Heterogeneity in hour-by-hour demand responses to the electricity spot price *

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Abstract

We estimate the hour-by-hour price elasticity of electricity consumption for wholesale and retail consumers in Denmark using hourly consumption data for 48 grid areas from January 2016 to December 2018. We use the Random Effects Instrument Variable (REIV) estimator where electricity spot prices are instrumented using the prognosis for wind-power production to overcome concerns of endogeneity.‡

For peak-hours our estimated price elasticities of -0.048 for wholesale consumption and -0.027 for retail consumption are modest in size. Similarly we find a relatively small effect from the introduction of a time-of-use tariff in the Copenhagen Metropolitan Area. Overall, our results suggest that decentralized, price-based tools to alter electricity demand should not stand alone. However, our results are not definitive and further research should be devoted to this topic.

Keywords: Electricity consumption • Electricity Price Elasticity • Demand responses • Wind Power Production • Random Effects Instrumental Variables estimation

Keystrokes: 70,500 which corresponds to 29.4 standard pages.

Individual contributions:

Thor Donsby Noe: 2.1, 2.3, 3.1, 3.1.2, 3.2.1, 4.1, 4.3, 4.5, 5.2, 5.4, 6.1, 6.2.1, 6.4, 6.5.1

Cathrine Falbe Pedersen: 2.2, 2.4, 3.1.1, 3.2, 3.3, 4.2, 4.4, 5.1, 5.3, 5.5, 6.2, 6.3, 6.5, 6.6

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‡On Github we provide a well-structured overview of Python and Stata code as well as all estimation tables with the complete set of time controls: github.com/thornoe/energy

Contents

1. Introduction

The focus of this paper is to estimate how the hour-by-hour electricity consumption responds to hourly electricity prices for wholesale and retail consumers. Estimating how price elasticities of demand of electricity has been an economic area of interest for a long time and increasingly so due to a growing share of renewables in energy production.

The electricity market has changed vastly over the past few decades in the direction of more competition and a larger share of intermittent, renewable energy production capacity. The climate crisis and the related ongoing political debate suggests that this will be equally, if not more, important in the near future. To policy makers and voters alike decarbonization is strongly linked to greater electrification, but this will only be true if the zero-emission, renewable energy production is able to meet demand. Efficient and environmentally sustainable electricity provision implies that electricity production and thus electricity supply fluctuates according to weather conditions, namely wind speed and sunshine. Heterogeneity and changes over time in demand responses can help predicting potential demand flexibility in the future as this is the main limit for further increasing the reliance on wind and solar power along with the infeasibility of electricity storage. From a policy point of view this can also reveal the potential for time-of-use tariffs (and other demand responses) which are being regarded as the most cost-efficient tool for promoting a more sustainable electricity consumption (Albadi and El-Saadany, 2008).

Using hourly observations for 2016-2018 we contribute to the existing literature by analyzing 48 local grid companies in Denmark for which aggregate electricity consumption is split into wholesale (large and medium-sized firms) and retail consumption (small firms and households). Furthermore, the problems of endogeneity resulting from the simultaneity of demand and supply mechanics is successfully handled by instrumenting the hourly spot price by the prognosis for wind power production as the current share of wind power greatly affects the marginal price of electricity in either price region. To account for heterogeneity across the grid companies we estimate the price-elasticity both grid-by-grid using pooled 2SLS (P2SLS) and jointly while controlling for grid-level unobserved effects using random effects instrumental variables (REIV) estimation.

We obtain estimates ranging between -0.019 and -0.048 for wholesale consumers, while they range between 0 and -0.035 for retail consumers. While consumption overall is quite inelastic it holds that wholesale consumption is more price-responsive than retail consumption which is in line with our theoretical predictions. Responsiveness is thus likely related to the degree of exposure to the real-time electricity price fluctuations. Results suggest that the prospects for using demand response (DR) mechanisms is limited and more centralized solutions may be called for when transitioning to an electricity market characterized by a large share of intermittent energy production.

