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Abstract

Using a unique and highly detailed data set of energy consumption at the appliance-level for 390 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 aggregate spot price data, is computed to be very small; roughly 2-5% daily cost reduction from shifting load up to seven hours ahead, indicating small incentives for households (and suppliers) to adopt dynamic pricing of electricity. In addition, end-use-specific income elasticites are also estimated, for the first time for Sweden, using again a SUR framework. The estimated income elasticties are large and significant, varying from a high of 0.8-1.25 for heating to a low of $0.2 - 0.5$ for lighting. Aggregate income elasticity is also high, varying from 0.5 to 0.81. 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

Keywords: Direct Metering, Residential Electricity Demand, Real time electricity pricing

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1 Introduction

Using a unique household data set for Sweden (for households not currently on real time pricing (RTP)) involving ten-minute metering of residential electricity consumption at the appliance-level, we explore two key issues involved in implementation of any RTP scheme; restrictions to load shifting and cost implications of load shifting. In addition, we are also able to provide a better understanding of the patterns of monthly end-use specific consumption, and provide the first estimates for Sweden of monthly end-use-specific income elasticity.

With the restructuring of electricity markets there has been an increasing focus on the efficient pricing of electricity. Sweden is not an exception, and introduced hourly retail pricing in October 2012.[1] Compared to the currently used average retail price, 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 (see e.g. Borenstein (2005); Energimarknadsinspektionen (2010); Kopsangas-Savolainen and Svento (2012)). 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 peak to off-peak hours within a given day, is rather scarce.

Given that data on household behavior under RTP is scarce, one way of empirically exploring this practicability would be to compare the timing of current within-day electricity consumption (by households on non-dynamic 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 e.g. lighting, since use of lighting is to a large extent determined by available daylight. Further, estimates of current within-day

[1] Every household has the right to have hourly prices (but not mandatory), without having to pay for the necessary metering equipment.

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 academic literature on electricity demand have been able to illustrate how residential electricity end-use level 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.

This paper 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-specific nature of the metered data we use provides a unique opportunity to obtain better understanding of appliance-specific consumption patterns. We are therefore able to provide, aggregating the data to monthly level, end-use specific income elasticity, for the first time for Sweden. Prior approaches to estimating monthly appliance- (or end-use)-specific income elasticity used the approach of Conditional Demand Analysis (CDA), with many limitations or a combination of metered data and CDA approaches (see section 2). Due to absence of any price information in the data, we are unable to estimate price responsiveness.

Using hourly data, 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 flexible-) 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 mone-

[2] To 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.

tary 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. Our estimation results have important implications for Swedish energy policy, and in particular for the government's stated goal of implementing RTP. The success of this pricing scheme depends heavily on demand response which, our results indicate, are unlikely to be large without substantial investments in new technology and a focus on it from the suppliers, who appear to have little to gain from this switch–at least in the short run–based upon our simple cost shifting experiments (see section 6.2).

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 energy market. Section 4 provides a description of the data used in this paper, together with a few summary statistics, while an analysis of the monthly consumption patterns by end-use follows in section 5. Section 6 details the estimation of load curves, along with computations regarding the cost of servicing different end-uses and cost changes due to load shifts. Section 7 provides a discussion of the policy context of our analysis, and concludes.

2 Literature Review

We turn now to a brief review of the literature on within-day and appliance-level electricity consumption. As emphasized earlier, a clear understanding of both price responsiveness and baseline consumption patterns are natural inputs to any analysis of policies concerning dynamic pricing. In particular, the success of RTP requires that consumers respond 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 –neccessary for such analysis– is sparse, and especially rare are studies using hourly data. The conditional demand approach pioneered in Parti and Parti (1980)

[3]Energy conservation is not the main policy goal of RTP and is also not something the suppliers are likely to be supportive about; see section 3 for a breif overview of the market structure of electricity 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 (see e.g. Energimarknadsinspektionen (2010))

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 is to combine data on total load with survey information on appliance holdings and, exploiting the heterogeneity in appliance portfolio, to estimate contribution from each appliance to total load. Households with a particular appliance are compared to similiar households without the appliance and the differences in total load are attributable to the appliance. 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 intensity of appliance utilization, and appliance size, between households. The mean response associated with each appliance is then estimated using the data from both types of households, those 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 conditional demand 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 the two models and provide a few recommendations regarding choice of end-use approach and what questions to implement in household surveys designed to disaggregate electricity consumption.

Turning to measures of price responsiveness, to our knowledge all estimates of residential price elasticity for Sweden are based on annual data, and we have been unable to find published (or unpublished) studies on end-use specific price and income elasticity. Although many studies (Andersson (1997); Brännlund et al. (2007); Damsgaard (2003); Krishnamurthy and Kriström (ming)) indicate significant price responsiveness, from a low of -0.13 to a high of -1.35, it is not clear how such estimates translate to a real time price context.[4] However, there is some experimental literature on how households

[4] The important literature pertaining to Sweden is summarized here. Brännlund et al. (2007) estimate

respond to dynamic pricing schemes for Sweden. For example, in a small-scale experiment, Swedish Elforsk Market Design and a few local suppliers in southern Sweden[5] analyze the short-run household response to staged price spikes in the interval of 3 to 10 SEK/kWh (Lindskoug (2006)). 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) succeding in reducing total load the most.[6] 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. 7), it is not clear how relevant these results are for more moderate (and frequent) price variations typically considered in dynamic pricing analyses.

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. Note first that the benefits ("welfare gains") of RTP are typically obtained from a more efficient allocation of consumption, where consumption is shifted from "expensive" to "cheap" hours. 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.

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 capacity) 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 the simulations in Boren-

price elasticity for space heating and find estimates of -0.13. They then estimate separate elasticities for electric heating, oil heating and distric heating ranging from -0.71 to -0.24 depending on specification. Damsgaard (2003) finds price elasticities ranging from -1.35 to -0.37 depending on heating system (using micro data). Andersson (1997) estimate the long-run elasticity for electric heating households to -1.36. Krishnamurthy and Kriström (ming) estimate price elasticity for Sweden to be between -0.68 and -1 using OECD survey data.

[5] Skånska 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.

[6] Interestingly, the load reduction from increasing prices to 10 sek/kWh was found not to be significantly greater than for prices of 3 SEK/kWh. However, note that households selfselected into this experiment.

stein (2005); Borenstein and Holland (2005) for a Nordic market setting, imposing capacity restrictions on nuclear and hydro power (reflecting the Nordic setting, with 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.

All of these simulations assume a constant-elasticity hourly demand function, implicitly assuming that household response to a price change is independent of time of the day and, further, implying at least some substitutability between hours.[7] This dependence of welfare computations 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 by Allcott (2011), finds that RTP causes no 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 in Borenstein (2005); Borenstein and Holland (2005); Kopsangas-Savolainen and Svento (2012) which indicate a slight increase in total consumption.

