University of Reading

Demand flexibility and price elasticity: an analysis of the intra-day price elasticity of demand

Conference or Workshop Item

Accepted Version

Ramirez-Mendiola, J. ORCID: https://orcid.org/0000-0001-7666-7440, Kang, R. and Torriti, J. ORCID: https://orcid.org/0000-0003-0569-039X (2025) Demand flexibility and price elasticity: an analysis of the intra-day price elasticity of demand. In: BIEE Research Conference 2025, 23-24 September, Oxford, UK. Available at https://centaur.reading.ac.uk/124616/

It is advisable to refer to the publisher's version if you intend to cite from the work. See Guidance on citing.
Published version at: https://www.biee.org/resources/demand-flexibility-and-price-elasticity-an-analysis-of-the-intra-day-price-elasticity-of-demand-2/

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in the End User Agreement.

www.reading.ac.uk/centaur

CentAUR

Central Archive at the University of Reading

Reading's research outputs online

Demand flexibility and price elasticity: an analysis of the intra-day price elasticity of demand

Jose Ramirez-Mendiola[1], Ren Kang[1,2], Jacopo Torriti[1]

[1] School of the Built Environment, University of Reading, UK

[2] Corresponding author: r.kang@reading.ac.uk

Abstract

Energy demand flexibility is widely considered a key part of the net-zero ambitions. However, many questions remain in regard to both the amount of flexibility available, and the most effective ways to harness said flexibility. Price-based incentives have been the go-to solution thus far for attempting to harness demand flexibility; the underlying assumption being that the price is the main factor at play when it comes to deciding whether or not to consume energy. In practice, however, what is observed is a large variability in price elasticity, or the responsiveness to time-varying energy rates. This variability depends on factors such as the on-peak to off-peak price ratios, uptake of technologies, and the wider context. It is observed not only across the consumer base but also throughout the day, as energy demand patterns are directly linked to broader activity patterns that dictate both the timing and intensity of energy demand. Understanding this intra-day variability in price elasticity is key to developing more effective demand flexibility interventions. However, to date, research investigating intra-day price elasticity remains limited. In this paper we present the preliminary results of the process of adapting an econometric model, originally developed to link energy wholesale prices to demand patterns, to a more targeted study of the intra-day price elasticity based on retail prices; that is, the prices actually experienced by end-users. The primary advantage of this model is that it provides a simple and straightforward way of assessing the extent to which price elasticity exhibits variation throughout the day. Moreover, the method proposed here can just as easily be applied to any other appropriate data set containing both fixed electricity tariffs - which do not vary based on the time of the day- as well as spot prices - where hourly rates change hourly. The analysis presented in this paper is carried out on a dataset collected as part of a Norwegian study from 2023 to understand households' responses to the changes in energy prices experienced during the recent energy crisis experienced in Europe. Unpacking the intra-day variability of the price elasticity of energy demand is critical, as the extent to which households are either able or willing to respond to price signals is heavily influenced by the time of day and broader daily routines. Therefore, it is important to understand whether the periods where households are more prone to respond to such *stimuli* overlap with the periods where flexibility interventions are needed the most. Effective policy-making relies on this kind of information. Placing consumers' demand patterns at the centre of policy-making debates increases the likelihood of implementing policies that are both effective and widely accepted. The paper concludes that intra-day price elasticity is key to developing demand flexibility interventions which reflect the timing of people's activities.

1 Introduction

Energy demand flexibility is widely considered a key part of the net-zero ambitions. The UK Government Clean Power 2030 Action Plan [1] states that demand flexibility will potentially grow 4-5 times to reach 10-12 GW by 2030 through smart vehicle charging, shifting household consumption, and enabling more responsive industrial demand, along with storage heating. However, many questions remain in regard to both the amount of flexibility available, and the most effective ways to harness said flexibility.

Price-based incentives have been the go-to solution thus far for attempting to harness demand flexibility; the underlying assumption being that the price is the main factor at play when it comes to deciding whether or not to consume energy.

The price elasticity of electricity demand is the percentage change in demand in response to a percentage change in price. This fundamental economic metric provides crucial insights into how consumers and industries adjust their electricity consumption in response to price fluctuations.

Its significance extends across various domains, including market design, energy policy formulation, and the strategic planning for energy transitions [2]. Academic research in this area has undergone a substantial evolution, particularly motivated by the energy crises of the 1970s, which highlighted the need for a deeper empirical understanding of demand responsiveness to changes in price. This initial wave of studies laid the groundwork, defining core concepts and establishing early benchmarks for short-term and long-term elasticity [2].

The trajectory of research has since advanced considerably, moving from foundational econometric models to more comprehensive meta-analyses aimed at synthesizing disparate findings and identifying sources of variation. A pivotal development has been the increasing emphasis on addressing methodological complexities, such as endogeneity and publication bias, which can significantly distort reported elasticity values.

