CERE Working Paper, 2018:4

Benefits of real-time pricing and rooftop solar PV generation: Explorations using Swedish micro-data*

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March 06, 2018

Abstract

Previous empirical literature on residential dynamic pricing for the Nordic market has questioned whether households will in fact appropriately respond, in view of the low price variability and price responsiveness in the Swedish setting. Household demand response is an issue of some importance in view of increasingly smart grids in which high shares of renewable supply are being promoted partly in view of these possibilities. In addition, an important development in the Nordic market relates to increasing thrust on household PV panels. In view of the interaction between RTP-driven and PV generation-driven load changes, an analysis of the combined effects in relation to system timing is important to understand, not least because this can affect the nature of benefits to households and the electric grid. Using a unique and very detailed dataset on household electricity consumption, in combination with simulated solar panel micro-generation data, these aspects are explored in an empirical framework similar to that used in the prior literature. Our findings indicate that even with minimal price responsiveness, household response to dynamic pricing can lead to load changes with sizeable benefits. In addition, the introduction of PV panels, contrary to what may be assumed at a first glance, appear to be beneficial to the electric grid, largely due to the time pattern of winter PV generation. Overall, our empirical findings provide tentative evidence to indicate that RTP, by incentivizing households to provide demand response at appropriate times, can aid in integration of renewables.

Keywords: Real time electricity pricing, energy demand, renewable energy, intermittency

JEL classification: D12, Q41, C10

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* This work was supported by the Academy of Finland Strategic Research Council project BC-DC (AKA292854); the Academy of Finland project Regulation and dynamic pricing for energy systems REDYFLEZ (288957). We thank Mahboobeh Farhadikashi for research assistance.

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1.Introduction

Electricity markets are facing challenging and remarkable changes. The main drivers for these changes relate to the intermittency in renewable generation and technical development in smart grids. Intermittency-related questions are at the forefront of research in energy economics (e.g., Gowrisankaran, Reynolds, & Samano, 2016; Hirth, 2013, 2016; Hirth, Ueckerdt, & Edenhofer, 2015, Huuki et al, 2017). In the existing literature (see, e.g., Borenstein, 2012; Milligan et al., 2011) the integration costs of renewable resources (RES) are divided into three categories relating to uncertainty, locational specificity and variability. A commonly used definition of integration cost components (Hirth et al., 2015) suggests three distinct cost components: The first, *profile costs,* result from the imperfect correlation between load and RES output, indicating the necessity of some form of backup capacity to maintain supply-demand balance at times with no RES production. The second, *balancing costs,* arise from RES output forecasting errors made in the day-ahead market. To maintain balance, prediction errors must be balanced with costly rapidly-adjustable reserve power in the intraday markets. The third, *grid-related costs* arise from expanding and reinforcing the existing transmission and distribution network. For example, good wind power locations are often located far from the existing transmission lines and load centres. These costs will need to be taken into account in defining new pricing and regulation models for the changing market. Some of these cost-related aspects are often missing from policy discussions and ignoring them could lead to policy decisions imposing needlessly large costs.

Wolak (Wolak, 2017) identifies four major market design features that need to be considered in scaling-up intermittent renewable generation capacity. The first of these relates to finding a match between the market mechanism and system operation. The actual price setting model must be consistent with real grid operations or otherwise suppliers are able to use the resulting arbitraging opportunities and efficiency cannot be attained. This necessitates the pricing model to be based on locational marginal pricing in a multi-settlement environment. The second market design challenge relates to finding efficient mechanisms for ensuring long-term resource adequacy. The current consensus in the literature suggests two approaches to solve this challenge: capacity markets or energy-only markets. Capacity markets are created by founding auction mechanisms to have the utilities bid their willingness to keep vacant capacities to be called on when needed. UK and Ireland among others have chosen this way (e.g., Teirilä, 2016). Energy-only markets are created through trusting that the load can be adjusted based on renewable supply. This approach in fact turns the electricity production process up-side down; instead of dispatching generators based on demand, as is common, demand is 'dispatched' based on supply. This aspect relates closely to our research question in this paper.

The third market design challenge relates to regulation, with distribution-related regulation in particular needing to be reconsidered. Here, too, literature suggests two basic approaches, either opening distribution pricing to more dynamic elements or changing it to power-based models. The fourth market design feature Wolak identifies, active involvement of final demand in wholesale and retail markets, is the focus of our analysis (with particular reference to the households). Per this feature, efficient pricing entails the default price for marginal consumption for all consumers be one that encompasses the system-wide cost, including the costs of managing intermittent generation. Typically, the hourly wholesale price is used as the relevant price (which may, or may not, be the most appropriate price in the Nordic context, as we briefly discuss subsequently). In any case, this form of pricing is still a long-run target since the share of these types of voluntary contracts among households is increasing very slowly (e.g., in Finland less than 10% of customers have real-time price based contracts, while for Sweden, it is lower still—less than one percent (Nilsson et. al., 2014)). The other side of this demand response coin relates to own (household-level) small scale renewable production through solar panels or windmills. This aspect has not, to our knowledge, been explored for the Nordic setting. Its importance will be subsequently illustrated but the key linkage is via altered household load pattern, in particular the connection between the pattern of microgeneration and system characteristics, aspects which have been shown to be of importance when analysing the systemic implications of distributed generation (e.g. the influential study of Gowrisankaran et al., 2016). These aspects, we illustrate, will also be of substantial importance to understand for the Swedish context in view of the ambitious targets for Solar PV generation (Lindahl, 2014).

Our objective here is to evaluate two distinct, and inter-related, aspects concerning household demand response (DR):[1] the extent to, and the manner in, which elastic households are able to respond to RTP; and the interaction between this response and micro-generation via roof top solar panels (interchangeably called "micro-generation"). Household RTP and solar PV are both major policy goals for Sweden (Swedish Energy Market Inspectorate (2017), Lindahl, 2014) and both relate to penetration of intermittent sources, albeit via very different

[1] In common with the literature, DR is a subset of many demand side management measures that focuses on financial incentives to help change demand. In our case, we consider passive DR i.e. consumer responses to price contracts only.

avenues. In addition, we indicate that for the Nordic context, their combined effect is of some importance to understand. These aspects of household demand and DR are evaluated combining a rich household consumption data set with accurately simulated solar generation data, generating a combined novel and unique data set. Our consumption dataset consist of hourly end-use specific observations for a random sample of Swedish households (see §3 for a detailed description) while our solar generation data are derived for this particular analysis based upon the HARMONIE Numerical Weather Prediction (NWP) model (Bengtsson et al., 2017). To our knowledge, these two aspects have not been combined before at the household level and this combination provides a rather unique opportunity to empirically examine the issues under consideration.

It will be useful to recall a few features of RTP prominent in the received literature before we detail our objectives more specifically. The long-run—in which capacity and generation technology are allowed to change-- benefits of RTP arise from both demand and supply adjustments, with peak(er) power capacity being reduced following an adjustment by the demand side (in terms of reduced peak demand). Overall, therefore, prices fall and consumers experience welfare increases and the system experiences increased efficiency. When RTP is optional—which has thus far universally been the case—it is in fact the short-run—with fixed capacity and technology-- effects of RTP which eventually determine the realization of the envisaged long-run benefits. We focus on the short-run, and in our counter-factual scenario, assume mandatory RTP in the fully competitive Swedish retail market, and note that there has thus far been very limited attention to this setting (we are unaware of any studies at all). Prior long-run analyses of RTP in the Nordic setting (Kopsangas-Savolainen & Svento, 2012) indicate the usual sources of efficiency gains. A more recent study (Huuki et al. 2017) considers explicitly the role of RTP in helping to integrate wind in the Nordic grid, and finds, in simulations with a representative consumer, that in the long run the integration costs of wind can be substantially reduced if consumption based demand response is complemented with supply side hydropower optimization. In any case, the only short-run analysis using household data we are aware of, Vesterberg & Krishnamurthy (2016), was focused upon clarifying the rather limited potential for RTP. Prior short-run household-data-based analyses of RTP, largely counterfactual (e.g., Borenstein, 2013a; Horowitz & Lave, 2014) but occasionally empirical (Allcott, 2011), have been focused on settings with regulated utilities, infrequently revised power rates, and very different generation and demand patterns from the Nordic setting. Consequently, aspects of micro-generation considered differ from those in the existing literature.