Further, Allcott (2011) notes that even if households on RTP are fairly price elastic, the gains are small; the estimated increase in consumer surplus amounts to roughly $10 per year or roughly 2 percent of annual household electricity expenditure.[8] 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 belive that there are short-run restrictions on the households possibilitiy to respond, further

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

[8] In 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).

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).[9]

In the context of Sweden, the Swedish Energy Market Inspectorate (EI),[10] 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)[11] 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.[12] However, the EI reports that during the first year of the RTP program in Sweden only about 8600 households had adopted this new pricing scheme (Energimarknadsinspektionen (2014)).[13]

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.[14]

[9] Borenstein (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 then the opposite with elasticity decreasing in demand levels. 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).

[10] The Swedish Energy Markets Inspectorate supervises the Swedish electricity market, and is responsible for an improvement of the functioning and efficiency of these markets. See http://www.ei.se/en

[11] The 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).

[12] This 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.

[13] One explanation of this rather low number is probably that as of spring 2014, only 68 (out of roughly 120) electricity suppliers 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.

[14] Fritz 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

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.

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, the 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% 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 maket, Elbas, to cover potential imbalances occuring between the closing of Elspot at noon and delivery the next day. In 2013, maximum system price was 1.825 SEK/kWh (in December) and average price was 0.33 SEK/kWh (source: http://www.svenskenergi.se).

The bulk of electricity produced in Sweden is by hydro and nuclear sources, constituting 43 and 44 percent of total production, respectively (figures for 2013, from SvK). The remaining production is from thermal (co-generation) plants and windpower, together with some smaller sources of peak capacity.[15] This peak capacity, loosely defined

will likely not yield sufficient potential cost savings for households.

[15] Shortages and blackouts are not an issue in Sweden due to large (surplus) capacity in hydro-power;

(following the previous literature, 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.[16] 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 to balance the variability of wind power generation. 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 emphazied 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 14 000 kWh for 2013 (source: `http://www.svenskenergi.se/Elfakta/Elanvandning/`). This is explained both by cold winters 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 "typical" household with electric heating consumes approximately 20 000 kWh per year. As of 2013, about 40 percent of all households were on fixed rate contracts with yearly or longer contract durations and about 30 percent are on variable rate contracts. The general trend is that households are switching from so-called default contracts to variable rate contracts.[17] For the previous eight years ($2005-2013$), the average fixed rate price was 0.49 SEK/kWh while the variab 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 climite

peak capacity is therefore relatively small.

[16] Svenska Kraftnät, 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 decided that the capacity reserve will be phased out by the 15 March 2020 and replaced by market-driven capacity and/or demand flexibility.

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

policy targets following the EU Climate and Energy Package (the 20-20-20 target), stipulating, among other things, a 20 percent increase in energy efficiency and 50 percent of energy consumption from renewable sources in 2020 (relative to 2009).[18] 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)).

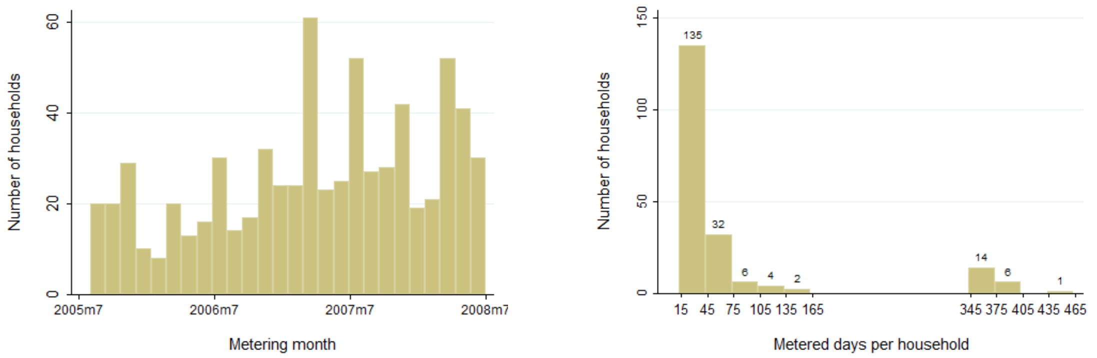
4 Data and summary statistics

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 potiential 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 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.[19] The project was carried

[18]The 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.

[19]The 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 reduce the external validity of the quantitative results. Nonetheless, provided households in the rest of Sweden have patterns of behavior which are not very



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

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

Figure 1: *Distribution of metered data.*

out between 2005 to 2008 and each household was metered for between 15 days and 16 months. Figures 1a and 1b illustrate 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 (already referred to) precludes an analysis of price responsiveness.[20] Table 1 provides summary statistics for household characteristics by heating source. Household income is reported in intervals, but we use interval regression to generate a continuous income variable.[21]

dissimilar, we anticipate the qualitative results to broadly hold.

[20]That is, even if average prices are available from Statistics Sweden, there are in reality many different contracts available with different prices.

[21]Results do not change when the original income variable, in intervals, was used. The continuous variable is used since it is more easily interpretable, in particular for our income elasticity results in section 5.

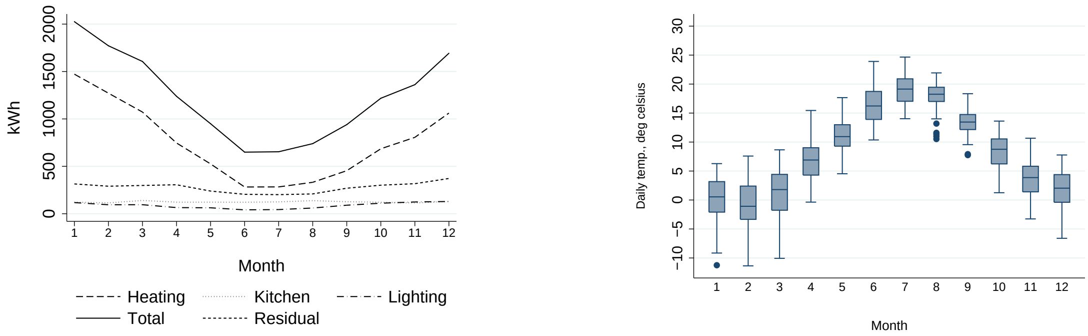
Table 1: Summary statistics for households by heating source.

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

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 varies between 1926 and 2007, with a mean year of about 1970, and is expected to have a substantial effect on heating consumption, where old houses are 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 owned by electrically-heated households) and income (slightly higher income for households with mixed heating). Overall, households with mixed heating tend to have slightly higher income, are slightly larger in size (both in m^2 and number of inhabitants) and slightly older than electrically heated homes. Nonetheless, the moderate

[22] We note that there is no information on what criteria were used to choose how many appliances are metered in each household. For our analysis, it is not critical that this figure be in proportion to the number of energy consuming appliances owned, a very plausible assumption; for convenience, we will use such an interpretation, particularly when we discuss, in section 5, income elasticity estimates based upon primary heating source.



(a) Monthly electric consumption by end-use.

(b) Daily outdoor temperature by month.