In practice, however, what is observed is a large variability in price elasticity, or the responsiveness to time-varying energy rates. Years of empirical research have failed to provide evidence of the relationship between short-term changes in price and demand. The variability in the reported effects of time-varying rates on peak electricity demand (with and without enabling technologies) is immense – ranging from about 0% to 60% for residential users in 337 pricing treatments [3]. This variability depends on factors such as the on-peak to off-peak price ratios, uptake of technologies, and the wider context [4]. It is observed not only across the consumer base but also throughout the day, as energy demand patterns are directly linked to broader activity patterns that dictate both the timing and intensity of energy demand. Understanding this intra-day variability in price elasticity is key to developing more effective demand flexibility interventions. However, to date, research investigating intra-day price elasticity remains limited.

The wide range of reported electricity demand elasticity estimates across studies is not solely a reflection of diverse consumer behaviours or market conditions. It is also influenced by a multitude of factors related to the research methodology, data characteristics, socio-economic context, technological landscape, and market structures. Understanding these determinants is crucial for interpreting existing findings and designing future research.

Traditionally, what energy economists measured was an average elasticity over relatively prolonged periods of time (days, weeks, even months), which disregards the details of what people do at different times of the day. When deriving short-term price elasticity, it seems counterintuitive to suppose that people have the same opportunities to respond to price changes that occur at different times of the day.

In more recent times, there has been a notable shift and growing interest in utilizing disaggregated data, often sourced from consumer surveys or smart meters, to capture individual household or consumer-level behaviours and heterogeneity. This moves beyond the limitations of country-level aggregated models that can obscure nuanced responses[2, 5, 6]. This shift has required the adoption of more suitable models for disaggregated data, such as Quantile Regression (QR) and Fixed Effects (FE) models, while aggregated data continues to be analysed using models like Autoregressive Distributed Lag (ARDL) and Error Correction Models (ECM). This methodological shift is a clear indicator of the ongoing efforts to strive for greater accuracy, and a more nuanced understanding of the complex dynamics of the relationship between demand for energy, price, and everyday activity.

The trends towards finer granularity of data and methodologies suggest that measuring price elasticity is of particular interest to those interested in understanding how effective demand-side interventions based on price can be.

In the specific context of shifting electricity demand within a single day, an especially informative metric is price elasticity at different intra-day time intervals, under the assumption that elasticity may vary over the course of the day. While a few studies have touched on this possibility (e.g., [7, 8, 9, 10], none have explicitly tested the hypothesis that price elasticity varies across different hours.

This paper’s key contribution to the literature consists of deriving empirically time of day price elasticity values – one for each hour of the day.

2 Methodology

In a previous study, we developed an econometric model to investigate the price elasticity of demand in the wholesale electricity spot market in Germany [11]. Said model looked at quantifying the responses to changes in the wholesale prices using total wholesale auction volumes as the dependent variable. As in many countries, however, The German wholesale market is a day-ahead market in which prices are determined in 24-hour blocks, which has the potential to distort the responsiveness of demand to changes in prices.

The present study focuses on adapting the econometric model developed in [11] with a view to apply it to a more targeted study of the intra-day price elasticity in the retail market, directly using residential energy demand as the dependent variable.

To this end, we are taking advantage of a recently released dataset from 2023 which stemmed from a study that monitored household energy consumption across Norway during the European energy crisis [12].

2.1 Data

The dataset used in this paper includes survey and smart meter data from 4,446 households, covering tariff types, demographic information, and other responses. The dataset covers the period from October 2020 to March 2022.

Some of these households were exposed to variable electricity prices that were reflective of the variability typically observed in wholesale markets. This means that this dataset offers a very good opportunity to study the responses of individual households to such variability, and therefore shed some light on the variations in price elasticity of demand for energy that are likely to be observed throughout the day, at a more granular level.

Three key parameters are used from the dataset for the analysis in this paper: (i) household-level electricity demand (kWh), (ii) hourly wholesale/spot electricity prices (NOK/kWh) by region, and (iii) household electricity tariff type.

The household-level demand data consist of hourly smart meter readings (kWh) from 1,136 households located in two regions of Norway, labelled as No. 1 and No. 3 in the dataset. Wholesale/spot electricity prices are divided into five regions in Norway, labelled No.1 to No.5 in the dataset. The households with smart meter data are located in Oslo region (No.1) and Bergen region (No.5). It is worth noting that this price is the wholesale price rather than the household-level tariff.

Although most household tariffs are tied to the day-ahead spot price, households also responded to the survey question: “What type of power contract do you have?” Responses included: “wholesale/hourly spot price,” “variable price,” “fixed price,” “other,” “do not have a contract,” and “unknown.” The variable price tariff is defined as a unit rate plus standing charges that can change at any time at the discretion of the utility company [13]. It is therefore fixed for a given period of time, and distinct from the wholesale/hourly spot price, which is dynamic and changes hourly.

2.2 Method development

The main purpose of this paper is to investigate the hourly price elasticity of electrical demand (ε), which is defined as the percentage change in demand in response to the percentage change in household tariff (electricity price). This is shown as the formula below:

$$\varepsilon = \frac{\frac{\Delta Q}{Q}}{\frac{\Delta P}{P}} \tag{1}$$

Where Δ denotes "change in", and Q and P are the household electrical demand and electricity price, respectively. The relationship between the Q and P could be explored using the following econometric model,

$$q_{d.h} = \alpha + f(h)p_{d,h} + x'_{d.h}\beta + v_{d,h} \tag{2}$$

Where:

$q_{d.h}$ is the household's hourly electricity demand, at day d, hour h.

