to price peaks (e.g. due to the restrictions discussed previously) their costs will increase substantially for those days.

The cost savings illustrated in table 3 are likely a *best case* scenario, for several reasons. First, as already mentioned, roughly half the variation in wholesale prices is transmitted to retail prices, implying reduced price variation and hence, lower cost savings. Secondly, the load shifting pattern illustrated above is likely not feasible, in reality. Indeed, we consider shifting of (total) load across as many as three hours or more as highly unlikely, since it requires households to completely alter their habits. It seems reasonable to believe that such a change in habits would lead to significant disutility for the household, at least in the short run when technology is fixed. Finally, in our load shift experiments, we treat the spot price as exogenous, a reasonable assumption when few households are on real time pricing schemes. However, if a majority of households switch to real time pricing and adjust their consumption to the hourly prices, one would anticipate that the price variation, and thereby cost savings, to potentially decrease, as noted elsewhere in the literature.

6 Conclusions

This paper set out to explore, using a unique data set on household hourly and appliance-level electricity consumption, the potential, and cost implications, to retailers and consumers, of Sweden’s thrust on real time pricing for residential electricity use. The appliance-specific nature of the metered data we use provides a unique opportunity to gain greater understanding of (appliance- and) end-use-specific electricity consumption patterns.

We estimate end-use specific load curves (conditional on household characteristics) and analyze how these correlate to possible restrictions on substitutability of load within the day, such as working hours, outdoor temperature, and (lack of) daylight. As emphasized in section 1, we do not explicitly explore substitutability of electricity, but rather analyze possible *restrictions* on substitutability. We argue that such restrictions impose significant limitations on any short-run attempt to shift load from “expensive” to “cheap” hours. Our findings from the estimated load curves are that household total

load has two peaks corresponding, roughly, to the morning pre-office hours (6-8 AM) and evening post-return-to home hours (6-9 PM). This is the period when the Nord pool spot prices are at their highest i.e. households consume the most when prices are their highest.

At end-use level, our analysis sheds light on relatively intuitive facts; households use heating when it is cold, lighting when it is dark and cooking before they leave for work and when they return home. Unsurprisingly, we find that the end uses with large shares of total load are heating, lighting and cooking, in that order. Based on these results, it is not evident that in the short-run, households have the possibility of re-allocating electricity consumption across hours, as this would essentially imply that households cook dinner during night, turn on lights when electricity is cheap and adjust heating to prices, rather than to outdoor temperature.

However, even in the presence of such restrictions, households may still adjust consumption to prices if the cost savings are substantial. By matching the estimated load curves with corresponding spot prices, we are able to explore potential cost-savings from re-allocating electricity consumption from peak to off-peak hours. We find very small gains; only 2-5% of reduction in daily cost obtain from shifting load up to 7 hours ahead (for an average February working day). As already discussed, these results should be interpreted as a best case scenario. On the other hand, it is also important to point out that as the share of intermittent generation increases, the price variation, and hence potential cost savings, may well increase. However, although potential cost savings increase in price variation, restrictions to load shifting may impose significant cost increases if households are unable to re-allocate load.

Our results, while novel and plausible, suffer from a few data-related drawbacks which call for caution in interpretation as well as in direct application to policy. Foremost of the drawbacks is the absence of household price data (and contract type) information; this adds “noise” to our estimate of the cost implications of load shift (in addition to not allowing an exploration of price sensitivity of households). Furthermore, the limited geographic variation in the households in our sample calls for some caution when extrapolating the results to the entire Swedish population.

We conclude with some thoughts on the broader implications of our study for RTP, and on the emission implications of dynamic pricing for Sweden, an aspect so far not mentioned. Both in Sweden and elsewhere, policy makers and economists have put much faith in dynamic pricing and associated (theoretical) efficiency gains. The results of our study appears to lend support to the view, expressed in a few other recent studies, that many of the previous findings in the literature regarding the benefits of RTP may be based on optimistic assumptions about households' ability, and incentives, to adjust consumption to prices. Nonetheless, much more work is needed before we can fully understand the potential, practicability, and efficiency of real time pricing for Sweden.

In the Swedish case, given that only peak capacity is polluting, load shifting as a result of dynamic pricing has significant implications for emissions from Swedish electricity generation. Indeed, either peak conservation or reduction in peak load via re-allocation of consumption at a large scale is likely to imply a substantial reduction in (the already small) peak generation, and hence, emissions from electricity generation. Similar to the case of the U.S., investigated in [Holland and Mansur \(2008\)](#), where dynamic pricing is seen to reduce emissions, there is scope for emission reduction in the Swedish case too. In the presence of the EU ETS, where Swedish producers have to purchase emission credits, avoided peak generation has added private (to the producers) and social (avoided emissions) benefits, beyond retailer and consumer cost reduction, implying that these benefits must also be considered in any computation of economy-wide welfare implication of dynamic pricing. Investigating these issues, while beyond the scope of the current analysis, is clearly an interesting and policy-relevant extension.