Turning now to the major objectives, this paper explores two aspects related to demand response that have thus far remain unexplored, certainly for the Nordic setting. The first question is regarding the ideal load profile under RTP, for a highly competitive retail market setting in the *short-run*. In a context where costs of different sources of power vary sizably, with peak(er) power being more expensive, the ideal system load profile is, ostensibly, one with small peaks, with the theoretical ideal being a rather flat load profile (as implicitly assumed in many studies e.g. Borenstein, 2007; Holland & Mansur, 2006; Kopsangas-Savolainen & Svento, 2012). The extent to which this idealized load profile can be realized, in turn, depends upon two factors: (i) the level and time-pattern of elasticity, with two alternative patterns encompassing opposing assumptions forming the boundary; high during off peak hours and low during peak hours, stemming from the derived demand nature and lack of storage, and its converse (stemming from the correlated nature of demand and prices); and (ii) levels of price differentials across the day, in particular between peak and off-peak hours; to the extent that price differentials across hours are pronounced, the effect of a given pattern of elasticity is amplified. However, we argue, and show quantitatively, that the rather moderate variation of price across a working day (at least on average) in the Nordic setting limits the degree to which consumers can be incentivized to shift, reflecting essentially the nature of production technologies used (largely base-load type of plants, with hydro and nuclear predominating). This part of our analysis extends the prior work of Vesterberg & Krishnamurthy, 2016 – in which the potential for, and benefits of, load shifts were examined – to settings where price responsiveness actuates consumers' willingness to do change load (encompassing cases of both energy conservation and load shifts). It also relates to prior examination of short-run effects of RTP upon consumer welfare (Borenstein, 2013a, Borenstein & Holland, 2005, Horowitz & Lave, 2014), particularly since the framework of analysis used here has many similarities with those used in this literature.

The second question relates to household load changes resulting from micro-generation, and the effects this has upon demand when households are assumed to be on an RTP contract. The two factors, RTP and micro-generation, represent the confluence of technological developments and energy policy, and present both an opportunity as well as a challenge for electricity markets. A key aspect for understanding the overall effect are the relative timing of demand and supply. We illustrate that for the Swedish case, micro-generation with RTP may actually lead to increased load disparity between peak and off-peak hours, in particular by reducing the demand for large parts of the off-peak period. It is not obvious, in fact, whether this is a desired or an undesired aspect, and we discuss this question in §5. This aspect of our analysis also raises an interesting point: one may conjecture that the welfare effects of RTP and the interaction with micro-generation depend upon the hourly pattern of elasticity and hourly price variation. These latter factors are in key roles in evaluating whether, and to what extent, there is load shifting or energy conservation (the latter of which is what has been empirically documented) as a result. In any case, the interplay between the timing of the household (and system) peak, timing of micro-generation, and (observed and conjectured) demand response is therefore a key aspect that can be explored with the demand framework outlined above, by examining alternative patterns appropriate to the Swedish context.

Our main findings may be summarised, in brief, as: In the counterfactual world we envisage, consumers respond with load changes on the margin consequent to RTP and solar PV generation. The resulting patterns of load, under virtually all plausible scenarios for elasticity patterns and price levels, result in peak shrinking and/or off-peak reduction, implying overall sizeable energy conservation. These findings from our (admittedly simple) simulations reflect the findings of most empirical studies that report overall load reduction and no off-peak increases. These aspects reflect the constraints placed upon household load by existing patterns of consumption and technology and indicate substantial difficulty in *reallocating* load across time. However, our results indicate that households have sizeable pecuniary incentives to be active players in the demand response setting with increasing shares on renewable and intermittent supply in the electricity market. Investigations regarding integration of intermittency is an active area of research, with rigorous empirical studies connecting household demand behaviour to systemic features of a future grid being scarce. Our contribution here lies in making precisely this connection: evaluating the possibility for RTP when households are assumed price-responsive but with varying magnitude over the day, using an extremely detailed household dataset. Thus, our study connects the literature evaluating the short-run benefits of RTP to that speaking to the systemic challenges of intermittent generation integration.

The plan of the paper is as follows: §2 details different data-sets used for the analysis, §3 provides details regarding the econometric model used for our simulations, along with detailing the various scenarios considered; §4 discusses the results of our policy simulations and §5 concludes with a discussion of the implications for policy and suggestions for further research.

2. Data

Two key types of data will be used for our analysis, detailed household electricity consumption, and estimates of micro-generation, across different periods, for the region corresponding to our data. The household electricity data originates from a metering project commissioned by the Swedish Energy Agency between 2005 and 2008 (Zimmerman, 2009) while the estimated photovoltaic (PV) production data is based on the HARMONIE Numerical Weather Prediction (NWP) model (Bengtsson et al., 2017). These two data sets are combined to yield an exceptionally rich data setting, with household electricity consumption available at very detailed (up to ten minute intervals, at the end-use or even appliance level) and PV production data at a matching time-scale. The precise way in which these data are used together in our analysis will be detailed subsequently. We begin with some brief remarks regarding major features of the data sets used.

2.1 Household Consumption Data

The Swedish Energy Agency commissioned the household metering project to increase the quality of data on Swedish residential electricity usage, and to assess the potential for energy conservation and increasing energy efficiency. We provide a brief overview of the data here, and refer the reader to Zimmerman (2009), and to previous published papers using the same dataset (Vesterberg & Krishnamurthy, 2016 and Vesterberg, 2016), for more details. In total, 389 households, sampled by Statistics Sweden (see https://www.energimyndigheten.se/Statistik/FESTIS/Elmatning-i-bostader), were metered at ten-minute intervals. 200 of the metered homes were detached houses, and the remaining 189 were flats. A majority of the households were located in the Mälardalen region, with only 10 households each located in northern and southern Sweden.[2] The project was carried out between 2005 and 2008 and each household was metered for between 15 days and 16 months.

[2] Overall, the rather narrow geographic spread of the sample tends to reduce the external validity of our quantitative results. Nonetheless, provided that households in the rest of Sweden have patterns of behavior which are not very dissimilar, we anticipate that the qualitative results of our analysis will broadly hold. In addition, given the pre-dominance of households located in the Mälardalen region, we will often refer to "households located in the Mälardalen region" as a proxy for our sample households. This interpretation will be particularly useful when we consider solar generation—since the solar panels we consider are located in this region. Nonetheless, we note that nothing much in our analysis for winter is dependent upon this assumption, given the rather small differences for a large part of the season in sunlight hours across the regions in which our households are located (less than an hour between Jan and March).

There are roughly the same number of observations for each calendar month, with roughly 80 households per calendar month.[3] In addition to the metering data, survey data was collected on household characteristics such as monthly household income, number and age of inhabitants, living area size, building year and type of main heating system. In this paper, we consider two main systems of space and water heating: electric and mixed. The mixed heating category may be understood as those using primarily a non-electric heating source, typically district heating, along with supplementary sources of space heating. Unfortunately, the data lacks household-level price data, precluding any estimation of price elasticities. Typically, Swedish households in that period had monthly-varying price contracts, or fixed (over a year or longer) contract, and we assume that households are on the former contract type for our analysis.[4]

We focus exclusively on (semi-)detached single family dwellings (villas, henceforth), since they are most important from a policy perspective as these households are assumed to be able to contribute with the most flexible load. Table 1 provides a brief summary of the (aggregated daily end-use) consumption and (annual) income of the sample households across two income groupings, high- and low, and heating type, electric- and mixed-heating (we direct the reader to Vesterberg & Krishnamurthy, 2016 for a more detailed analysis of household characteristics). Apart from the obvious differences in heating, and hence total, consumption, the variation in end-use load across heating types is minimal. Much of the variation in non-heating end-uses, in fact, appears strongly related to income. As also anticipated, household heterogeneity in different (non-heating) end-use types is substantial, even for higher income households. The picture that emerges therefore is of households varying substantially in most end-uses apart from heating, while total daily load, driven largely by heating, is on the whole predictable for electrically heated households and varies substantially for households with mixed heating (where the electric component of heating can be considered "discretionary"). In any case, different household types possibly react differently to the same price signal. More interestingly, given that the variation in contract type, and hence the marginal price, is minimal across these households,[5] it appears that non-price related aspects such as income and

[3] Two reasons were provided by the Energy Agency for the relatively short metering period for most households: a limited number of metering devices and a focus on observing as many households as possible within the time frame of the metering project.

[4] We note that it is highly unlikely that any of the households are on dynamic pricing contracts--which were not widely offered during the time period of the survey. Even today, very few households in Sweden have chosen dynamic pricing contracts.

[5] Note that in view of the competitive market for retail electricity, prices for the same contract types do not substantially differ across retailers. While contract types do differ by heating category (with electrically heated households receiving a lower price), this is invariant across retailers. Thus, to the

household demographics play an important part in driving demand, lending further support to the basis of our empirical analysis.