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

Notes: see section 5 for detailed description and definition of end-uses.

differences between these two types of households motivates the relatively simple load curve estimation framework, with load curves for houses which are electrically heated only an intercept shift; see section 6.[23]

The monthly average for a household with electric heating corresponds to an annual load (multiplying the average monthly load by twelve) of roughly 17 000 kWh, slightly less than the 20 000 kWh assumed by Statistics Sweden for the reference household (see section 3). 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; i.e. during warm summer months even households with electric heating only have very small heating consumption. This seasonal pattern is illustrated in fig. 2a below, where we present average monthly consumption by end-use (see section 5 for definition of end-uses.) 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 cold (see fig. 2b), this pattern is anticipated.

[23]Multiple sources of space heating are commonly used in Sweden. On very cold days, a secondary heating system as well may be used by households which do not primarily use electricity; this also helps explain observations of non-negative heating consumption for households which report that they do not have electric heating. For example a house which is connected to the central heating system (via district heating) might activate an electric heating system as a secondary source on colder days.

5 Understanding Monthly Electric Consumption

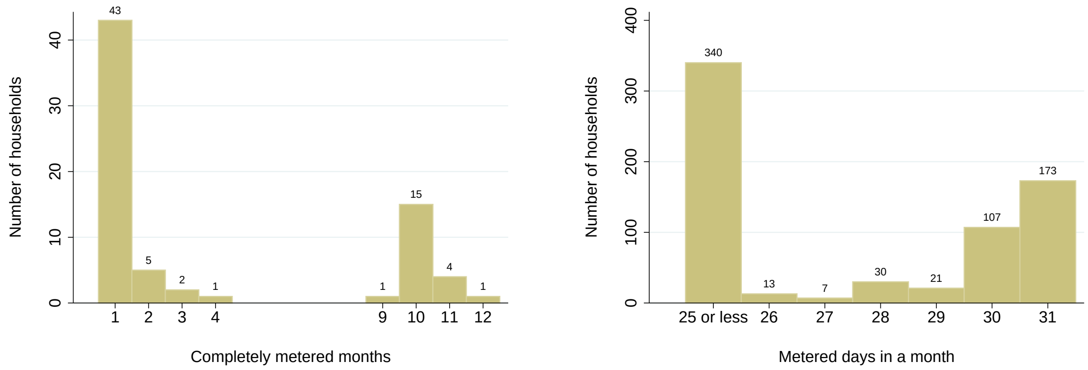
We turn now to presenting a model of montly end-use-specific electricity consumption. The analysis of monthly end-use specific consumption provides more insight regarding the patterns of consumption, and sets the stage for understanding daily behavior subsequently. In addition, the analysis here provides, for the case of Sweden, first estimates of end-use specific income elasticity, leading to a better understanding about which end-uses are more responsive to income. This aspect of our data set helps assess complex policies and marketing strategies that target a specific appliance type. Since direct metering data are not commonly collected, such an analysis has, as already mentioned, hitherto been carried out using the Conditional Demand Analysis (CDA).

5.1 Data Summary

The original data, available at ten-minutes intervals, were aggregated to the monthly level.[24] Further, we aggregate the load from individual appliances to end-uses. These end-uses include "kitchen" as the sum of all kitchen appliances (stove, oven, microwave etc), "lighting", and "heating" as the sum of all heating appliances – for example air heating pumps, radiators, and water heating appliances. Appliances that do not fit in any of these three catogories are aggregated into a "residual" end-use (for example TV, computers, etc). The categories are selected based on their expected share of total load, where heating is by far the largest load, followed by kitchen and lighting.

Since households are metered for different number of months and in different years, we have housholds varying across two dimensions: month and year of observation. In addition, given that different households are metered for different number of months (as already referred to in section 4), our data are highly unbalanced across this dimension (see figures 3a and 3b). Considering only households metered for complete months, the mean total electric consumption is 1324 kWh and 1012 kWh for households with and without electric heating, respectively. Given the seasonality of heating consumption,

[24] Given that only one household was metered for 12 complete months, annual end-use-specific income elasticties cannot be estimated without scaling up monthly data to annual. This is the reason for the choice of a month as the level of aggregation considered, in addition to the fact that a month is also a billing period and that households were asked to provide monthly household income data, rather than annual.



(a) *Monthly household metering.*

(b) *Days metered within a month.*

Figure 3: *Distribution of metered data.*

however, we also present total consumption data for the winter period (November to March). As anticipated, for these months, differences in mean total consumption between homes which are electrically heated and those which are not are more substantial, at 1943 kWh and 1297 kWh, respectively. Recall (from table 1) that the average income of the households without electric heating (i.e. with mixed heating) is slightly higher.

There are in total 691 observations for 198 households.[25] However not all of the 691 monthly observations span the 28, 30 or 31 days of that month, since many households are not metered for the complete month. Figure 3b shows the distribution of the number of days metered in a month. Out of 691 observations, only about 280 correspond to completely measured months. Close to half of the monthly measurements (340) include months with 25 or less days of metered data. This poses a problem in ensuring that all households in the sample have consumption data for a full month–the typical billing period. We address the issue here in a relatively simple way, by scaling up the consumption amounts for months that have up to 5 missing days of metered data, using average daily consumption for that month. For example if a month consists of 26 daily measurements that sum up to 100 kWh, we simply divide 100 kWh by 26 and multiply it by number of days in that particular month (28, 30 or 31). We provide a brief check of whether this method introduces substantial changes in our estimated income elasticity.

[25] As can be seen from the figure 3a, only 72 (of a total of 198) households were monitored for complete months, for any duration between one and 12 months. In particular, 50 households were monitored for between one and three months, and 21 households were monitored for between nine and 12 months.

5.2 Econometric Approach

The econometric framework used is the Seemingly Unrelated Regression (SUR) approach where the different end-uses constitute the equations and monthly consumption data for all households (for that end use) constitute the observations. In more detail, the estimated equations for end-use k is

$$Y_{i,m,y} = b + \delta_y + \gamma_m + \alpha_i + \beta X_{i,m,y} + \epsilon I_i + v_{i,m,y} \tag{1}$$

where i, m, y represent respectively the household, month and year index, with X the vector of covariates and I household income.[26] We use the double log functional form i.e. Y, end-use electric consumption, and income, I, are entered in log, implying that ϵ is the income elasticity of consumption for that particular end-use (for ease of notation, we do not index the coefficients with k). Note also that there are "fixed effects" for each of the three dimensions, controlling for effects specific to that dimension. In particular, household-specific fixed effects, α_i, help account for repeated observations from households.