$p_{d.h}$ is the regional spot/wholesale price, at day d, hour h.

$f(h)$ is the function capturing how the price-demand relationship varies across the day,

$x'_{d.h}$ are the control variables such as hourly dummies,

$v_{d,h}$ is the error.

α and β are the parameters to be estimated from the model.

A Trigonometric Approximation (Smooth Fourier Transformation) approach is applied to $f(h)$ using sine and cosine functions as below:

$$f(h) \approx c + \sum_{s=1}^{S} [\delta_s \cos\left(\frac{2s\pi h}{H}\right) + \gamma_s \sin\left(\frac{2s\pi h}{H}\right)] \tag{3}$$

This enables price elasticity to follow a smooth, cyclical intro-day pattern and avoid sudden jumps between consecutive hours. This also ensures continuity across midnight, allowing the elasticity value to be "smooth everywhere". The smaller the number of trigonometric terms S is the smoother $f(h)$ is. In practice, the value of S is chosen incrementally from 0 until any additional value that is added becomes statistically insignificant. By adopting equation (3), the model becomes:

$$q_{d.h} = \alpha + (c + \sum_{s=1}^{S} [\delta_s \cos\left(\frac{2s\pi h}{H}\right) + \gamma_s \sin\left(\frac{2s\pi h}{H}\right)])p_{d,h} + x'_{d.h}\beta + v_{d,h} \tag{4}$$

In addition to the trigonometric approximation, the model also considers the interaction between the categorical 'Hour' variable and price by introducing *dummy* variables for each hour of the day (1 to 24). This enables the model to estimate a separate price elasticity coefficient for each hour. The baseline coefficient represents the elasticity in the reference hour (hour 0, or midnight, in our case), while the coefficients on the interaction terms capture how the elasticity at each specific hour differs from that baseline. To achieve that, equations (3) and (2) are expanded to (5) and (6):

$$f(h) = \beta_h + \sum_{s=1}^{S}[\delta_s \cos\left(\frac{2s\pi h}{H}\right) + \gamma_s \sin\left(\frac{2s\pi h}{H}\right)] \tag{5}$$

$$q_{d.h} = \alpha + \theta_h + (\beta_h + \sum_{s=1}^{S}[\delta_s \cos\left(\frac{2s\pi h}{H}\right) + \gamma_s \sin\left(\frac{2s\pi h}{H}\right)]\,)p_{d,h} + x'_{d.h}\beta + v_{d,h} \tag{6}$$

Where θ_h and β_h are the dummy variables for the hour h:

$$\theta_h = \sum_{j=1}^{23} \theta_j \cdot 1(h = j) \tag{7}$$

$$\beta_h = \beta_0 + \sum_{j=1}^{23} \beta_j \cdot 1(h = j) \tag{8}$$

Where $1(h = j)$ is a dummy variable that equals 1 if the observation is in hour j, and 0 otherwise. And β_0 is the baseline variable at hour 0 (midnight).

The model was built and implemented in Python. Figure 1 summarises the process that was followed to analyse the data and determine the price elasticity.

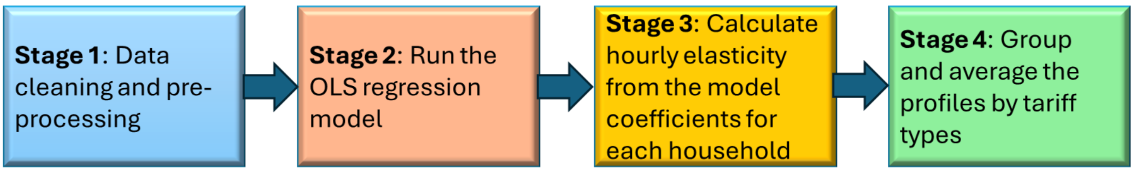

Figure 1. The process that was used to determine the hourly elasticity grouped by tariff types

2.2.1 Data cleaning and pre-processing

Household demand profiles, tariff regions, and tariff types were stored in separate datasets, each identified by a household ID and timestamp. The first step in the analysis was to align all datasets with the demand profile and tariff region, and then group households by tariff type (e.g., fixed price, spot price, etc.).

In total, 1,136 households were selected, each with hourly electricity consumption data and corresponding regional spot prices. Of these households, 717 reported spot price contracts, 97 fixed price, 154 variable price, 16 other types, 5 no contract, and 147 unknown. Given the earlier definition of variable price – where the rate does not change hourly and therefore behaves similarly to fixed price – households on variable tariffs were grouped with fixed-price households. For comparison, this yielded two statistically meaningful groups: 717 households with spot price contracts and 251 households with fixed price contracts.

2.2.2 Run the OLS (ordinary least squares) regression model.

Equation (6) was used to formulate the OLS regression model, with the processed data from Step 1 as inputs. This regression estimates how electricity demand responds to price, allowing the response to vary by time of day.

2.2.3 Calculate hourly elasticity for each household

For each household, the regression results were used to calculate hourly price elasticities. This step iterates across all 24 hours, extracting the relevant price coefficients (elasticity proxies) from the model to build a 24-hour elasticity profile for each household.