The paper proceeds by giving a brief account of related studies in section 2. Section 3 covers the price formation in the electricity market by going into detail with the market itself in 3.1, the production side in 3.2 and perspectives of the demand side in 3.3. The data used for our empirical analysis is described in section 4 while we go into details with the econometric estimation methods in section 5. Results from the analysis are presented and discussed in section 6 before concluding in section 7.

2. Literature review

Estimating price elasticities of electricity and has been an area of interest for economists for a long time and increasingly so. Deregulation of the electricity market made it important to measure how a broad spectra of consumers (mostly residential, industrial and commercial) react to changing electricity prices.

Over the past decades the supply side has on one hand become even more volatile following decentralization and the increased share of renewable energy driven by political goals and competitive establishment costs while on the other hand the process of interconnecting electricity markets has help equalize prices between countries and regions.

In the case of a very inelastic electricity demand Wolak and Patrick (2001) outlines how an oligopolistic supply side can capitalize on intraday peaks in demand, however, firms that are able to have a more flexible energy use can face clear advantages in the market while on aggregate making it possible to further increase the share of renewables in the electricity supply.

Thus, it is of importance to conduct better empirical estimations of how consumers respond. In particular because time-of-use tariffs and other price instruments are often are often considered as policy tools to incentivize a decreased consumption of power. In the following we highlight the key contributions in this area.

2.1. Modest price elasticity of demand

Patrick and Wolak (2001) were among the first to estimate the demand-side responses to electricity prices for intraday-markets. For firms in England and Wales they find the overall magnitude of the real-time price elasticity of electricity demand to be quite low, though significant. However, for 5 specific industries an elasticity of -0.05 is found on half-hourly consumption. Similarly a very small overall flexibility is found for the Netherlands with a peak elasticity of -0.004 for hour-by-hour total Dutch consumption Lijesen (2007), however only 15% of the load is actually traded in the market price.

Regarding residential electricity demand most estimates of the demand response to price changes of electricity are in the range -2.01 to -0.004 in the short run and -2.25 to -0.04 in the long run as reported in Espey and Espey (2004), who does a meta analysis of 248 estimates in 36 non-time-of-day studies. With the median being -0.28 in the short run and -0.81 in the long run, elasticities tend to be bigger in the long run which is in accordance with economic reasoning since consumers better can modify their capital stock in the long term.

2.2. Heterogeneous effects

Being able to use the average firm-level responses within each code of British Industrial Classification (BIC) Patrick and Wolak (2001) find a substantial heterogeneity across industries not only in terms of the magnitude of the own-price elasticity of electricity demand but also in the within-day patterns of cross-price elasticities.

Fan and Hyndman (2011) estimate yearly own-price elasticities for Southern Australia at the aggregated level using a log-linear model for consumption on a half-hourly basis. The authors find heterogeneous effects across quantiles, depending on how extreme the weather is.

Likewise, under extreme prices Alberini et al. (2019) find that Ukrainian households become more attentive and elastic due to price changes and rather complicated tariff schemes.

2.3. Endogeneity problems

Estimating demands-side responses to shifting electricity prices is associated with potential problems of endogeneity as price and consumptions/production are simultaneous. That is, a higher expected demand can push up the overall prices and vice versa. An example of such a mechanism is that increasing demand-side competition can lead to imports of electricity from more expensive energy sources (Burke and Abayasekara, 2017) resulting in price increases. Furthermore, an unobserved factor can influence both prices and demand.

Therefore, for yearly data lagged prices are often included to avoid an omitted variable bias and to combat endogeneity (Lijesen, 2007), however, this inclusion creates a dynamic bias instead. This bias is likely to be bigger when estimating long term elasticities (Okajima and Okajima, 2013).