Given that we have only limited data regarding determinants of energy consumption at the end-use level and that many of these omitted factors are likely to be similar across end-use categories, we anticipate some correlation between the unobserved components of each end-use. These concerns are easily accounted for in the standard SUR framework, and are an important motivation for our choice of this framework. We have data on consumption (kWh) for each end-use (kitchen, heating, lighting and residual), which is the dependent variable in eq. (1). The independent variables are largely the same for all end uses, and include: living area (m^2), household size and log of income.[27] However, for heating end-use, we additionally include monthly mean outside temperature as well as an indicator for electrically heated homes, since such homes are anticipated to have

[26] To be precise, the equation for the k^{th} end-use is $Y^k = \boldsymbol{\psi} + \beta^k X^k + \epsilon^k I + \boldsymbol{v}^k$, where $\boldsymbol{\psi} = [\boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\delta}]$ is the matrix of all fixed effects (of dimension $M \times 3$), and Y^k a vector of consumption data for the k^{th} end use, of dimension M, X^k is the matrix of dependent variables of dimension $M \times k_1$, with k_1 the number of covariates. The number of observations for each of the K end-uses, M, is reported in table 2, separately for the imputed and raw data configurations.

[27] Note that while the original data set does include household location details, the version provided for use does not include even an indicator of the region in which households are located–North, South or Mälardalen. As a result, we are unable to include fixed effects for region-effects, a relatively simple way to account for fixed differences across the distinct regions of Sweden.

at least an intercept change (i.e. they begin with a much higher consumption level for heating).

The aggregate (over end uses) income elasticity can be easily computed from the end-use specific elasticities (as in the CDA approach). In more detail, using the identity $Y = \sum_{k}^{4} Y_k$, aggregate elasticity can be shown to be $\epsilon = \sum_k^4 (p_k \times \epsilon_k)$, where $p_k = \frac{Y_k}{Y}$ and Y_k denotes the load of the k^{th} end use with estimated income elasticity ϵ_k. Intuitively, aggregate income elasticity is a weighted sum of the end use elasticities, with weights being the share of the particular end use in total load Y. Estimated aggregate elasticities are displayed in table 3.[28] Note that the imputation method is described in the preceding section and that the "raw data" estimations use only households metered for a complete month(s). We find relatively few differences for the two data configurations, raw and imputed, in our results, discussed next. We also point out that compared to prior analyses using a combination of CDA and direct metering (e.g. Bartels and Fiebig (2000); Bauwens et al. (1994)) our framework for analysis is relatively simple (see footnote (33) for details); the results are also easily interpreted, since there are no interaction terms, unlike with the CDA approach (compare e.g. eq (10) in Parti and Parti (1980)).

5.3 Results

Since ours is the first study reporting end-use level income elasticity for Sweden, we provide a range of estimates, for different data configurations. Given the limitations of our data (small data set, lacking many interesting economic variables), we view these estimates as establishing a baseline for further investigation of end-use specific household demand in Sweden. We begin our discussion with the results of estimation of the simple framework in eq. (1) and subsequently discuss the robustness of our results to the assumption that electrically heated homes differ from non-electrically heated ones

[28] Recall that we use monthly data for estimation of eq. (1), and that more than a third of the households have at least two months of data (see fig. 3a). Thus, every observation is associated with aggregate elasticity (i.e. p_k varies for each observation). We present, in table 3, the aggregate income elasticity estimated at the sample average share, $\overline{p_k}$. Standard error of ϵ is computed using the delta method.

	Kitchen	Heating	Lighting	Residual
Imputed data (N=310; H=109)				
Log (income)	0.4567***	0.7956***	0.2996***	0.3877***
	(0.036)	(0.096)	(0.047)	(0.062)
Living area (m^2)	-0.0026**	0.0006	0.0024*	0.0020
	(0.001)	(0.002)	(0.001)	(0.001)
Number of people in household	-0.0012	-0.5923**	0.3523***	0.3693**
	(0.077)	(0.180)	(0.101)	(0.126)
Mean monthly temperature (°C)		0.0114		0.0000
		(0.017)		(0.010)
Electric heating (1=Yes)		2.1839***		
		(0.557)		
Raw data (N=240;H=67)				
Log (income)	0.4901***	0.8374***	0.3659***	0.3321***
	(0.035)	(0.104)	(0.045)	(0.051)
Living area (m^2)	-0.0031***	0.0000	0.0014	0.0026*
	(0.001)	(0.002)	(0.001)	(0.001)
Number of people in household	-0.0684	-0.6338***	0.2150*	0.4748***
	(0.078)	(0.191)	(0.099)	(0.113)
Mean monthly temperature (°C)		0.0096		0.0091
		(0.018)		(0.011)
Electric heating (1=Yes)		2.1111***		
		(0.561)		
$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$				

Notes: (i) Seemingly Unrelated Regression coefficients (standard error in parentheses). The dependent variable is monthly end-use specific demand (in kWh). All regressions include household, year and month fixed effects (not reported).
(ii) Sample sizes vary by data categorization, are indicated ("N=") beside respective categorization, and refer to the number of observations used by each equation. Note that "H" denotes the number of households whose data are used in the regressions.
(iii) The imputation procedure is described in the text. Standard errors are estimated using the huber-white sandwich estimates of the covariance matrix, with degree of freedom corrections.

Table 2: End-use specific regression results.

	Kitchen	Heating	Lighting	Residual	Overall	N
Imputed data						
Whole sample	0.457***	0.796***	0.3***	0.388***	0.591***	310
	(0.036)	(0.096)	(0.047)	(0.062)	(0.054)	
Electrically heated	0.476	0.990	0.265	0.361	0.747***	181
	(0.043)	(0.106)	(0.052)	(0.068)	(0.068)	
Non-electrically heated	0.447***	0.796***	0.200**	0.313***	0.499***	129
	(0.039)	(0.096)	(0.069)	(0.087)	(0.052)	
Significant difference	No	Yes	Yes	No		
Raw data						
Whole sample	0.490***	0.837***	0.366***	0.332***	0.611***	240
	(0.035)	(0.104)	(0.045)	(0.051)	(0.056)	
Electrically heated	0.466	1.025	0.512	0.485	0.812***	134
	(0.048)	(0.113)	(0.061)	(0.069)	(0.074)	
Non-electrically heated	0.435***	0.837***	0.458***	0.445***	0.591***	106
	(0.044)	(0.104)	(0.056)	(0.064)	(0.052)	
Significant difference	No	Yes	Yes	No		

Notes: (1) Income elasticity estimates from the SUR framework (standard error in parentheses). 'Observations' correspond, as in table 2, to those used for each end-use.
(2) "Whole sample" results are those from table 2. Separate income elasticity for homes with and without electric heating are esimtated by introducing into the SUR framework an interaction between the income variable and the indicator for electric heating (in addition to the income variable itself). The number of observations for homes with and without electric heating correspond to the number of homes in the regression sample with and without electric heating.
(3) The 'Significant difference' row reports the significance of the interaction term.
(4) The "Overall" column corresponds to the aggregate (over end uses) income elasticity, whose computation is detailed in the text.