Table 1: Sample Summary Statistics

Variable	High Income		Low Income	
	Electric heating	**Mixed heating**	**Electric heating**	**Mixed heating**
	Daily End-use consumption (kWh)			
Kitchen	0.20	0.16	0.12	0.15
	[0.26]	[0.24]	[0.17]	[0.23]
Heating	2.25	0.82	1.92	1.17
	[1.23]	[1.03]	[1.31]	[1.63]
Light	0.17	0.14	0.11	0.14
	[0.21]	[0.17]	[0.15]	[0.19]
Residual	0.49	0.53	0.21	0.4
	[0.63]	[0.53]	[0.30]	[0.36]
Total	3.11	1.65	2.36	1.86
	[1.47]	[1.21]	[1.47]	[1.8]
Household Income (SEK)	45752	45013	24838	22049
	[2762]	[2592]	[12253]	[14994]

We next compute the hourly load for these four representative types of households. Subsequently, electricity usage is aggregated to average hours by computing first hourly consumption and then the average electricity usage by hour and month and by household type. The resulting average load profile for winter months (January to March, for 2006 to 2008) is illustrated in Figure 1 (corresponding figures for summer months is available upon request). The fixed price and spot price for the corresponding period are illustrated in Figure 2. Figure 1a indicates that there is a distinct load pattern within a day, with usage being substantially smaller during off-peak (e.g., night time or working hours) compared to peak hours, most notably during 5pm to 10pm. This pattern is plausibly explained by working hours and daily routines, with households using more electricity when at home and, e.g., cooking dinner.

extent that contract types do not differ across income categories, for which there is little evidence, marginal price for the same heating source in fact are anticipated to be almost the same across household income categories.

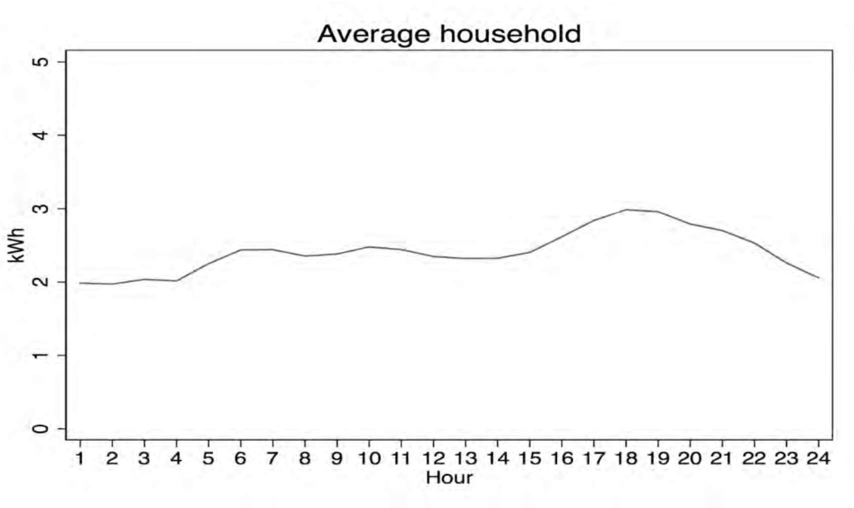


Figure 1a: Average hourly household consumption in January-March 2006-2008

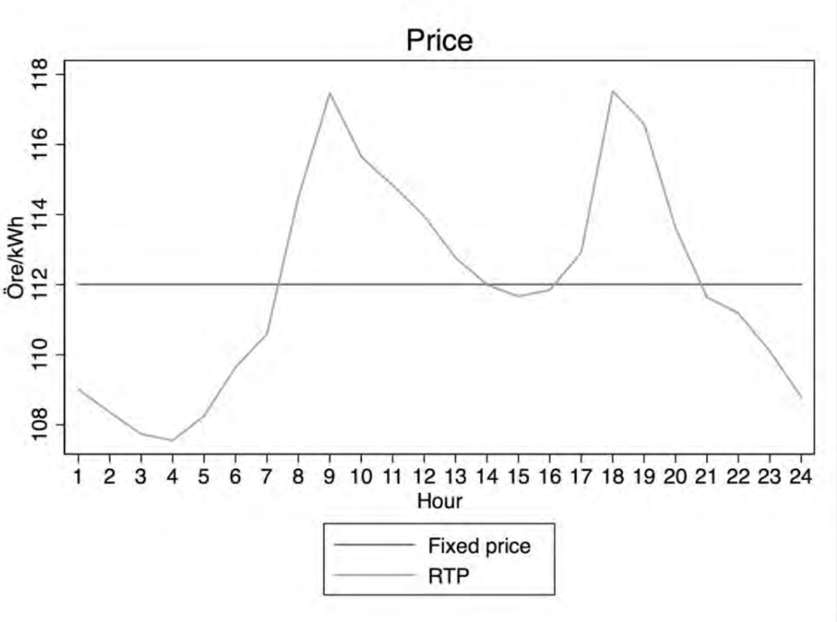


Figure 1b: Average hourly fixed and Nord Pool spot prices for January-March 2006-2008

2.2 Electricity Price

As detailed later, we use two sets of prices: a fixed-over-the-month price ("fixed price") that households in the sample currently face, and a hypothetical RTP, based upon the wholesale spot price. While data regarding the price contracts chosen by the sample households are unavailable, we consider them as being on monthly-fixed-price contracts (these being by far the largest contract share at the population level, see https://www.scb.se/hitta-statistik/statistikefter-amne/energi/prisutvecklingen-inom-energiomradet/omforhandling-och-byten-av-elavtal/).[6]

In our analysis, we make use of two distinct pricing schemes, both of them based on the spot price for the relevant time period. First, following practice in the previous literature,[7] we define the fixed price as the average of the spot price, plus certificate fees, energy tax, mark-up and sales tax. This price acts as the baseline price, and should be thought of as a plausible fixed-price contract. The dynamic price that we subsequently use in our analysis is then the hourly spot price plus certificate fees, energy tax, mark-up and sales tax. By construction, the average dynamic price will be equal to the fixed price, which allows us to focus on the effects of introducing price variability while keeping price levels fixed.

The two pricing schemes are displayed in Fig 1b. A striking aspect of this figure is the low variability in the hourly (average) spot price, in particular between the peak and off-peak periods. This is in contrast with the substantially large variability in price reported in the papers focused on the U.S. context (e.g. Table 8.2, 8.3, Allcott, 2011; Table 1,Borenstein, 2013). As explored in detail in Vesterberg & Krishnamurthy, 2016, the lack of sufficient variability on average means that the cost implications to the consumers, on average, are not substantial, a conclusion that was robust to the use of more extreme (maximum) prices instead (see table 4).[8]

[6] An alternative is to use the population averaged figures for different price contracts and retailers, data for which are available from the market regulator (although not for the period under consideration). There are a few drawbacks associated with this option, though, including the difficulty in comparing this retail price with the hypothetical real-time price (which, recall, is based on the spot price) as well as the lack of substantial variability in price contracts across retailers (the only source of variability is actually across contract types). In the interests of transparency and simplicity, we do not resort to these alternatives but we note that, in view of the comments in footnote 6, the actual choice of a price does not matter for the substantive questions we discuss.

[7] Note that there are three components to a household electric bill in Sweden: a retail price component; a transmission price component; and a tax component, often a substantial amount, up to 40% of the total bill (i.e. at about fully a quarter of the retail plus transmission price). The transmission tariffs may also be time-varying, and both it and the tax component depend upon consumption. There are thus three prices available for use: the marginal retail price; the marginal retail plus transmission price; and the average price per Kwh, including the tax component. Following the previous literature, we assume that households base their consumption decision upon the marginal retail price—inclusive of cost recovery for the retailer-- for our computations.

[8] There is more variability in the hourly data than indicated in the hourly average, particular during the active part of the day i.e. between 08 and 20 hours (see the associated box plot in the Appendix A), as also indicated in Vesterberg & Krishnamurthy, 2016 (figure 4). A caveat is that large variations are very infrequent occurrences (as can be shown using a histogram, available upon request). In addition, as will be seen subsequently, even a doubling of the average price profile does not lead to changes in the load patterns, indicating that the use of more extreme prices cannot substantively affect our findings, as also observed in Vesterberg & Krishnamurthy, 2016). Finally, it is important to note that the use of extreme but infrequent prices has not been previously found to alter demand to any appreciable extent: Holland & Mansur, 2006 found that few households actually changed their load following price spikes that led to a more than doubling of the price (largely due to the very small benefits accruing to the households).

We emphasize that our objectives are to understand changes in the patterns of load under different scenarios for price and elasticity patterns; consequently, shifts in the level of price which leave their patterns unchanged do not affect our substantive conclusions. They will however affect our cost computations and this issue will therefore be revisited in that context.