Bönte et al. (2015) were able to use wind speed as an instrument for the spot market price, however, the motivation of this strategy is specific to Germany due to their feed-in-tariff for Renewable Energy Sources that is designed to directly affect the price. Likewise, Graf and Wozabal (2013) tried using emissions right and prices for primary energy as instruments but to limited success. For the US Burke and Abayasekara (2017) use the state level share of coal and hydro as an instrument for yearly prices as they were generally the two cheaper sources of electricity.

2.4. Estimation methods

The estimates rely on a wide range of different empirical approaches to an extent that cannot simply be explained by different data structure. Thus, no clear *best practice* has yet been established for this field of research.

When data is limited to total electricity demand it is common to apply a pooled two-stage-least-squares (P2SLS) regression and either include a time trend (Lijesen, 2007) or estimate the elasticity year-by-year (Bönte et al., 2015).

For more dis-aggregated data different methods can be utilized. Unobserved heterogeneity must be accounted for, usually by including unit-specific time-constant unobserved effects. On household level data one such option is to use a Seemingly Unrelated Regression Equations (SUR/SURE) model (Vesterberg et al., 2014), however, Alberini et al. (2019) still use P2SLS with a rich set of background variables.

Lastly, identification strategies that rely on using past prices as instruments often rely on Dynamic Panel Estimation using Generalized Methods of Moments (GMM) (Genc, 2016) and intertemporal substitution can be modelled using Quasi Maximum Likelihood (Wolak and Patrick, 2001).

3. The electricity market

In order to understand how the price of electricity is formed it is necessary understand how the nature of the supply side, demand side and the workings of the electricity market. The electricity market differs from the majority of other markets because demand and supply must synchronize completely at all times. Storing electricity is possible, but at best highly inefficient and thus too costly to implement practically. Instead supply must be at least as great as demand at all times if blackouts are to be avoided. Historically this has been ensured through the production of a surplus of electricity. This is, however, costly both in terms of inefficiency and because of the associated negative externalities due to carbon dioxide emissions from fossil fueled power plants.

3.1. The electricity market design

The electricity market consists on one hand of the physical infrastructure required for electricity generation and transport while it on the other hand also being a well-organized market.

There are several ways to organize such a market. Within the European Union most of the decisions related to the organization of the energy market happen at the supranational level. It In recent years the electricity market has undergone great changes following the Third Energy Package. The package aims at improving the functioning of the energy market by ensuring more competition and transparency through unbundling of suppliers from operators, greater independence of regulators, more cross-border cooperation and better transparency in retail markets. [1]. This has increased the number of actors on the electricity market that now comprises consumers, producers, distributors, Independent TSO (Transmission System Operators - the owner of the transmission infrastructure), DSO (Distribution System Operators) and balance responsible actors. The responsible TSO in Denmark is Energinet, while the grid companies serve as DSOs (56 in total by December 2018).

In recent years the electricity market has undergone many changes to induce competition and reduce surplus production and thus "unnecessary" carbon dioxide emissions. The move towards more market liberalization still recognizes that that the distribution net

[1] https://ec.europa.eu/energy/en/topics/markets-and-consumers/market-legislation

constitutes a natural monopoly. In many countries including Denmark the TSO in charge of maintaining and building the grid is still a public firm while the remaining market operators are private. Competition is then ensured by letting thirds parties get access to the electric grids in a transparent way. This is only one of several ways to organize a market which has been adopted by member states of the EU, that furthermore wants to promote a single energy market. This is elaborated in section 3.2.1.

Firms and residential households enter the energy market differently. They face different prices that are formed in different ways. This is described further below.

3.1.1. The retail market

The retail market is comprised by the suppliers and the consumers. The group of consumers consists of both small firms and residential consumers. In the retail-market the suppliers act as intermediaries between the power generators and the consumers. The suppliers then enter the wholesale market (described below) on behalf of the retail consumers and buy electricity from the generators. The consumers are then offered a contract that traditionally has implied that the retail consumers face a single fixed price.