Table 3: End-use specific income elasticity.

only in the intercept.[29] A priori, one anticipates a positive income elasticity for all end uses; living area and number of people in a household, however are more difficult to interpret in this context. For instance, if the "production" of services in a household exhibits any form of returns to scale (as is sometimes the case in demand estimation; see e.g. Browning et al. (2013) and references therein), then increases in the number of individuals living in a home is not necessarily linked to increased usage, conditional on other factors. We see this to be the case particularly for heating, with a negative significant coefficient in both data configurations. Overall, we see that across both data configurations and end uses, number of persons is positively related to lighting and residual consumption, negatively to heating demand and insignificantly to kitchen demand. In the case of living area, on the other hand, both sign and significance vary across data configuration and end-use. For raw data, increases in living area leads to reduction in kitchen demand and an increase in residual demand; with imputed data, on the other hand, it is lighting demand which is increased. Overall, living area appears not to be a major determinant of end-use heating demand, after controlling for number of people in household and income.

In the short-run (i.e. conditional on appliance stock), it is usually anticipated that the consumption of end-use services, and therefore usage of electricity, increases with income. The estimated income elasticity is seen to be positive for all end-uses and across both data configurations, being highest for heating (at 0.79 and 0.86 for imputed and raw data, respectively) and lowest for lighting (at 0.29), using imputed data (residual, at 0.33, using raw data). The estimated income elasticities are comparable to, but substantially lower than, those in Bartels and Fiebig (2000) who report elasticity estimates–albeit for a very different usage pattern and context– of 0.68 for lighting (and

[29] All SUR regressions reported in tables 2 and 3 pass a battery of specification tests commonly used to assess the SUR system (estimated here using the FGLS approach). The results of these tests are not reported in the tables for brevity but are available from the authors upon request. These tests encompass the following hypotheses: (i) all coefficients excluding (month-, year- and individual-) fixed effects are zero (i.e. $\beta = \epsilon = 0$, in the notation of eq. (1)); (ii) same as (i) but for each equation; (iii) in addition, for separate estimation of income effect by heating source, in table 3, that the interaction term is jointly zero for all equations; and (iv) the Breusch-Pagan test of correlation of residuals across all equations. We are able to reject the null (of equality) in all of the regressions reported in table 2 and table 3, and note that (i), in particular, may be viewed as a test for "model goodness of fit" when fixed effects are used. As already noted, GLS is not equivalent to OLS in our estimation, and therefore, the relevance of the test for cross-equation correlation is not a determining factor for the choice of GLS.

0.26 for water heating). The relatively high elasticity, of close to 0.5, for kitchen end use is a bit puzzling, and (given the low level of kitchen consumption) is probably more easily explained by change in patterns of usage across income, with higher income households having greater number of people and a higher usage pattern (i.e. more advanced cooking), and potentially using more appliances. Finally, as anticipated, the electric heating dummy, introduced only in the heating end use, is significant and positive, with a substantial magnitude, while average monthly temperature is never significant (but of the correct sign).

We turn next to investigating whether the end-use-specific income elasticity is different between households depending upon whether they are electrically heated or not. As already discussed, electrically heated households differ from those not electrically heated only modestly, owning a slightly higher number of appliances, living in slightly larger homes and having slightly higher income, in both the full and regression sample (income for households with electric heating and with mixed heating for the regression sample is 40 760 and 42 210 SEK, respectively). This last feature provides a motivation for exploration of the sensitivity of our results to the assumption of identical income elasticity between households with electric heating and with mixed heating. In the interests of parsimony, we allow only income elasticity to differ between these two types of heating sources. We provide results, in table 3, of estimating the SUR system in eq. (1) modified with the addition of an interaction between log(income) and the indicator for electric heating. Income elasticity estimates for raw and imputed data are reported separately. As with all slope-and-intercept-difference regressions, significance of the interaction term implies difference in income elasticity between households with electric and mixed heating, and is reported in the "Significant difference" row in table 3.

We turn now to understanding the income elasticity estimates in table 3.[30] Noteworthy differences between households with electric and mixed heating are limited to heating and lighting end-uses, and this is true for both data configurations. Electri-

[30] Note that the full sample ("whole sample") income elasticity is not directly comparable to the subsequent two elasticities due to the specifications being slightly different i.e. the "whole sample" model does not nest the other two models. The full sample regression allows an intercept difference for heating end-use between households with electric and mixed heating, whereas the subsequent two specifications provide a slope difference for all end-uses.

cally heated households also turn out to be have higher income elasticity (at 0.99 and 1.02 for imputed and raw data respectively) than non-electrically heated households (at 0.79 and 0.83), with a substantial difference (0.2 and 0.17, for imputed and raw data respectively). This accords with the basic data and, to an extent, with intuition; recall from table 1 that mean monthly heating demand for electrically heated households is about 40% higher than for households with mixed heating, implying consequently a substantially higher electric bill (even accounting for the moderate price difference between the two households). If non-electrically heated households switch on electric heating appliances only occasionally, it is unlikely that small changes in income lead to large changes in usage patterns. Overall, income elasticity for heating is very high for both types of households, irrespective of the data configuration, and are always higher (and close to unity) with the raw data.

For lighting, the differences are a very modest 6.5%, for both data configurations. This is again consistent with basic data (from table 1), which indicate only a 7% difference in terms of raw demand, as well as intuition, since there is no strong reason to anticipate that lighting demand differs substantially. Overall, lighting elasticities differ substantially between raw and imputed data when income elasticities are allowed to differ between households with and without electric heating, with estimates using raw data being twice as large as those using imputed data. The large magnitude of lighting elasticity with the raw data (at 0.51 and 0.45 for electrically and non-electrically heated homes, respectively) is somewhat surprising; one explanation for this result is the strong relation between income, home and household size.[31] Turning now to residual usage, income elasticity does not significantly differ between homes with and without electric heating, and varies only moderately between raw and imputed data. Given that residual consumption involves a variety of appliances, there is no clear guide as to why one category of household should differ from the other in income elasticity; however, from the data in table 1, it is evident that electrically heated households have a higher number of appliances and, in so far as these do not all belong to the other three end uses, provides

[31] Lighting is an end-use with a strong gradient in efficiency of usage; coupled with an anticipated relatively fixed demand for this service, a priori we anticipate the technology shift (resulting in efficiency increase) to dominate or counteract the increase in demand. This is a reason for the "surprise" regarding the rather high income elasticity for lighting.

a basis for an anticipation that income elasticity may moderately differ.

Finally, similar to end-use elasticities, we find high aggregate income elasticity, at 0.61 using the raw (and 0.59 using the imputed) data. Income elasticities as large as this are rarely obtained using aggregate household level data[32] ; for Sweden, these vary from about 0.15 in Krishnamurthy and Kriström (ming) to a high of 0.33 in (one of the log specifications in) Damsgaard (2003). As for the end-use case, elasticities estimated using the raw data are larger than those estimated using the imputed data. We also observe that electrically heated households have a higher income elasticity than non-electrically heated ones, driven largely by the heating elasticity (discussed above). For households with electric heating, aggregate income elasticity is a very high 0.81.

To summarize, income elasticity varies across end-uses and data configurations, but is always highest for heating, higher than 0.8 for any configuration and as high as 1.025 for electrically heated households (estimated using raw data). Our elasticity estimates for lighting, while moderately large (between $0.2 - 0.51$), are nonetheless lower than the 0.68 reported in Bartels and Fiebig (2000). Our aggregate income elasticity estimate, at 0.61, is much larger than the few estimates available for Sweden.