2.3 Micro-generation data

We assume that each household has, installed on its rooftop, a 2.5 kW roof top solar panel producing electricity for self-consumption. The photovoltaic (PV) production estimate from this panel is based on the output of the HARMONIE Numerical Weather Prediction (NWP) model (Bengtsson et al., 2017), ensuring that the output is not only reflective of approximate seasonal weather conditions but also based upon detailed aspects of local weather. Given that the production from a solar panel can be highly dependent upon specific aspects of local weather conditions, the computations we perform provide a measure of confidence that our production figures are on the whole accurate. To this extent, therefore, we treat both load and generation as observed outcomes, albeit with some error in the case of generation.

Turning next to the details of the NWP model, HARMONIE is a physical model which describes the interaction processes related to the state of the atmosphere, and produces a numerical forecast of the prevailing weather conditions as an output. This output includes all relevant parameters needed for obtaining a realistic estimate of the electricity production of a PV system, as described in more detail below. The NWP model output includes the direct, diffuse, and net solar radiation components, which are used to determine the direct, diffuse and ground reflected radiation components impinging the PV panel surface (Stein, Holmgren, Forbess, & Hansen, 2016). The angular reflection losses from the PV panel surface for direct radiation is determined by utilizing the calculated angle between the sun and the panel surface, while diffuse and ground reflected radiation loss is determined according to the slope angle of the PV surface (Martin & Ruiz, 2001). The PV module temperature is modelled utilizing solar radiation, wind speed and ambient temperature values, and the description of the PV module type and integration level (Stein et al., 2016). The time-dependent conversion efficiency and electricity output of the PV system is finally determined by utilizing the PV’s technology-dependent coefficients with solar radiation and modelled PV module temperature values (Huld & Amillo, 2015).

The hourly time series used in this study consists of consecutive NWP forecasts, initialized daily at 06 UTC. The forecast horizon for each of these forecasts is +16 - +39 hours, i.e., from 22 UTC the same day to 21 UTC the next day. The dataset can thereby be considered as a next day forecast. The PV production estimate was produced with the following settings:

- Latitude: 60.203561
- Longitude: 24.961179
- 10 PV Panels, 250 Wp each, 2.5 kWp in total
- Technology: Poly-Si
- Integration level: Semi-integrated
- Slope: 30 degrees from horizontal
- Orientation: South.

The monthly and daily estimations of accumulated production are shown in Figures 3 and 4. It should be noted, that the PV power conversion model does not take accumulated snow cover on the panels or shadowing effects into account, but gives an estimation of the electricity produced in snow-free conditions.

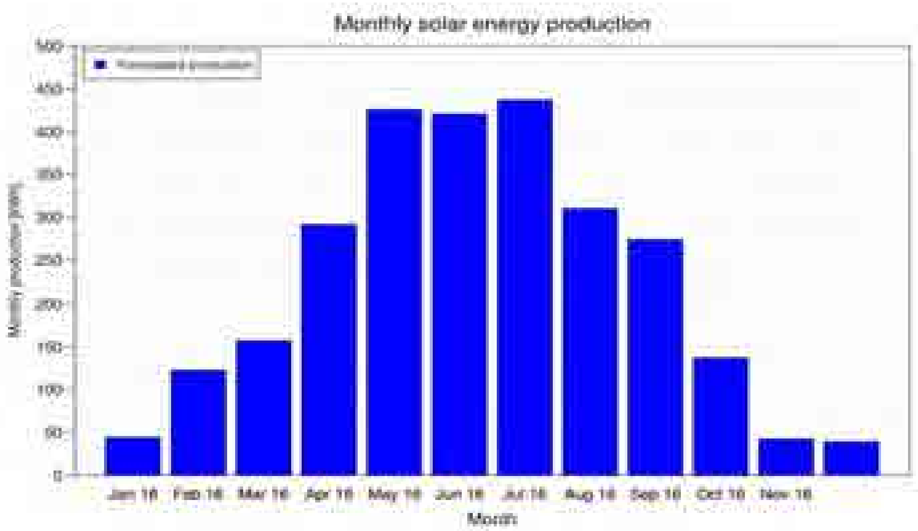


Figure 2a: Monthly solar energy production in 2016

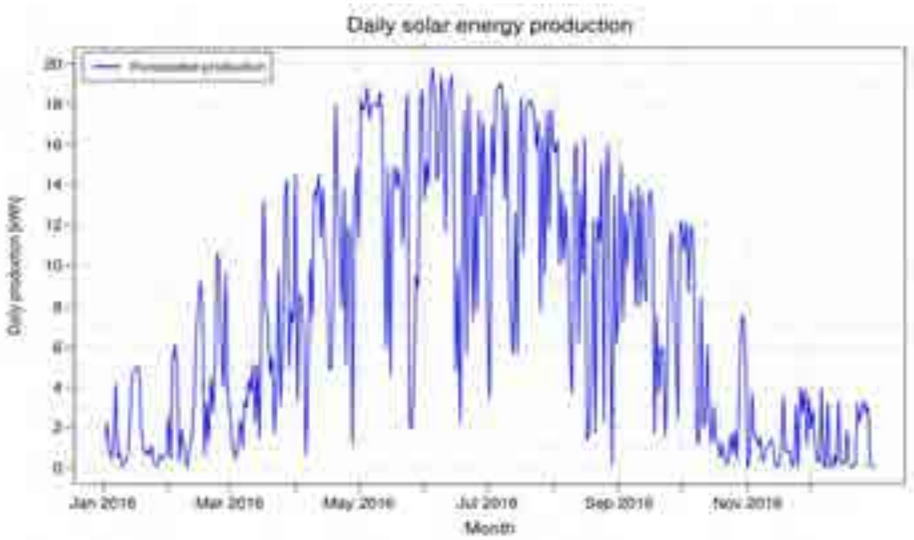


Figure 2b: Daily solar energy production in 2016

3. Modeling Approach

3.1 Swedish Electricity Market setting

The broad approach we follow may be understood by considering key aspects of the Swedish electricity system: demand share; supply situation; and market conditions. First, household demand is a rather small part of overall (at 23%), meaning that moderate changes to aggregate household demand are unlikely to substantially alter wholesale market conditions (but they clearly can lead to changes in levels of many aspects, including peaks). Second, Sweden is a part of the Nord pool common electricity spot market, and has a largely base-load driven electricity system (with over 90% of generation being Nuclear and Hydro), with peak generation being insignificant and with overall sufficient capacity to meet most peaks using baseload (although the merit order curve indeed does have cost differences, see THEMA, 2015). Third, the electricity sector is fully de-regulated, with generation and retailing fully separated. Finally, the retail market is highly competitive and price contracts of differing billing durations (monthly to annual or even longer) are freely chosen by households,[9] with retailer switching being rather easy.

As regards the policy framework, despite being almost entirely fossil and pollution free, policy makers have set ambitious targets to increase penetration of intermittent renewables. In addition, Swedish governments have expressed support for demand response and in particular RTP to help reach the goal of a more efficient electricity system, and for helping cope with the challenges of integrating increasing amount of intermittent generation. This connection between RTP and intermittent integration, which is somewhat different from the reasons prevalent in the received literature on RTP, will be examined subsequently in §5. In addition, there is also a sizeable subsidy regime targeting increased penetration of solar panels and storage technology. While somewhat surprising at a first glance (in view of the long and dark winters), solar panels in fact can provide a substantial part of household load for many months of the year when heating demand is negligible, as our analysis subsequently indicates.

3.2 The Empirical Framework

Similar to prior empirical studies, our analysis is carried out using data on a (representative) household sample. We recall a few key features of the Swedish electricity market setting: the moderate importance of residential sector, and the rather moderate shift in merit order curves anticipated to result even if RTP contracts were to be widely used. As a result, in this setting, we focus on household-level analysis, assuming that the hypothetical RTP contracts are based upon exogenous wholesale price, one that is unaffected by RTP adoption by the sample households. This approach has also been used in a prior study of short-run effects of optional RTP schemes (Borenstein, 2013b), albeit in a very different setting.