2.2.4 Aggregate and average elasticity profiles across households, grouped by tariff type

Finally, the 24-hour elasticity profiles of individual households were aggregated and averaged within each tariff group. This produced a single representative 24-hour elasticity profile for households on spot price tariffs and another for households on fixed price tariffs.

To provide further insight into the impact of demand on price flexibility, we also present the distribution of hourly electricity demand for the fixed-price and spot-price groups, along with the corresponding price signal.

3 Results

Figure 2 illustrates the average 24-hour electricity demand of the fixed-price and spot-price groups plotted against the regional spot price signal. Figure 2 presents the same demand profiles but plotted against the estimated elasticity for each group. For the sake of simplicity, we divide the discussion of the observed results according to the following time intervals.

2am – 10am

As we have previously discussed, electricity is a particularly peculiar ‘good’ to study through the lens of price elasticity as the demand for it needs to be supplied in near-real time. In practice, this means that unexpected behaviour can emerge when we zoom into the intra-day dynamics and the relationship between demand and price.

As Figure 3 shows, the period comprised between 2am and 10am is arguably the most interesting, primarily due to the high variability in the apparent responsiveness of overall demand to changes in the electricity spot prices. The relatively large variation observed during this period can be partially explained by the typically lower demand levels which correspond to periods of inactivity (sleeping). Lower average demand levels mean that a small absolute change in demand corresponds to a larger percentage change, which in turn affects the estimated price elasticity of demand at the corresponding point in time.

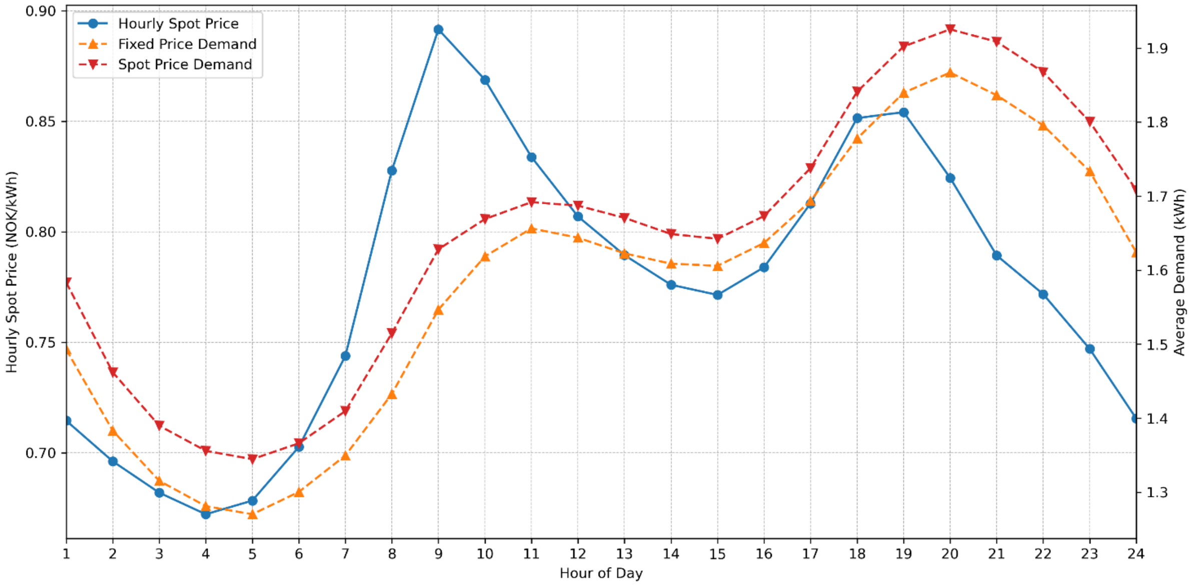

Figure 2 - Comparison of Price and Demand profiles.