6 The Load curves

6.1 Estimation Details

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 (see appendix A).

Similiar to the estimation of income elasticities, and following Bartels and Fiebig (2000, 1990), we also use a SUR framework for estimation of the end-use load curves with

[32]For e.g. Parti and Parti (1980) report an estimate of 0.15, and among the other studies they compare their with, the highest estimate is of 0.4. The survey of Bohi and Zimmerman (1984, table 1), however, indicates that some of the older studies reports high long-run income elasticities, to much larger than 1.

a total of 24 hourly equations for each end-use. However, 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.[33] The actual equation estimated for end-use k and hour t is (omitting the t superscript on coefficients for notational simplicity):

$$\overline{Y}_i^k = b^k + \delta_y^k + \beta^k X_{i,d,t} + v_{i,y}^k \tag{2}$$

where $\overline{Y}_i^k = \frac{\sum_{d=1}^{D} Y_{i,d}^k}{D}$ is the mean daily load for hour t and end-use $k = 1, ..., K$ for household $i = 1, .., N$, $X_{i,d,t}$ are the control variables and δ_y^k denotes a year dummy accounting for year-specific effects (if any) on daily consumption (year indices are suppressed on X and Y). 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 (2) as modeling the consumption of household i on an *average* february day.[34] Thus, the percentiles of (predicted or actual) consumption, based upon equation (2), refer to those of the relevant household on an average February day, an interpretation which facilitates our subsequent discussions regarding household behavior. We define total load of hour t as the sum of the K

[33] It 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)).

[34] An alternative approach would be to use the data from every day in February, which leads to the following equation for the t^{th} hour (with obvious notation):

$$Y_{i,d}^k = a^k + \alpha_i^k + \delta_y^k + \beta^k X_{i,d,t} + \epsilon_{i,d}^k.$$

This approach provides additional benefits in terms of accounting for individual-level “unobserved heterogeneity” (as is typical with “fixed effects”) or any other cause leading to violation of the usual orthogonality conditions at the individual-equation level, due to the inclusion of the household “fixed effects”, α_i. On the other hand, in our load curves below, the interpretation in terms of households (e.g. “median household on a average day in february”) is more complicated, since there is variation across two dimensions, now; day and household. Nonetheless, we find that both formulations of the equation for the t^{th} hour provide almost identical load curves, both in pattern and magnitudes (the load curves for the formulation in this other approach are available upon request).

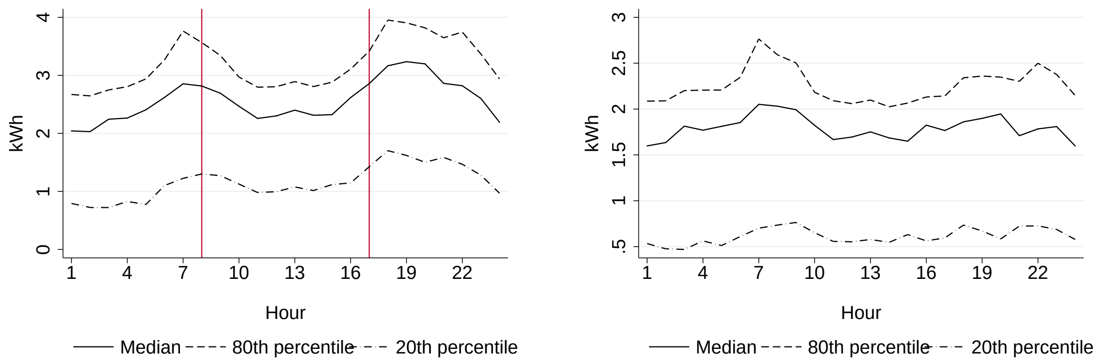
end-uses in that hour, i.e. $\hat{\overline{Y}}_{i,t}^{total} = \sum_{k}^{K} \left(\hat{\overline{Y}}_{i,t}^{k} \right)$.[35]

The complete list of control variables are similar to the ones used in section 5: (hourly) mean outside temperature ($°C$), building year, living area (m^2), indicator for electric heating, income (in SEK), and number of inhabitants. The motivation for inclusion of the independent variables is the same as for the estimation of income elasticities: as heating is by far the largest component of total load, outdoor temperature is expected to significantly affect electricity consumption; a similiar 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 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 likely is positively correlated with both the number of appliances possessed and their efficiency. Finally, we include retail prices to control for price variation between households.[36]

The benefits of SUR referred to in section 5 apply here too, although we here estimate a separate SUR system for each end-use with 24 hourly equations. In particular, as with the estimation of income elasticities, it is quite likely that unobserved determinants of household behavior are common to all hours and joint estimation across hours is likely to yield efficiency gains. Secondly, 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 Xs varies across equations). We estimate equation equation (2) 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 $\widehat{\overline{Y_i}}$) to illustrate household heterogeneity in terms of hourly load . 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

[35]We note that metered total load differs from the computed (as sum of end uses) total by a small amount, due to the presence of a few non-metered appliances. 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.

[36]As pointed out earlier, the metering data set does not include retail prices. Neither do we have information on contract type (monthly, annual, etc) for each household to match households with the correct prices. However, average prices for different contract types are available from Statistics Sweden which are used as an approximation. We test for different contract types but find no change in results, and therefore use average price for monthly contracts in our main results. Note also that prices for different contracts co-vary.



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

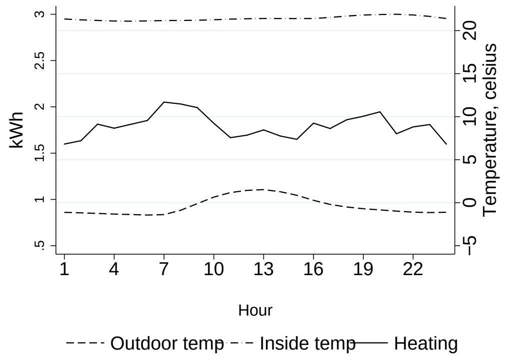
(b) Heating consumption by hour.

Figure 4: Total and heating load curves for an average February working day.

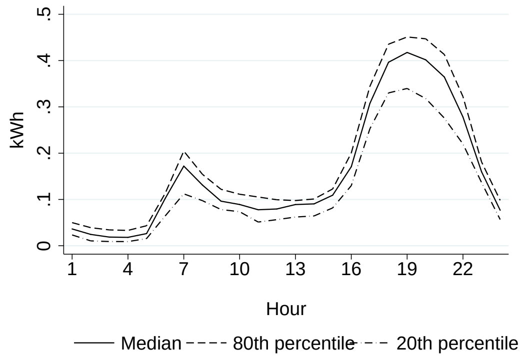
in June are to be found in appendix A (the estimated coefficients are not reported but are available upon request).