The overall logic of our approach is based upon treating the demand for electricity as a *derived demand*, where household appliance holdings and external factors (temperature and daylight, among others) determine demand patterns, in particular the baseline demand for

[9] Note that retail contract types and prices do differ by home type (villas and apartments), but these are not relevant for our analysis, since we restrict it to villas.

underlying services (e.g., heating and lighting). Household preferences then determine the degree to which a given demand will be adjusted to reflect prices. Naturally, for modest price changes, deviations from a baseline demand are anticipated to be comparably modest; the moderation of changes indeed are the *premise* of many RTP programs, including the Swedish ones (Swedish Energy Market Inspectorate (2017)). The precise magnitude of these deviations, implied by the price elasticity and the price patterns considered, and their patterns over a day, will be assessed in the different scenarios regarding the magnitude and patterns of the price elasticities. Our approach is in contrast to much of the literature on RTP, e.g., Borenstein, 2005, 2007, 2013, Kopsangas-Savolainen & Svento, 2012, Horowitz & Lave, 2014 , which assume a fixed (and identical) magnitude of price elasticity across the day.[10,11]

We work in a setting very similar to many previous studies, using the familiar double-log specification. We explore the following scenarios, which differ in both the magnitude and the pattern of elasticities and prices, augmented by solar generation: baseline (fixed price and elasticity), RTP-a and RTP-b (time-varying price, PV production and time-varying elasticity, under the two sets of assumptions detailed later). We conceptualize total demand, Q, as being composed of two components, a fixed and a varying, where the fixed component A is thought of as being largely determined by a target level of utility (corresponding to household appliance holding) and estimate the fixed component based on the baseline elasticity estimates. In subsequent scenarios, demand is adjusted to scenarios for prices, elasticities, and solar production (non-stored, non-grid-connected), holding A fixed. Thus, our load curves for different scenarios may be obtained as different and time-varying scaling of the demand. The baseline and scenario-specific load curves will subsequently be used to answer a variety of policy-relevant questions.[12]

The effects of heterogeneity in demand across household types will also be explored to the extent they are relevant for the questions of interest. We focus on working days during winter months, which are of most interest in the demand response discussion for Nordic countries, and indicate whether any new issues arise when considering the summer (non-

[10] That said, similar to these studies, we also assume no cross-price elasticity, leaving an evaluation of the degree to which this particular aspect is important for future evaluation.
[11] An exception is the study of Holland & Mansur, 2006 which reports that when peak demand is elastic and off-peak inelastic (our RTP-a scenario), average system load *decreases*.
[12] This approach, of decomposing demand into two component with one varying, has been used in many prior studies, including Borenstein, 2013b; Holland & Mansur, 2006; Horowitz & Lave, 2014.

winter) months.[13] A variant of the route we take (considering a hypothetical RTP program with plausible elasticities and a demand function based upon actual household data) has been used in for analysing an opt-in RTP program using daily aggregate consumption data (Borenstein, 2013), and in a part of the analysis for a mandatory RTP program using hourly consumption data (Horowitz & Lave, 2014), both for very specific U.S. contexts. The functional form we choose, the double log, is widely used in the literature examining the benefits of RTP, e.g., Borenstein, 2005, 2013; Kopsangas-Savolainen & Svento, 2012;Holland & Mansur, 2006.

3.2.1 Demand Specification

We turn next to detailing the determination of baseline demand and how micro-generation is accommodated. We define the baseline demand as $q_t = A_t p^{\epsilon}$, where p and ϵ denote a constant (over hours-of-the-day) price and price elasticity, respectively. Demand for households on RTP is defined as $q_t = A_t p_t^{\epsilon_t}$ where both prices and elasticities vary across hours. Given an elasticity, note that demand is fully specified by the scaling parameterA_t. Following the literature cited, we assume that at given prices and elasticities, this scaling parameter takes on a distribution equal to the actual distribution of quantities demanded. In our case, the constant price used to compute the scaling parameter is chosen to be the load-weighted monthly average of the Nord Pool spot price, as already discussed. The model can easily be modified to explicitly include other determinants of electricity demand, for example temperature. However, in the current context we focus exclusively on the role of prices. Next, choosing a non-zero ε, based upon our reading of the empirical literature for the Nordic setting, we compute a pattern of baseline demand, i.e. the A_t parameter. We then fix A_t, replace p by p_t, and set the elasticity to the RTP level ϵ_t, replacing fixed elasticity and price with those varying over time (across hours or time periods).

As regards RTP, the key assumption is that, in the short-run, with no household storage capacity, a fixed working schedule, and no technological response, households have limited possibilities of shifting load (at least, not without significant disutility) during: (a) hours when they are not at home,[14] and (b) when they can use very little electricity in any case (e.g., late in

[13] We note that, for villas during the weekdays for all the winter months (November-April), heating accounts for about 65% of total demand for electricity, and lighting for another 10% (see Vesterberg & Krishnamurthy, 2016).

[14] Clearly, some demand (e.g., laundry) may be shifted to this period via “smart” washing machines; yet, the magnitude of load shifted is likely very small, as already documented

the night). During other times, they may shift load or reduce consumption depending upon their willingness to trade-off the disutility of doing so with the benefits accruing. Note that different types of heating systems can, and will in our empirical analysis, be accounted for by suitably changing A_t (e.g., estimating separately A_t for households with differing heating systems). In addition, price responsiveness can be allowed to differ across income levels; for example high- and low-income households, where high-income households are assumed less elastic since they more easily can afford price spikes, an assumption that has some empirical support (although the relationship between price and income elasticities are generally complex, see the review in Krishnamurthy & Kriström, 2015).

Using the model framework detailed here, we explore how much "demand response" a representative (or the *average*) household can contribute with RTP, using as a baseline a household with a price and elasticity identical across hours. Household solar generation is accommodated by assuming that it correspondingly reduces demand for grid-based electricity, with the new net demand being $q_t - S_t$, with S_t the supply of electricity from the solar panel in hour t. For simplicity, we assume that the solar panel is introduced to the household costlessly, since we do not evaluate the cost-effectiveness of solar panels. Rather, our interest centres around the time pattern of solar generation, relative to the system and household peak.

3.2.2 Elasticity patterns

We explore two patterns of elasticity: a fixed-over-the-day and a peak-off-peak pattern. For the latter, we consider two variants: high during the off-peak and low during the peak, in our view the more plausible one; and its converse.[15] The (absolute values) of the elasticities for the respective patterns are set, based upon our reading of the literature, to: 0.025 (baseline); 0.1, 0.025 (peak, off-peak; RTP-a) and 0.025, 0.1 (peak, off-peak; RTP-b). These elasticities are among the most commonly used ones in the literature on RTP (e.g. (Borenstein, 2013b)).[16,17]

[15] We note that the elastic-during-peak and inelastic-during-off peak (what we call the RTP-a scenario) was briefly investigated in the evaluation of a short-run effect of RTP for the U.S. in Holland & Mansur, 2006.

[16] In the prior literature on simulating the effects of RTP, elasticity estimates used have been rather low. Borenstein & Holland, 2005 use estimates varying between -0,025 to -0.15 while Borenstein, 2005 and Kopsangas-Savolainen & Svento, 2012, both use very similar estimates of elasticities.

[17] Only a few studies provide estimates for either RTP-based elasticities or elasticities based upon higher frequency (higher than monthly e.g. daily or hourly) data. Faruqui & Sergici, 2010 survey 15 pilots regarding the application of dynamic pricing, finding estimates varying from-0.047 to -0.069, depending upon many factors. For industry, Wolack & Patrick (1997) estimate RTP-based elasticities varying between -0,01 and -0,1 for the UK. Finally, an influential study by Allcott (Allcott, 2011) reports a reduced form elasticity of -0.1.

They can also be justified both on grounds of plausibility, with a study by Borenstein (Borenstein, 2013) stating that "..in the short-run, it seems unlikely that elasticity of demand is larger than 0.1 (in absolute value).." (p.23), and upon the rather low elasticities for the Nordic setting (although we are unaware of any estimates of hourly demand elasticity, for the Nordic or any setting).[18] We subsequently explore the degree to which alternative estimates used in the literature affect our findings. While assuming only two distinct values and patterns for elasticity may appear limiting at a first glance, it is important to note that this is already a generalisation of much of the previous literature that has used an identical value of elasticity for different hours of the day. Also, as will be evident upon an inspection of the load curves subsequently, the day can naturally be divided into "peaky" and "flat" regions of consumption, lending this assumption some empirical support.

For the baseline scenario, we choose as the fixed price the average monthly (for the relevant month) spot price as a proxy for the monthly price most households face. We then use the contemporaneous hourly spot price as a proxy for RTP prices. Finally, solar production data was based upon the solar profile for the year 2016. Given our focus on understanding the salience of the timing of micro-generation, the mismatch in the time period considered between consumption and micro-generation data is not of much consequence, since the gross seasonal patterns (particularly sun rise and sun set times and average hours of sunlight) are unchanged across years. Due to the distinct pricing schemes for electrically and non-electrically heated households, we provide results for both households separately, noting that our RTP scenarios do not differ across these households, consistent with the prior literature (e.g., Horowitz & Lave, 2014).