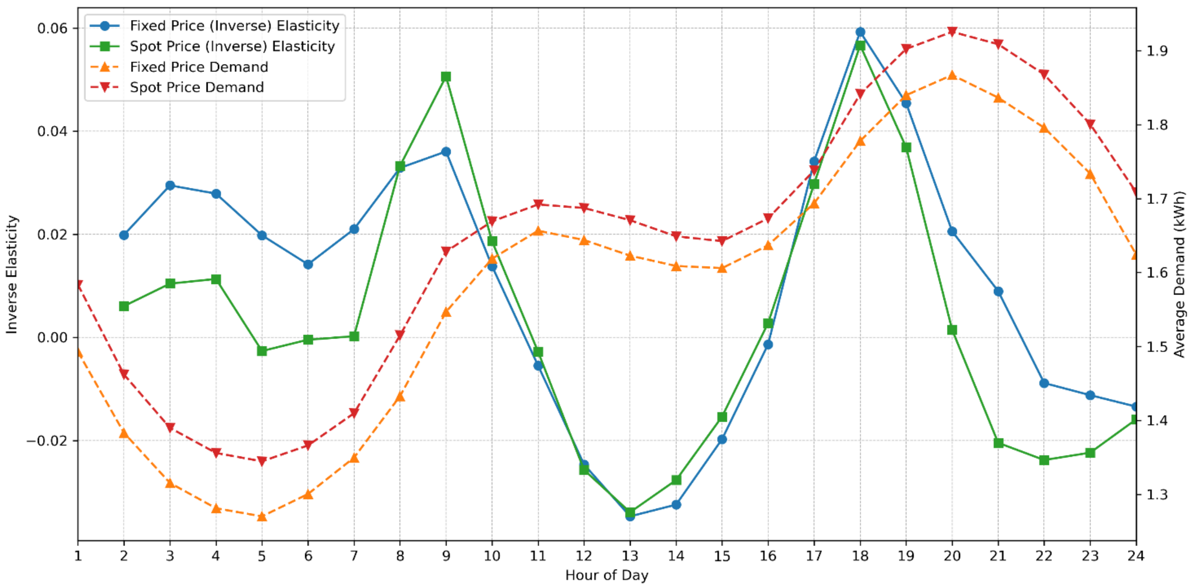

Figure 3 - Comparison between Elasticity and Demand profiles.

As Table 1 shows, however, there are only two hourly intervals within this period where the response typically expected is observed. That is, demand decreases as the price increases or, conversely, as the price decreases demand increases. Across all other intervals, the changes in (average) demand appear to follow the changes in price (i.e. increase with increase, and decrease with decrease).

A possible explanation for this is the relative time scarcity in relation to the boundaries between peak and off-peak periods, which mark the points at which tariffs drastically change. Therefore, it is possible that the 'sense of urgency' to make the most of the overnight off-peak period is playing a role in the observed distortions. Additionally, demand is generally much lower at this time of day, which means that relatively modest changes in demand make up for a relatively larger proportion of total demand observed at any given time. This is worth noting as this is likely to amplify the observed distortions.

When we look at the relative changes in the price elasticity estimates throughout the period of interest, it is generally observed that the estimates either increase or decrease across both groups of consumers.

Interestingly, though, there are two intervals worth further discussion as the estimated price elasticities exhibit changes in the opposite direction. These are the intervals comprised between 3am - 4am and 5am - 6am. In both of these intervals, the price elasticity of the consumers exposed to fixed rates *increases* relative to the previous interval. Conversely, the price elasticity of the consumers exposed to variable rates *decreases* relative to the previous interval.

Table 1 - Summary of observed changes in price elasticity estimates from 2am to 10am.

Interval	Observed change	
2am – 3am	↓ Price; ↓ Demand;	↓ Elasticity (Fixed rate)
		↓ Elasticity (Variable rate)
3am – 4am	↓ Price; ↓ Demand;	↑ Elasticity (Fixed rate)
		↓ Elasticity (Variable rate)
4am – 5am	↑ Price; ↓ Demand;	↑ Elasticity (Fixed rate)
		↑ Elasticity (Variable rate)
5am – 6am	↑ Price; ↑ Demand;	↑ Elasticity (Fixed rate)
		↓ Elasticity (Variable rate)
6am – 7am	↑ Price; ↑ Demand;	↓ Elasticity (Fixed rate)
		↓ Elasticity (Variable rate)
7am – 8am	↑ Price; ↑ Demand;	↓ Elasticity (Fixed rate)
		↓ Elasticity (Variable rate)
8am – 9am	↑ Price; ↑ Demand;	↓ Elasticity (Fixed rate)
		↓ Elasticity (Variable rate)
9am – 10am	↓ Price; ↑ Demand;	↑ Elasticity (Fixed rate)
		↑ Elasticity (Variable rate)

Table key: Expected behaviour highlighted in _green_; unexpected behaviour highlighted in _red_.

10am – 6pm

Both households with fixed tariffs and those with variable (spot) tariffs displayed similar elasticity patterns between 10am and 6pm. In both cases, elasticity increased steadily after 10am, reaching its highest point around 1pm. After this morning peak, elasticity declined continuously, reaching its lowest point at 6pm. This suggests that the responsiveness of households to price signals is strongest around midday but reduces its elasticity as the evening peak approaches. Notably, the reduction in the strength of the tariff signal is more pronounced than the reduction in actual energy consumption between 10am to 1pm, as shown in Figure 1. Based on this curve, both household types are most responsive to tariff changes at 1pm, which therefore represents the most effective time to target load-shifting or energy reduction measures. This finding is consistent with the observation in [10] that electricity demand is least elastic during peak hours and more elastic during off-peak hours.

Electricity demand patterns were also similar for both household types, although households on spot tariffs generally consumed more than those on fixed tariffs. Demand for both groups showed a gradual increase after 10am, with the first daily peak occurring at 11am. This was followed by a dip, reaching the lowest demand point around 3pm – likely reflecting reduced household activity after lunchtime. Demand then increased again, reaching approximately 1.8 kWh at 6pm, before continuing to increase into the evening. The detailed hourly patterns of price, demand, and elasticity are shown in Table 2.

6pm - 2am

Households with fixed tariffs experience the lowest price elasticity at 6pm, a time when those with variable (spot) price tariffs also feature the lowest price elasticity for this group. The minimum price elasticity for the two groups is very similar. Between 6pm and 9pm the price elasticity increases. This is especially the case for those households with spot price tariffs, which from 9pm can be defined as elastic, meaning quantity demanded is relatively sensitive to price changes.