Total load is displayed in fig. 4a, illustrating the median consumption together with the 80th and 20th percentile consumption. Note the rather large, and expected, difference between the median and the 80th and 20th percentile, driven to a large extent by differences in heating load. We elaborate more on this below, when we discuss the load curve for heating (see fig. 4b). 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 two two peaks correspond roughly to working hours (typically 8 am – 5 pm in Sweden), illustrated by the two vertical lines.

In fig. 4b we illustrate the estimated load curve for heating. First of all, note the large differences between households, with the median heating load almost 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 when compared to for example electricity consumption from lighting or kitchen (roughly 0.5 kWh thoughout the day, comparable in magnitude



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



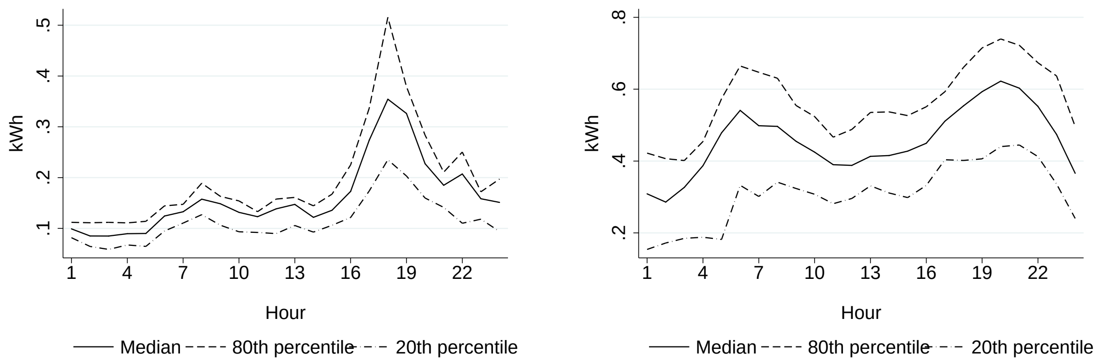
(b) Lighting consumption by hour.

Figure 5: Heating and lighting load curves for an average February working day. Other details similar to those in fig. 4a

to peak lighting or kitchen load for the 80th percentile household, see fig. 5b and fig. 6a). 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. Distinct morning and evening peaks for the heating load curve are also evident from fig. 4b (for all levels of consumption, although it is less pronounced for the 20th percentile).

Turning to fig. 5a, we illustrate the median heating load together with average outdoor and indoor temperature. The heating load curve appears (approximately) to be the mirror-image of outdoor temperature, as would be expected. Interestingly, although there is a decrease in heating load during the mid-day, this does not lead to a corresponding decrease 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 utility derived from it (i.e. without reducing indoor temperature during periods when householders are at home). Further, the mean indoor temperature is surprisingly high, compared to the recommendations of minimum indoor temperature of 18 degrees celsius by The National Board of Health and Welfare (see http://www.socialstyrelsen.se/publikationer2013/2013-11-29).

The load curve for lighting is displayed in fig. 5b. Here households appear to be rather homogenous in their consumption, with both the 80th and 20th percentile close



(a) Kitchen consumption by hour.

(b) Residual consumption by hour.

Figure 6: Kitchen and residual load curves for an average February working day. Other details similar to those in fig. 4a

to the median. There is a smaller peak during the morning, and a larger one between 4 pm and 10 pm, and these peaks corresponds 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 policy measure.

The load curve for the kitchen end-use is displayed in fig. 6a. Households appear to be rather homogeneous in terms of kitchen electricity use, since the percentiles have very small separation. 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 only marginal (compared to 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. The magnitude of kitchen load is comparable to that of lighting, and is rather small in comparison to heating. Finally, we illustrate the load curve for the residual electricity consumption in fig. 6b. 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 afternoon peak, occurring roughly at the same time as the other end-uses.

There might of course be individual appliances, such as laundry, that are "easily shifted" and therefore at 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 similiar appliances consume very small amounts of electricity compared to e.g. the end-uses displayed above (laundry load is only one percent of total February load for the average household), and shift of these loads are 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 might change the pattern of the load curve.

6.2 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. It is instructive to first understand the average Nord pool spot price for a working day in February, bearing in mind that the price is 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.

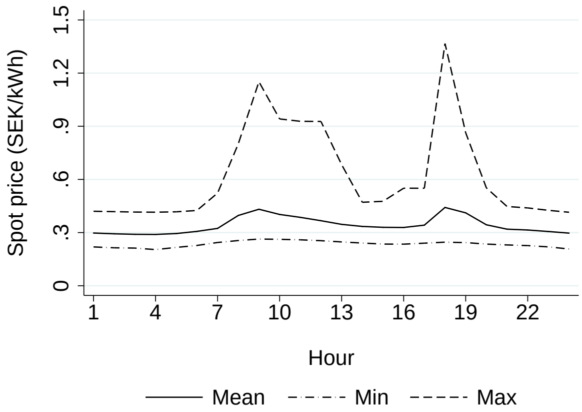


Figure 7: Hourly Nord pool spot prices (price area three in Sweden) for February (2006-2008).

Two price peaks are evident from fig. 7, in which the mean, minimum and maximum hourly spot prices are graphed; one at roughly 9 am and another at about 5 pm, with maximum price peak being more pronounced. Comparing the spot price to the estimated 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 price and second, 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 (from price area three in Sweden), 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 supplier's cost, or as a proxy for household cost when on RTP.[37] Further, EI estimates that roughly 50 percent of variation wholesale prices translates to

[37]It 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. The 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.

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 spot price by $\bar{p}^t$ and the predicted hourly load for end-use k as $\widehat{Y}^t_{h,k}$, where h denotes the median, 20th or 80th percentile. To obtain the cost C^t_k of servicing end-use k in hour t, we simply multiply the predicted hourly load with the mean spot price for that hour:

$$C^t_k = \widehat{Y}^t_{h,k}\bar{p}^t,\ t = 1,..,24,\ k = 1,...,4. \tag{3}$$

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

$$C^d_k = \sum_{t=1}^{24} \widehat{Y}^t_{i,k}\bar{p}^t = \sum_{t=1}^{24} C^t_k, \tag{4}$$

computed separately for the median and the 20^{th} and 80^{th} percentiles.

Table 4: Daily cost (in SEK) of servicing different end uses for average February working days.

End-use	Median household	80^{th} percentile household	20^{th} percentile household
Using average daily 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 daily 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 4 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 load from a given end-use 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 (i.e. similiar to the approach used in Bartels and Fiebig (2000), although they only shift the load for one appliance; pool pump);[38] this implies that evening hours now show 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 lowest hourly 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 out this experiment for the mean 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 5: 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 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 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 5 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.[39] Even if we shift the whole load curve

[38]Note 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 for shifting 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.

[39]At 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 neccesary metering equipment are same for all households, and such costs are not evidently not included

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 are unable to respond to price peaks their costs will increase substantially for those days.