Given the time pattern of solar generation and that of price responsiveness, it is evident how these two patterns relate to each other is quite important. To illustrate, for the winter it is the case (see e.g. Fig 3) that solar generation (S_t) is large during the office hours period (due to the short hours of sunlight in a large part of the season), but small during all other time

[18] Previous literature for the Swedish setting using either quarterly or annual (Bo, 1997; Brännlund, Ghalwash, & Nordström, 2007; Damsgaard, 2003) data , obtained elasticity estimates varying between -0.13 and -1.36. Using OECD survey data, Krishnamurthy & Kriström, 2015 computed the price elasticity from a low of -0.27 to a high of -1.4. To our knowledge, there are no prior estimates of hourly or even daily elasticity estimates for Sweden, while the limited estimates available in the literature for daily or hourly settings (see footnote 17) all point to very low elasticity estimates. To summarize, due both to the very short-term nature of our data set, the relatively low elasticity estimates used in simulation studies evaluating RTP, including for the Nordic setting (see footnote 16), and the low elasticity estimates when higher frequency data (e.g. daily, hourly) are used, we use estimate from the lower end of those available for Sweden.

periods. In particular, note that the supply thus is large when the household is inelastic, and zero (or much smaller) when the household is elastic (i.e. under the RTP-a scenario below). This aspect will be seen later on to have important implications.

4. Results

We evaluate the scenarios detailed above for working days for the years 2006-2008 for a villa. The following patterns for elasticities and prices are used for the analysis (repeated from §3):

Baseline: Price and elasticity are constant: P=112[19] and ε= -0,025.

RTP-a: (peak elastic): Time varying elasticities: ε= -0.1 during peak and ε= -0.025 during off-peak, and time-varying prices.

RTP-b: (off-peak elastic): Time varying elasticities: ε= -0.025 during peak and ε= -0.1 during off-peak, and time-varying prices.

4.1 Winter Season

We first discuss results for the winter season, which we define here to be January 1-March 30.[20] Subsequently, we discuss our findings for the summer month of June (July-August are excluded by virtue of their being national vacation months). We note that the winter months are the focus of policy discussion, due to the extreme seasonality in electricity demand induced by heating and lighting demand, the largest components of electricity consumption, being negligible between May and September.

4.1.1 RTP-a: Peak elastic, off-peak inelastic

In Figure 3 we present our simulation results for winter months for an average household. Figures of simulation results for baseline differences can be found in Figure A1 and for different household types for winter months can be found in Figure A2 in the Appendix (similar figures for summer months are available upon request). It is evident that the household load curve has two peak regions, a larger one between 16 and 21 hours, and a

[19] The fixed price is defined as the average of spot price plus certificate fees, energy tax, sales tax and a small (3 öre) mark-up. The last, we note, is assumed based on available information from many Swedish retailers, and our load curves are robust to alternative assumptions regarding mark ups.

[20] We exclude December due to two concerns: first, that the substantial number of holidays can lead to reduced working days and adversely affect our estimates of load shift and energy conservation; second, it is not clear whether elasticity increases or decreases as a result of the many holidays.

much smaller one between 05 and 07 hrs. Correspondingly, there is a large peak in the spot price during the evening times (between 17 and 21:00 hrs and very slightly offset from the demand peak), and a slightly smaller one in the morning (see Fig.1b), although the morning system peak price persists until 12 noon.[21, 22]

We turn next to considering the effects of introducing an RTP scheme. With high elasticity during the peak and low during the off-peak, we already anticipate that some shrinking of the peak will occur, and our intuition is confirmed for all household types (see Appendix for Figures A2 for different household types). For the average household, we find reduced peak load and *unchanged* off-peak loads, and this is generally true for all household types. Clearly, then, households have *reduced* daily load, instead of *shifting* load from peak to off-peak, and the pattern of load reduction follows from the assumed elasticity patterns and the price variation. There are two plausible explanations for the resulting new load pattern: the first, that the variation in price between peak and off-peak is insufficient to lead to increases during the off-peak (conditional on household consumption patterns); and the second, that price elasticities may also be too low in absolute levels to provide the incentive to increase consumption during the off-peak. We explore these aspects in more detail later but note them for future reference. Turning to the more interesting electrically-heated households (see Figure 4 in the Appendix), we note almost identical patterns of change, the only difference being the steeper reduction (in absolute levels) in peak consumption. An interesting finding is the lower level of the peak for lower income households.

For the households in the sample, we simulate household hourly generation from the 2.5 KW roof-top panels using the Harmonie weather forecast data (meteorological estimate), for both winter (January to March) and summer (June) months. The production schedule, which can be directly seen in figure 3 (separate figures for the production schedule are available upon request) has features evident from the load curves: winter (summer) generation commences around 07 (05) hrs, peaks in the afternoon, and stops around 16 (18) hrs. The intuition regarding the effect of non-grid-connected solar panels,[23] with no storage possible, is straightforward: they reduce demand during

[21] For a detailed description of the load curves, including end-use specific ones, and the system peak, we refer the reader to Vesterberg & Krishnamurthy (2016).

[22] For completeness, note that the load curve for the four types of households (electrically heated and mixed heating and low, high income, figures in Appendix) differ in that: electrically heated high income households have a pronounced, and slightly shifted, peak (in comparison to the average household curve in Fig 3); households with mixed heating have similar patterns to the other group with lower level of demand.

[23] Our assumption that households do not provide excess supply to the grid is merely for simplicity, and doing away with this assumption has no effect upon our insights in the context considered, as we discuss

production periods. In our setting, since production only increases towards the end of the morning peak (around 09 hrs) in the winter, as indicated in Figure 3, the effect is to substantially reduce *off-peak* demand, with possibly a more pronounced effect upon non-electrically heated households due to their smaller consumption. This is also the finding in our empirical experiments; solar panels with a fixed price leads to sizeable reduction in consumption during the off-peak production period, essentially 09-14 hrs (Figure 1 in Appendix A), almost but not quite the same level as the consumption effect post-RTP. The combination of RTP and solar panels then leads to substantial reduction in consumption during this period.

Our findings thus far may be summarized as follows: the combination of RTP and solar panels, in the winter months, under the RTP-a assumptions, reduces both peak and off-peak demand, leading also to a substantial reduction in total demand. Notice that the derived load curve now has two peaks at hours 06 and 21. This naturally is related to the assumed time windows for elastic hours. In any case, we reiterate that despite industrial demand being both larger and more responsive, systemic and long-run benefits of household RTP may nonetheless be sizeable. However, to the extent that household benefits are what drive household adoption (as is commonly assumed in the empirical and policy literature), and household hourly price elasticity patterns (representing the intrinsic willingness to substitute load across hours) are what drive household benefits, the empirical question is this: what are the cost savings to households of reducing demand in the pattern thus indicated? We present these daily savings for different types of households in our analysis in Table 2.[24]

next. Clearly, with standardised and small panels of the sort we consider, there is likely not much, if any, excess--beyond own consumption--for supply to the grid during the winter months. During the summer months, however, excess power--illustrated in the load curve in fig 2-- may be supplied to the grid. However, this does not affect the shape of the load curve since it is already at zero during these periods.

[24] We note that we present household implications in terms of daily costs because they are what households are most likely to care about. Household bill changes are also a key focus of many empirical analyses of RTP programs, real (Allcott, 2011) or hypothetical (Borenstein, 2013b; Horowitz & Lave, 2014).

Figure 3: Average household load with demand response (RTP-a) and own production

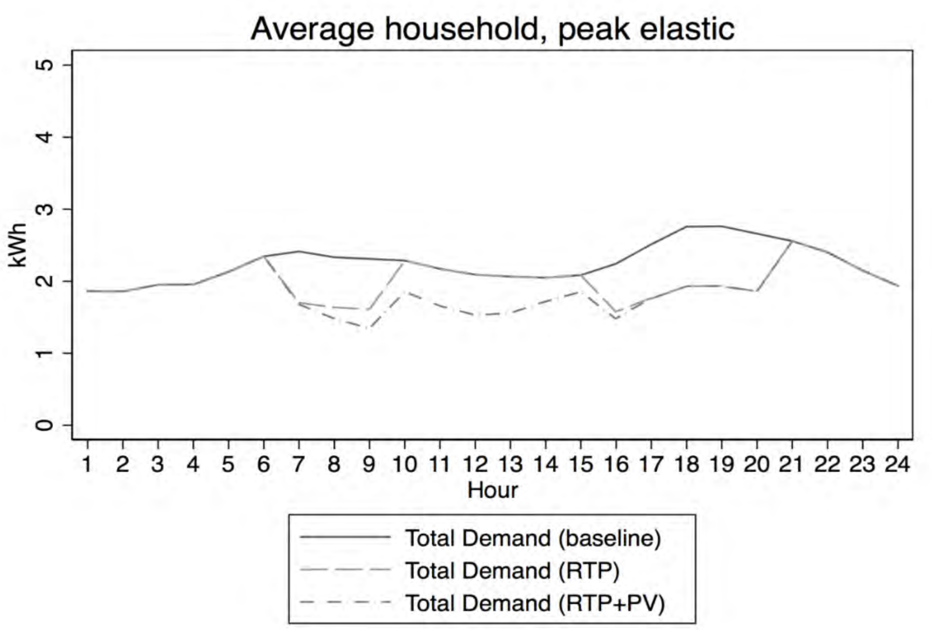


Table 2: Daily cost saving for winter: RTP-a

	High income		Low income	
WINTER, RTP-a	Electrical heating	Other heating	Electrical heating	Other heating
Baseline	83.8	44.2	63.5	50.1
RTP-a (savings as share of baseline)	0.125	0.099	0.127	0.093
RTP-a + Solar (savings as share of baseline)	0.167	0.1809	0.182	0.165