For households with fixed tariffs, demand peaks at 8pm with an average of 1.867 kWh, the highest across the 24-hour period. It begins to decline slightly after 8pm but remains elevated through 10pm. From 11pm to 2am, demand gradually decreases from 1.734 kWh to 1.383 kWh, which is an obvious consequence of reduced consumption during late-night hours.

With regards to households with spot price tariffs, these follow a similar trajectory, peaking at 1.925 kWh around 8pm, which is slightly higher than households with fixed tariffs. Demand remains consistently high through 9 pm and 10pm, then declines modestly. By 2am, average demand among these households falls to 1.462 kWh, reflecting decreased activity.

Prices under both fixed and spot price tariffs are relatively high during the evening compared with the rest of the day – they are only marginally lower than during the morning peak. Prices rise leading into the evening, peaking at 6pm. From 6pm to 8pm, prices remain relatively stable and elevated, with a slight decline after 8pm. By 11pm, prices fall, and continue a gentle decline into the early morning.

Evening hours involve routine or essential household activities (e.g., cooking, lighting, heating/cooling, family time). These needs are less flexible, so consumers do not reduce usage significantly even if prices change, leading to lower observed elasticity. Even under spot pricing, consumers may not monitor prices actively in the evening [14]. They may either not see price signals in real-time or choose convenience over savings [4]. Because consumption is already near peak levels, there may be limited capacity to increase usage further, even if prices drop, resulting in fixed demand with low elasticity or non-elasticity.

Elasticity increasing while demand remains high suggests that, as night approaches, usage is no longer necessity-driven as during core evening peak time, but starts becoming price-driven. Other analyses of Norwegian data suggest that households with automated smart charging of their electric vehicles synchronised their load in night hours [15]. The peak demand for automatic smart charging is lower than that for manual smart charging. This can be attributed to lower electricity consumption from other appliances during night time.

Figures 4 and 5 display standard boxplots of hourly electricity demand for the fixed-price and spot-price groups, respectively. In each boxplot, the median is shown as a solid horizontal line, while the 25th and 75th percentiles form the lower and upper edges of the box. Outliers are shown as individual points beyond the whiskers, and the mean value is indicated by a solid red line. These are just to illustrate the hourly distribution of demand across households subject to different pricing schemes, and the potential effects of this on the observed demand.

As Figures 4 and 5 show, the magnitude of the outliers of the observed demand distributions tend to be higher in the sample of households subject to the variable (spot) pricing, relative to the sample of households subject to the fixed pricing. This would appear to indicate that households subject to the variable pricing exhibit more erratic events demand, potentially associated with more drastic variability in prices.

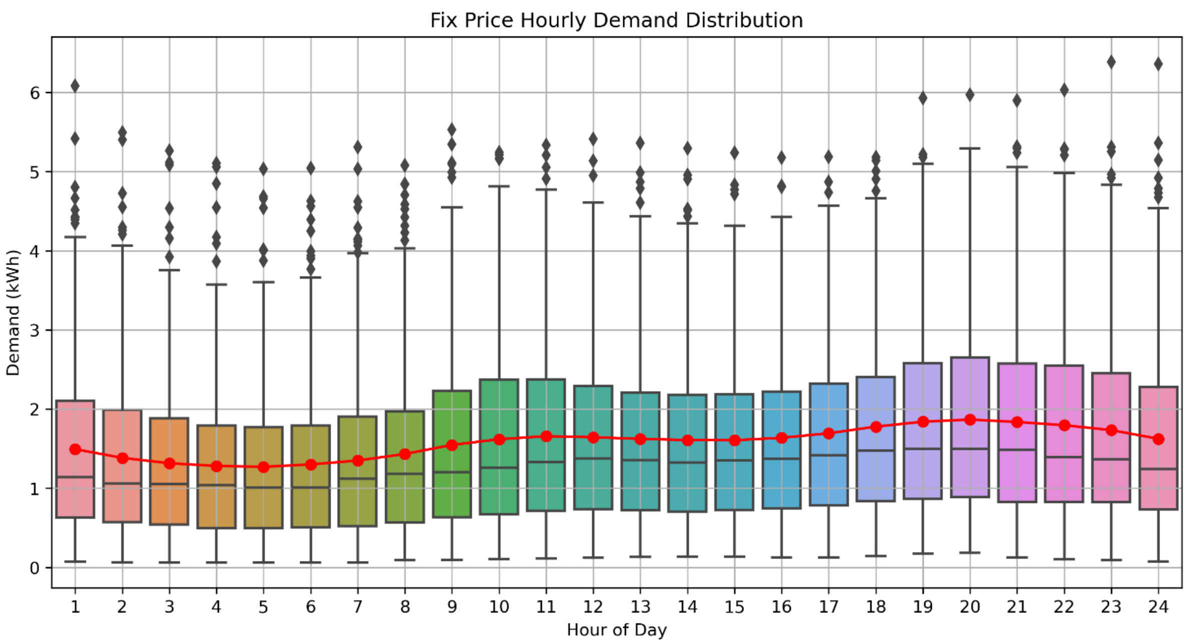

Figure 4 - Hourly demand distribution for households subject to fixed tariffs.