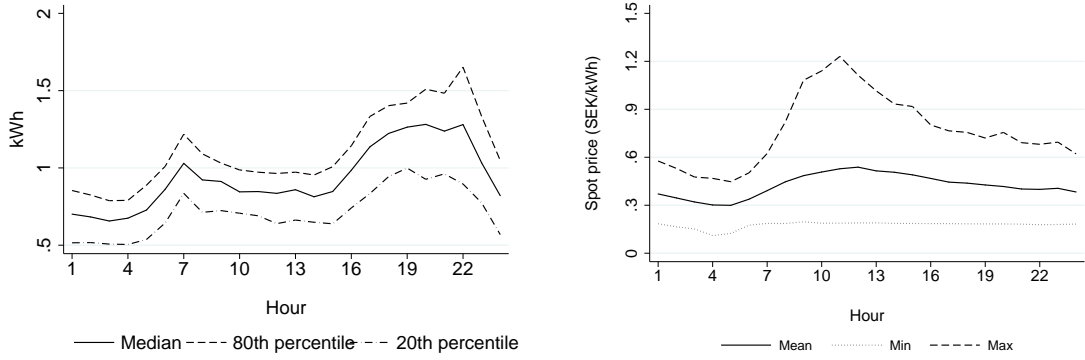
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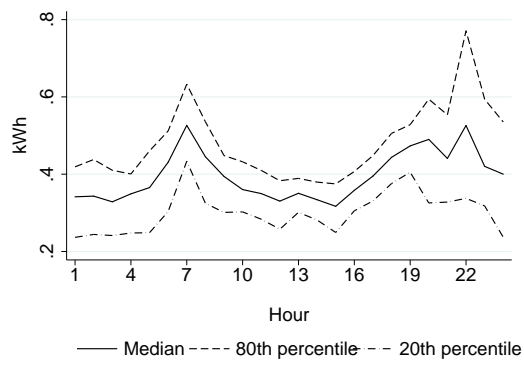
(a) Total load for average working day in June (b) Nord pool spot prices for weekdays in June

Figure A.1: Total load curve and Nord pool spot prices for June.

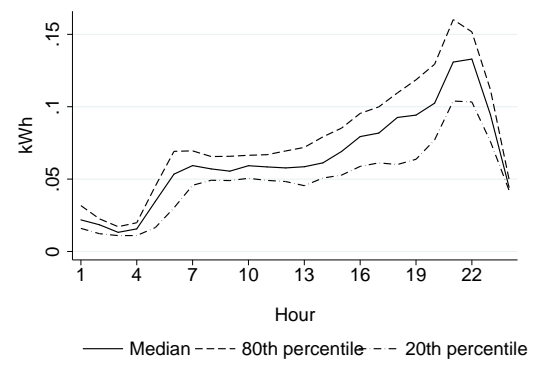
Appendix A Load Curves for June

Appendix B Load Curve: goodness-of-fit

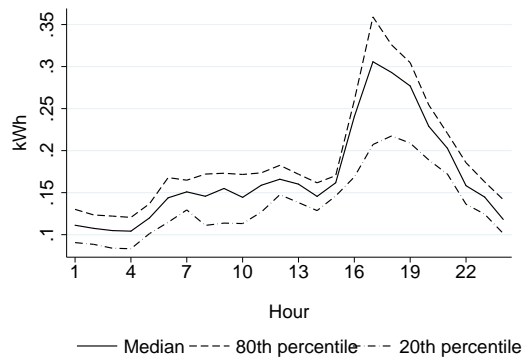
All SUR regressions used to generate the load curves in section 5.2 pass a battery of specification tests commonly used to assess the SUR system (estimated here using the FGLS approach). These tests encompass the following hypotheses: (i) all coefficients excluding the constant and year-fixed effects are zero (i.e. $\beta = [\beta_1, \dots, \beta_{24}] = 0$, in the notation of eq. (1)); and (ii) the Breusch-Pagan test of correlation of residuals across all equations (i.e. a null of “no correlation”). We note that test outlined in (i) may be viewed as a test for “model goodness of fit”, particularly when fixed effects are used. As already noted, GLS is not equivalent to OLS in our estimation framework, and therefore, the (Breusch-Pagan) test for cross-equation correlation is not a determining factor for the choice of GLS. We are able to reject the null for all of the tests, whose results are reported in table B.1.



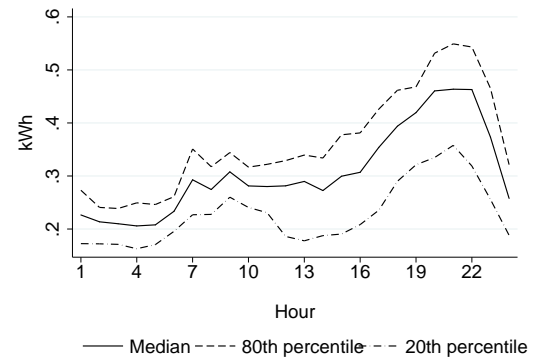
(a) Heating load



(b) Lighting load



(c) Kitchen load



(d) Residual load

Figure A.2: End-use load curves for average June weekdays.

Table B.1: Goodness-of-fit measures for February load curve estimation.

	N	Wald test	Breusch-Pagan test
Total	40	0.000	0.000
Heating	40	0.000	0.000
Lighting	40	0.000	0.000
Kitchen	40	0.000	0.000
Residual	40	0.000	0.000

Notes: p-values for the specific test indicated reported. Note that ‘N’ reports the number of observations (households) in each of the 24 hourly equations.