The savings in Table 2 are in %age of daily baseline cost (computed, recall, with a fixed price and elasticity). Cost savings for an electrically heated high (low) income villa from RTP response amount to 12.5% (12.7%), which aggregates to approximately 230 SEK or 23€ (198 SEK/20 €) winter time monthly savings. This represents a non-trivial fraction (8%) of the approximately 300€ monthly electric bill for the average electrically heated villa in Sweden (including transmission prices). We note, however, that the assumption of a possibility of shifting load purely by virtue of elasticity might overstate the possibility of savings. Indeed, at least in the short-run, there may well be utility costs of reducing or shifting load. Once accounted for, these may render the apparently "easy" savings less valuable.[25] It is also worth noting that prior analyses of RTP indicate that it is not necessarily a 'green' instrument, in the sense that demand shifts needs have ambiguous effects upon CO_2 emissions. In our combined RTP+PV scenario, CO_2 emission reduction for the Nordic setting is probable since own PV production reduces the use of high emitting technologies during the day time. This provides a second channel for utility increases, since there are indications (e.g., Ruokamo et al. 2018) that households put increasing weight to combined pecuniary and environmental benefits.

4.1.2 RTP-b: Peak inelastic, off-peak elastic

Next, we turn to briefly discuss RTP-b, where the pattern of elasticities is assumed to be the converse of that in RTP-a, high off-peak and low peak elasticity. We illustrate the resulting load profile for the average household in the winter in Figure 4, while Figures for specific household types are in the Appendix A.[26] Results differ from those for RTP-a in intuitive ways: unchanged peaks, off-peak demand falls throughout. Introducing solar generation exacerbates the fall in off-peak load, ensuring that the peak-off peak difference in household load is larger under this scenario. Obviously, neither of these elasticity patterns may be true for some households. For example, some households may be equally elastic (or inelastic) during all hours, and some households may be very elastic for some hours. To summarize, under RTP-b, energy conservation is actually larger than with RTP-a (since the off-peak hours are more numerous) and the introduction of solar PV generation leads to even larger off-peak reductions, due to the overlap of the elastic period with high solar-generation period.

We present the savings for the RTP-b scenario in Table 3. These savings with RTP now amount to 20% (20%) for an electrically heated high (low) income household, aggregating to 370 SEK or 38€ (286 SEK or 29€), translating to a sizeable 12.7% (9.7%) of the total monthly average electric bill for an electrically heated household.

[25] Further context to the electric bill may be obtained by considering that the average Swedish household spends about 5% of expenditure on electricity. Thus, under the common assumption regarding inattentiveness to electricity prices, the resultant savings of less than 1% of total income may not be worth the utility costs of reallocating or reducing load, a finding highlighted also in Allcott, 2011.

[26] The differences across the key household types, high and low income and electric and mixed heating, are straight forward: fall in off-peak load is rather high for high income electrically heated households; somewhat lower and about the same magnitude for high and low income mixed heating households.

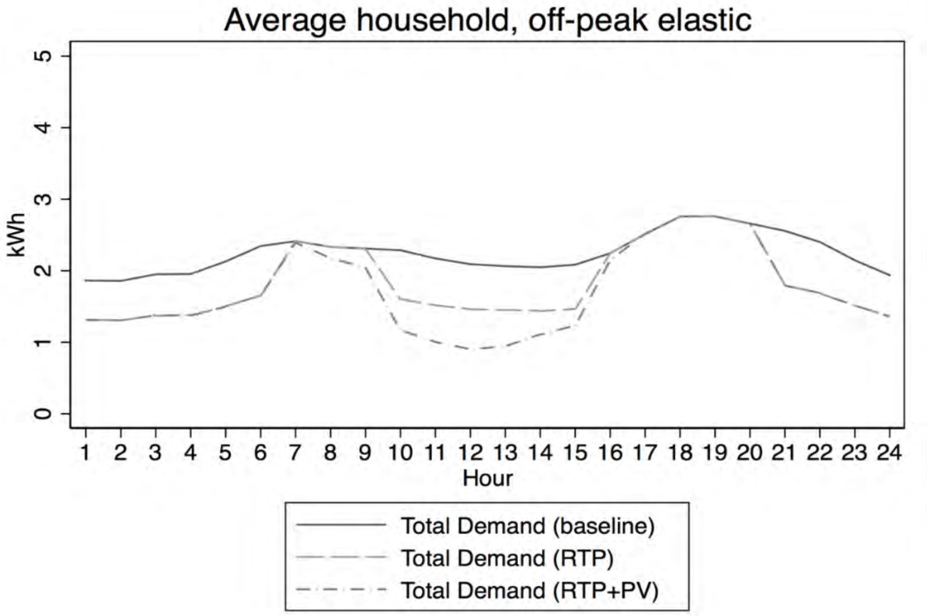


Figure 4: Average household load with demand response and own production (RTP-b)

Table 3: Daily cost saving for winter: RTP-b

	High income		Low income	
WINTER RTP-b	Electrical heating	Other heating	Electrical heating	Other heating
Baseline	83.8	44.2	63.5	50.1
RTP-a (savings as share of baseline)	0.200	0.165	0.203	0.161
RTP-a + Solar (savings as share of baseline)	0.242	0.246	0.256	0.233

We emphasize that, in common with the prior empirical literature, our key finding of energy conservation in the RTP-a (RTP-b) scenario arises from lack of increased consumption in the off-peak (peak) hours. This finding is driven largely by the low price variability between peak and off-peak periods, and has also been reported in the prior literature. We also note that the difference between our findings here, of substantial household cost savings from RTP, and those in a previous study, Vesterberg & Krishnamurthy, 2016, relate to the key assumptions: here we assume price responsiveness, and evaluate the effects of an RTP price while in the previous study, we evaluated the cost savings of load shifts (without either evaluating their feasibility or assuming a specific pattern or value for elasticity). Our findings here in fact serve to emphasise the previous findings, since we find no load shifting in any scenario of price and elasticity. This speaks to the remarks made both here and in the previous study: price variability across the day is far too small to make load shifts attractive, even in the absence of any specific costs of shifting load.

4.1.3 Robustness: Alternative Elasticities

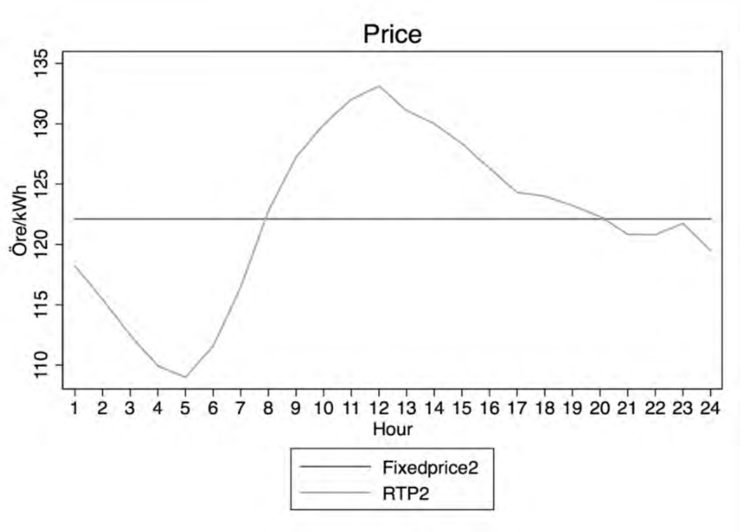
We note that we have not found any likely pattern of elasticities that does not lead to energy conservation, as opposed to the load shifts typically assumed in previous studies. To illustrate, the most common assumption in the literature is that of constant and low elasticity, -0.025. Using this assumption, for instance, there is a sizeable amount of conservation (16 percent for the average household, see Figure 1 in Appendix A), larger than we find in either of our two patterns. In fact, we find that neither a doubling of elasticities--for either RTP-a or RTP-b scenarios-- nor of prices leads to a "flat" load profile (i.e. of sizeable load shifts). Rather, we find that our assumptions lead to larger energy conservation than in the RTP-a and –b scenarios. In particular, for some of these alternative scenarios the magnitude of the peaks remain similar, although the morning peak is shifted slightly to the right (figures available upon request).