The cost savings illustrated in table 5 are a likely *best case* scenario, for several reasons. First, as already mentioned, roughly half the variation in wholesale prices is transmitted to retail prices, implying less price variation and hence smaller cost savings. Secondly, the load shifting pattern illustrated above is likely not feasible, in reality. Indeed, we consider such shifting of (total) load across as many as three hours or more is highly unlikely, since it requires the household to completely change 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, one would anticipate that the price variation, and thereby cost savings, to potentially decrease, as noted elsewhere in the literature.

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in the above calculations. Therefore, it is not certain that policy makers should interpret this results as an argument for promoting RTP to households with low(er) consumption levels.

7 Conclusions

This paper set out to explore, using a unique data set on household appliance-level electricity consumption, the potential, and cost implications, 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-specific consumption patterns. We are therefore also able to provide, for the first time for Sweden, end-use specific income elasticity, using household-level metered data (unlike prior approaches using the CDA method or a combination of metered data and the CDA method, with many limitations). We find rather high income elasticity, varying substantially across end-uses; heating has the highest elasticity, at 0.8, while lighting has the lowest (0.3), with kitchen and residual end-uses lying in between, at 0.45 and 0.39 respectively. The magnitude of the estimated income elasticity across end-uses is robust to different data configurations and methods of accounting for the differences between electrically and non-electrically heated households. Our aggregate elasticity estimate, of 0.61, computed using end-use elasticities, is similarly higher than that in the existing literature.

We also 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 analysis reports 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), and that the largest part of the peak load by far tends (unsurprisingly) to be heating and lighting, and this is the period when the nord pool spot prices are at their highest. That is, households consume the most when prices are the highest. At end-use level, this analysis sheds light on relatively intuitive facts; households use heating when it's cold, lighting when it's dark and cooking before they leave for work and when they return home. Unsurprisingly, we find that the end uses with large shares of the 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 make dinner during night, turn on lights when electricity is cheap and adjust heating to prices, rather than to outdoor temperature.

However, even in 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% daily cost decrease from shifting load up to 7 hours ahead (for an average day). As discussed above, these results should be interpreted as best case scenario. On the other hand, it is also important to point out that as the share of intermittent generation increase, the price variation, and hence potential cost savings will 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. Finally, if households switch to RTP contracts and re-allocate load, the resulting long-term reduction in costly peak capacity, and resulting lower prices, will of course also benefit households. However, this benefit will only be realised if households do respond to price variation, something our results indicate is questionable.

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 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 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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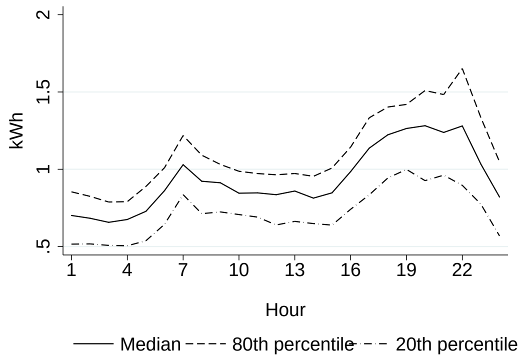
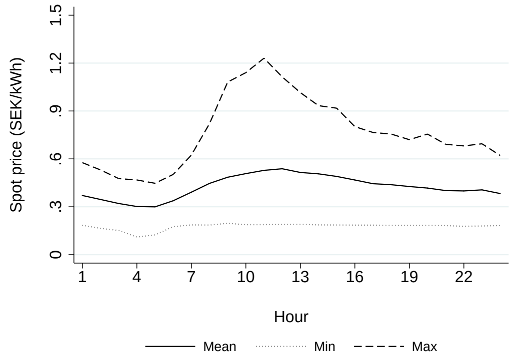
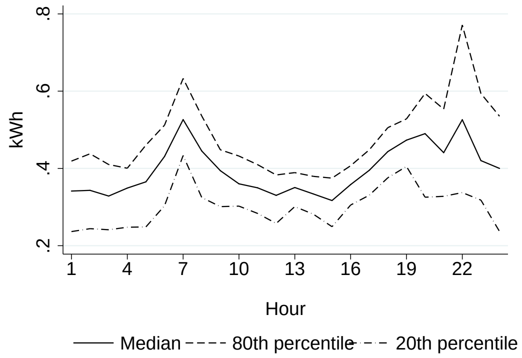


(a) Heating load in June

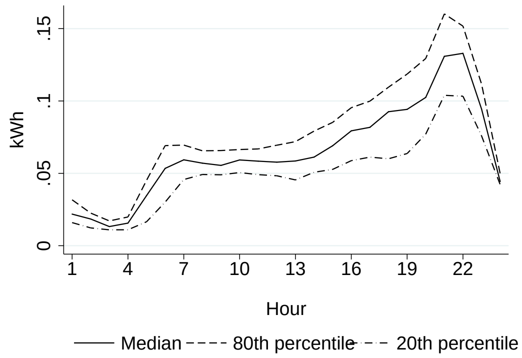


(b) Nord pool spot prices

Figure A.1: Total load curves for an average June weekday and Nord pool spot prices for weekdays in June. Other details similar to those in fig. 4a

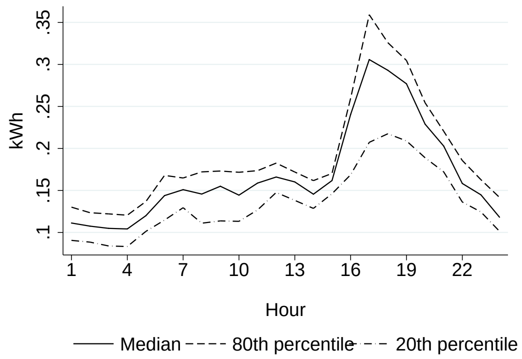


(a) ???

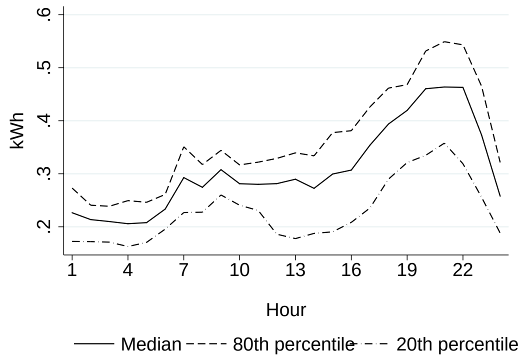


(b) .

Figure A.2: Heating and lighting load curves for average June weekdays. Other details similar to those in fig. 4a



(a) Kitchen load



(b) Residual load

Figure A.3: Kitchen and residual load curves for average June weekdays. Other details similar to those in fig. 4a

Appendix A Load Curves for June

Appendix B Load Curve: goodness-of-fit

Table B.1: Goodness of fit 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: (i) p-values for the specific test indicated reported. (ii) Wald test for total load is for estimated total load (instead of using the sum of all appliances), as is the case for the load curves. See section 6.
(iii) The tests carried out are described in footnote 29; in particular, the wald and the Breusch-Pagan tests correspond to (i) and (iv) respectively in footnote 29.
(iv) The wald test results reported are for the entire SUR system; recall that one SUR system is estimated for each end-use.