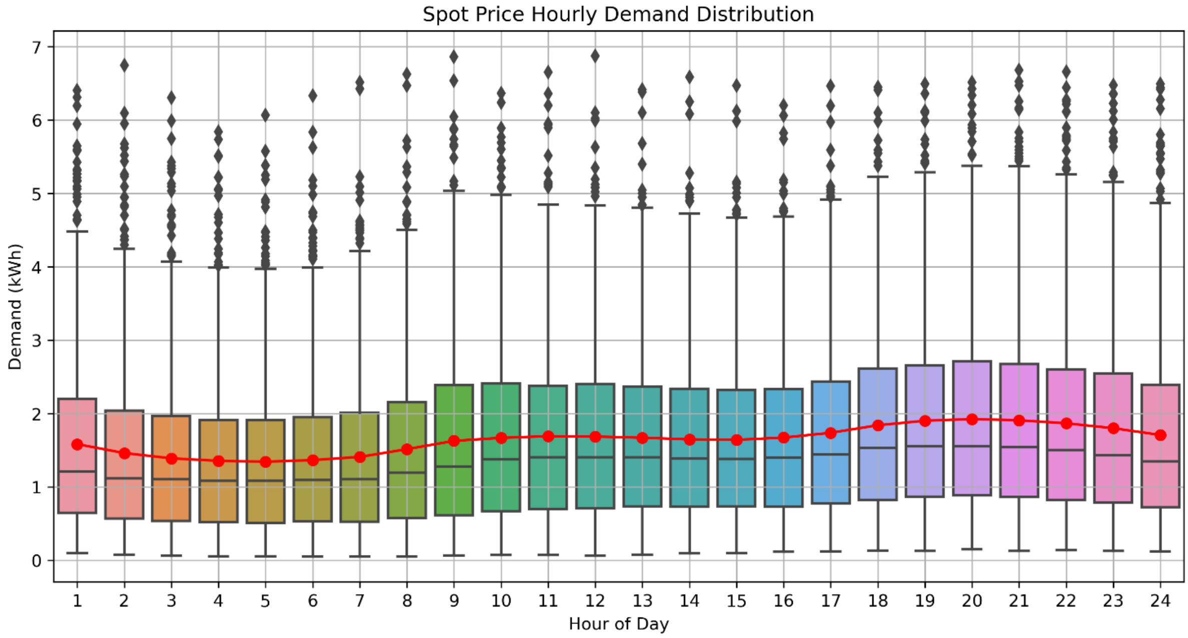

Figure 5 - Hourly demand distribution for households subject to variable (spot) tariffs.

4 Conclusions

The results presented in this preliminary study of the intra-day price elasticity of electricity demand by Norwegian households are consistent with the results of the hour-by-hour regression pattern presented in [11], which shows that in the German wholesale market there are two periods throughout the day where demand is most inelastic around 9:00 and 20:00, respectively.

This analysis of Norwegian households shows that the most inelastic periods consist of 9:00 and 18:00, which would appear to indicate that the changes in price elasticity leading towards the evening demand peak are observed earlier when looking at the effects of retail prices in isolation, as opposed to the wholesale market.

The preliminary results are encouraging as they show that retail markets, like wholesale markets, exhibit variability in price elasticity of demand. On the one hand, this is a positive finding as it is sometimes assumed that the relatively rigid time use schedules in the residential sector may limit the extent to which domestic consumers might be receptive of price-based demand response mechanisms such as hourly time-of-use tariffs. On the other hand, findings also reveal that at certain times of day, changes in retail prices alone are insufficient to temporarily reduce electricity demand. In the case of the Norwegian data analysed in this paper, the lowest spot price elasticity of demand occurs around morning and evening peak periods.

To this date, only a limited number of studies have been devoted to the analysis of intra-day price elasticity of demand for electricity [11]. It is therefore necessary to further explore this area in order to better understand the factors that shape daily patterns of price elasticity, with potential applications including more effective consumer segmentation by retailers and improved targeting of households suited to spot price tariffs.

The model presented in this study, when implemented on energy demand and price data from the Norwegian residential sector, provides further evidence of variation of price elastic responses throughout the day. As previously noted, however, these results only provide a preliminary picture.

A key limitation, for instance, is that at present the only explanatory variable used is price, and no distinction is made between days and/or seasons. There is ongoing work, however, to try and improve the model by incorporating other explanatory variables such as temperature, day type, and seasonal variations (e.g. holiday periods). Based on the available data, it would also be worth exploring the significance of the differences across different households' sub-samples grouped by, for instance, income, education level, dwelling type, heating system type (i.e. resistive vs air-source heat pump vs gas boiler vs district heating), EV ownership, etc. In principle, having access to energy storage devices should enhance the observed elasticity of owning households, but this is a hypothesis that requires testing.

Further, in order to address endogeneity issues arising from the interdependence between demand for energy and price, we intend to implement a two-stage least squares process to mitigate any resulting biases. Further work is also needed to better understand the effects observed across the price elasticity profiles of 'fixed price consumers'. Due to the limited number of 'nominal' fixed priced consumers, we also included some of the consumers labelled as 'variable tariff customers'. This decision was made on the basis that the data documentation indicates that the tariffs said 'variable tariff consumers' were exposed to were only variable over the longer term (i.e. yearly increases), but essentially fixed over the short term, and therefore, consistent with the fixed price sub-sample for the purposes of intra-day variability analysis. These issues will be addressed in a forthcoming publication.