4.2 Summer Season (June)

Solar production for June is, predictably, longer, and peaks between 06 and 16:00 hrs (as indicated in Figures 1 and 2 in Appendix B). In addition, demand for heating and lighting are both very low, and the household demand curve in the baseline scenario is rather flat, with the previous two peaks now being considerably muted (indeed, except for high income electrically heated households, there is no evening peak to speak of). Finally, spot prices for June (see figure 5) follows a similar pattern, being considerably less peaked but with a higher average price level and lower volatility. Consequently, the estimated load curve with solar PV generation essentially implies zero demand between the hours of 07 and 15, with a slow increase to baseline level between 18 and 03 hrs.

The introduction of RTP in June has smaller implications than for the winter (at least in levels). Both peak and off-peak demand are lower between 07 and 12 hrs, for all household types. To summarize, for the month of June, which can be considered a representative month for very sunny and warm period (June-August), the introduction of RTP (both RTP-a and RTP-b scenarios) leads to a very small effect upon total load while the introduction of a solar panel leads to essentially no load from the grid for about eight hours during the day. It is important to emphasize that this result follows from two features of electricity consumption in this month: far lower demand (daily and across all hours) driven largely by the near-total absence of heating demand, as well as the rather minimal daily variability from the (rather high) average price level. Finally, the cost savings in June are substantially larger than the corresponding savings during winter, with magnitudes of between 48 to 61 percent, driven largely by the availability of sun light.

Figure 5: Summer spot price.



5. Concluding discussion and points for further research

5.1 Our Findings

There is by now a substantial literature, largely simulation-based, exploring the long-run implications of RTP. The findings of this literature is largely one of welfare gains, often sizeable, typically premised upon load shifting over the day (often with no energy conservation). The relatively small literature empirically evaluating these programs, using fine-scale data from households, however, is more mixed, and largely finds little to no load shift with often sizeable energy conservation. Our analysis is primarily related to the latter strand, using a rich and extremely detailed household electricity consumption and solar PV generation data for Sweden to explore two distinct aspects related to an electricity grid “of the future”: RTP and (solar-PV-based) micro-generation. These two aspects have received substantial attention in Swedish policy, with RTP contracts (at least in theory) available across the country and solar PV-related subsidies also available to many household installations (Lindahl, 2014).

We explore the possibility for load changes under very similar conditions (demand functions and elasticities) used in the previous simulation literature, but with extremely detailed consumption data from 200 households whose consumption was measured at 10-minute intervals. Our analysis revolves around answering three questions: (i) under the conditions assumed in the simulation literature, does load shifting occur? (ii) How does energy consumption during the day vary with different patterns of substitution between peak and off-peak hours? and (iii) How does the timing of solar PV generation affect the household load curve? We consider two patterns of daily elasticities, in addition to the standard constant-across-the-day: peak elastic and off-peak inelastic and its converse. Our overall findings may be summarized as: energy conservation, for all patterns of elasticities considered. The explanation for these findings largely being insufficient price variability across hours of the day (also documented in other studies). Finally, introduction of solar PV generation in this setting largely exacerbates the load difference between peak and off peak, since generation in the important season (winter) is limited to the off-peak times.

It has been shown in prior work (Vesterberg & Krishnamurthy, 2016) that, for the Swedish electricity market, households' monetary incentives to shift load are low. Our results here suggest that different assumptions regarding elasticities, including a moderate-but-constant-across-the-hour, does not substantively modify these prior findings, since load shifts do not occur under all scenarios considered here. The size of the cost savings are now larger, however, since we allow for energy conservation, not just for load shifts as in Vesterberg & Krishnamurthy, 2016. The addition of solar PV generation in fact tends to further suppress the incentives for load shifting and tends to increase the peak-off peak load disparity for residential demand in Sweden, at least for the winter season when price peaks tend to receive most attention. Two factors, clearly, drive our results: unchanged baseline load, and the low levels of off-peak prices (i.e., low intra-day price variability). While intra-day price variability may alter with increased share of intermittent generation, it is not obvious what the resultant patterns will look like. In fact, current predictions for the medium-term for Sweden, while suggestive, are not definitive on this aspect.[27]

[27] On the one hand, increases in share of wind generation is anticipated to reduce the level of spot prices while also being likely to lead to an increase in its variance, both within-day and across seasons. On the other hand, increased connectivity to the rest of Europe may to some extent dampen this volatility. For discussions on prices for the future with more intermittency, see, for example, Sweco (2016) for Sweden and Astaneh and Chen (2013) for the Nordic market, Woo et al. (2011) for the US and Ketterer (2014) for Germany.

5.2 Discussion and policy implications

It is worth exploring some of the implications of our findings for policy, in light of the prior literature. To do so, we attempt to reconcile the differing views on the benefits of RTP, and to contextualize the said benefits. The setting of much of the prior literature has been, as already mentioned, contexts where regulated utilities make infrequent price changes. Even here, it has been found that a large part of the short-run benefits are captured simply by monthly varying prices (Holland & Mansur, 2006), something that is part of an active choice in the de-regulated Swedish setting. As regards systemic long-run benefits, these too may be context dependent, and are generally related to increased efficiency rather than reduced capacity (Borenstein & Holland, 2005).

In the Swedish policy literature (e.g., Swedish Energy Market Inspectorate (2017)), RTP has been promoted for somewhat different reasons, related to the increased intermittency anticipated in the system, consequent to the rather ambitious targets set by the Swedish government for intermittent, largely wind, generation. The problems posed in integration of sizeable amounts of intermittent generation are well known (see, e.g., Hirth et al., 2015; Würzburg & Linares, 2013 and references therein) and have been touched upon in the Introduction, so will not be repeated here: suffice to say that this scenario calls for some amount of demand flexibility as an aid to minimizing the costs of integrating intermittent generation. To our knowledge, this view has not as often been articulated in the economics literature on RTP. In this view of RTP, our key findings, the lack of "flatness" of the load curve and the increase in variability in daily load consequent to the introduction of microgeneration, need not represent a drawback. Rather, two aspects determine the systemic value of this form of "demand flexibility": the shape of the system load curve in the future; and the timing of wind generation in relation to system load.

Turning to the former, if demand patterns in the medium term future are similar to the present (as they are anticipated to be, see, e.g., THEMA, 2015), then load during the "active" part of the day (08-20:00) is rather valuable; thus, any load reduction in this period is indeed more valuable than at other times. Due to wind patterns, winter intermittent generation is likely to be rather variable during the part of the day when demand is high,[28] and thus, demand

[28] On average, winter is windier than summer; however, this difference is dwarfed by the larger variance during the winter. In addition, it is typically windier during the day (10:00-20:00) than at night, in the

flexibility during the day is rather valuable. Thus, both because (a part of) the "off-peak" system demand (and therefore price) is rather high, and because flexibility during the active part of day is even more important with increasing intermittent penetration, household load reductions during the "off-peak" are rather valuable, and represent a systemic benefit. That they, in addition, are beneficial to the household indicate that there is indeed scope for RTP to assist in integration of intermittent generation, particularly with increased capacity for household storage anticipated in the future.

This also helps reconcile some of the previous findings (e.g., Vesterberg & Krishnamurthy, 2016) that indicate limited short-run possibility for load shifts. Our findings here indicate that even in the absence of load shifts, price-responsive households with substantial usage (electrically heated villas, in particular) can benefit from RTP via energy conservation at relevant times. We hasten to add that it is not price responsiveness per se that is key to our findings[29]: rather, it is the differential price responsiveness over the day, coupled with prices varying by hour. Further, these benefits arise even when household price responsiveness is assumed rather low, as is likely true in the Nordic setting. Our findings, in fact, strengthen the case for RTP from the perspective of integrating intermittent energy sources, a case that has been repeatedly made by the Swedish regulator (albeit with optimistic assessments of load shifts that may not be feasible in the short-run).

In any case, our findings indicate that even in the absence of load shifts, RTP may play a role in helping integrate intermittent energy sources. Particularly interesting policy implications related to market design arise with roof top solar PV, which is increasingly popular in Nordic residential settings. Given that solar PV generation in the winter peaks during a part of the day with substantial system demand but low household demand, new market actors e.g. "aggregators", a type of player already active in certain market settings, may be allowed to take advantage of this substantial load and offer it in the intra-day markets. In this context, in fact, household demand reductions, either purely RTP driven or, more interestingly, solar PV driven, are likely to be more valuable than indicated purely by the wholesale price, since the intra-day prices, and more so balancing prices, are far higher than the wholesale. These aspects also speak to the market design changes that may need to be in place to accommodate the Nordic policy makers' goals of substantial amount of intermediates.

winter. These both factors ensure that, for the winter season, generation is high between 10:00-20:00 hrs but so is variability in generation.

[29] Recall that all our scenarios involve time-varying elasticities *and* prices

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