Addressing the limitations highlighted above would allow for wider applicability of the type of model presented in this study. This includes scenarios such as energy retailers interested in clustering consumers based on their responsiveness to price at different times of the day. In the near future, however, such applications are likely to remain within the realm of research. As price-based demand flexibility interventions such as time-of-use tariffs are more widely adopted, an increasing number of datasets are emerging that combine metered demand for energy as well as price. This will in turn allow for more opportunities to test existing modelling approaches, and further improve them, so as to provide a more detailed picture of the intra-day variability of price elastic responses across a given population.

It is worth noting that achieving fully responsive demand patterns might prove unfeasible. Nevertheless, there are substantial benefits to be had from understanding, inducing and harnessing demand flexibility as much as possible.

5 References

[1] UK Department for Energy Security and Net Zero [DESNZ], 'Clean Power 2030: Action Plan: A new era of clean electricity', Policy paper, Dec. 2024. [Online]. Available: https://www.gov.uk/government/publications/clean-power-2030-action-plan

[2] X. Zhu, L. Li, K. Zhou, X. Zhang, and S. Yang, 'A meta-analysis on the price elasticity and income elasticity of residential electricity demand', *Journal of Cleaner Production*, vol. 201, Nov. 2018, doi: 10.1016/j.jclepro.2018.08.027.

[3] A. Faruqui, S. Sergici, and C. Warner, 'Arcturus 2.0 : A meta-analysis of time-varying rates for electricity', *The Electricity Journal*, vol. 30, no. 10, pp. 64–72, Dec. 2017, doi: 10.1016/j.tej.2017.11.003.

[4] I. Öhrlund, Å. Linné, and C. Bartusch, 'Convenience before coins: Household responses to dual dynamic price signals and energy feedback in Sweden', *Energy Research & Social Science*, vol. 52, pp. 236–246, June 2019, doi: 10.1016/j.erss.2019.02.008.

[5] A. Niromandfam and S. P. Choboghloo, 'Modeling electricity demand, welfare function and elasticity of electricity demand based on the customers risk aversion behavior', Oct. 15, 2020, *arXiv*: arXiv:2010.07600. doi: 10.48550/arXiv.2010.07600.

[6] X. Labandeira, J. M. Labeaga, and X. López-Otero, 'A meta-analysis on the price elasticity of energy demand', *Energy Policy*, vol. 102, Mar. 2017, doi: 10.1016/j.enpol.2017.01.002.

[7] S. Fan and R. J. Hyndman, 'The price elasticity of electricity demand in South Australia', *Energy Policy*, vol. 39, no. 6, pp. 3709–3719, June 2011, doi: 10.1016/J.ENPOL.2011.03.080.

[8] A. Knaut and S. Paulus, 'Hourly price elasticity pattern of electricity demand in the German day-ahead market', Energiewirtschaftliches Institut (EWI), Universität Köln, 2016. Accessed: Oct. 12, 2021. [Online]. Available: http://hdl.handle.net/10419/144865

[9] S. Kulakov and F. Ziel, 'Determining Fundamental Supply and Demand Curves in a Wholesale Electricity Market', Nov. 15, 2019, *arXiv*: arXiv:1903.11383. doi: 10.48550/arXiv.1903.11383.

[10] J. Chong, 'Real-Time Price Elasticity in Electricity: Evaluating Regression-Based Methods', *SSRN Electronic Journal*, Feb. 2021, doi: 10.2139/SSRN.3732118.

[11] J. Chong and J. Torriti, 'Time-varying price elasticity of electricity demand', in *44th International Association for Energy Economics (IAEE) International Conference*, Riyadh, Saudi Arabia: IAEE, 2023. Accessed: July 10, 2025. [Online]. Available: https://www.iaee.org/proceedings/article/18120

[12] M. Hofmann, S. Bjarghov, and S. Nessa, 'Norwegian hourly residential electricity demand data with consumer characteristics during the European energy crisis', *Data in Brief*, vol. 51, p. 109687, Dec. 2023, doi: 10.1016/j.dib.2023.109687.

[13] Ofgem, 'Energy price cap explained'. Accessed: Aug. 26, 2025. [Online]. Available: https://www.ofgem.gov.uk/information-consumers/energy-advice-households/energy-price-cap-explained

[14] F. El Gohary, M. Nordin, P. Juslin, and C. Bartusch, 'Evaluating user understanding and exposure effects of demand-based tariffs', *Renewable and Sustainable Energy Reviews*, vol. 155, p. 111956, Mar. 2022, doi: 10.1016/j.rser.2021.111956.

[15] M. Hofmann and K. B. Lindberg, 'Evidence of households' demand flexibility in response to variable hourly electricity prices – Results from a comprehensive field experiment in Norway', *Energy Policy*, vol. 184, p. 113821, Jan. 2024, doi: 10.1016/j.enpol.2023.113821.