The residential electricity consumers have historically not been treated as 'genuine demanders' (Kirschen, 2003). Instead of facing the actual cost of electricity they instead sign contracts where a distributor acts as a middleman that trades electricity in the market on behalf of its customers, but they receive a premium for undertaking the market risk. The distributors and the consumers then undergo contracts where the price of electricity is typically fixed for up to a year. This insulates the retail consumers from the spot price that better reflects the cost of electricity production at a given point in time. This "distance" to the actual price of electricity is exacerbated even more by the tariffs on electricity that the residential consumers face. These are particularly high in Denmark as they on average make up 62 percent of electricity bills excluding VAT (20 percent).[2]. That is, in addition to the cost of electricity itself each consumer pays a distribution grid tariff, a transmission grid tariff, an electricity tax, PSO (Public service obligation) and sales tax (VAT).

It is, however, worth noting that the way residential customers are settled is likely to change in the future as smart meters are adopted more widely. It is becoming increasingly common that customers are offered a variable electricity price that follows the fluctuations

[2] elpris.dk

of the average price in the market, even more so by 2020 all consumers in Denmark will have smart meters installed and the option to get charged according to the spot price for the corresponding hour for which they consume. The prospects for smart meters are discussed further in section 6.5.

For instance Denmark has decided to enrol smart meters to all consumers by 2020 in the Energy Agreement from 2013. In Denmark several grid companies have already rolled out the smart meters which allows for more flexible settlement such that demand can respond to different prices.

3.1.2. The wholesale market

Large and medium-sized electricity consumers [3] enter into the wholesale market for electricity. Here electricity is bought and sold in different markets depending on how well in advance before the actual time of delivery the electricity is traded. Electricity is thus traded via either

Long term contracts Electricity bought and sold further ahead of time than the day before consumption can be agreed upon by undergoing long term contracts or from trades in the forward market. In the forward market futures, forwards, Electricity Price Area Differentials (EPADs) and put and call options are traded. The products are traded either bilaterally or as stocks at NASDAQ OMX Commodities and serves as a way to reduce risks by ensuring a fixed price or insurance against realized price differentials. The value of the futures (and forwards) shifts based on the reference price that is the official nordic day-ahead price.

The day-ahead market The day-ahead market (the spot market) is where the majority of electricity is traded either for specific hours or blocks thereof. The price is determined in a multi-unit double-auction where all bids and asks are aggregated to form the hourly supply and demand - while the market clearing price is determined by where they intersect subject to the capacity constraints in the market. All the actors in the market (generators, distributors and wholesale clients) pay or receive the same price within a price region. Distributional bottlenecks between regions entails price differences within the market. This price, also referred to as the spot price, thus reflects the amount which power producers believe they can supply which in

[3] In Denmark this entail firms that consume more than 100.000 kWh a year, to whom hourly settlement is obligatory.

turn depends on weather prognoses, expected plant shutdowns etc. but also how much consumers (retail and wholesale) are expected to consume given the physical constraints of the electric grid. It should be noted that Nord Pool Spot have both lower and upper price caps outside of which bids are reduced by a fixed percentage rate.

The intra-day market The day-ahead market closes at 12 pm the preceding day but from 2 pm and up until an hour before time of delivery trade can occur on the intra-day market where. Here electricity is sold in blocks, hours and 15 minute intervals. Similar to the spot-market this is operated by Nord Pool. The quantities traded in the intra-day market is much smaller than in the day-ahead market but this is likely to change as a larger share of the production capacity is constituted by renewables due to uncertainties regarding weather prognosis. From 2016 to 2017 the traded volume in the intraday-market increased by 35 per cent for the Nordic/Baltic/German markets.[4]

The balancing market If gaps between supply and demand remain after the closing of the intra-day market they must be balanced by the responsible system operator. Each of the actors in the market rarely live completely up to their obligations for instance more or less wind power can be produced or firms may consume unforeseeable large or small amounts of electricity. This necessitates that the responsible Transmission System Operator (TSO), Energinet[5] in Denmark, balances during the delivery period.

3.2. Production and supply of electricity

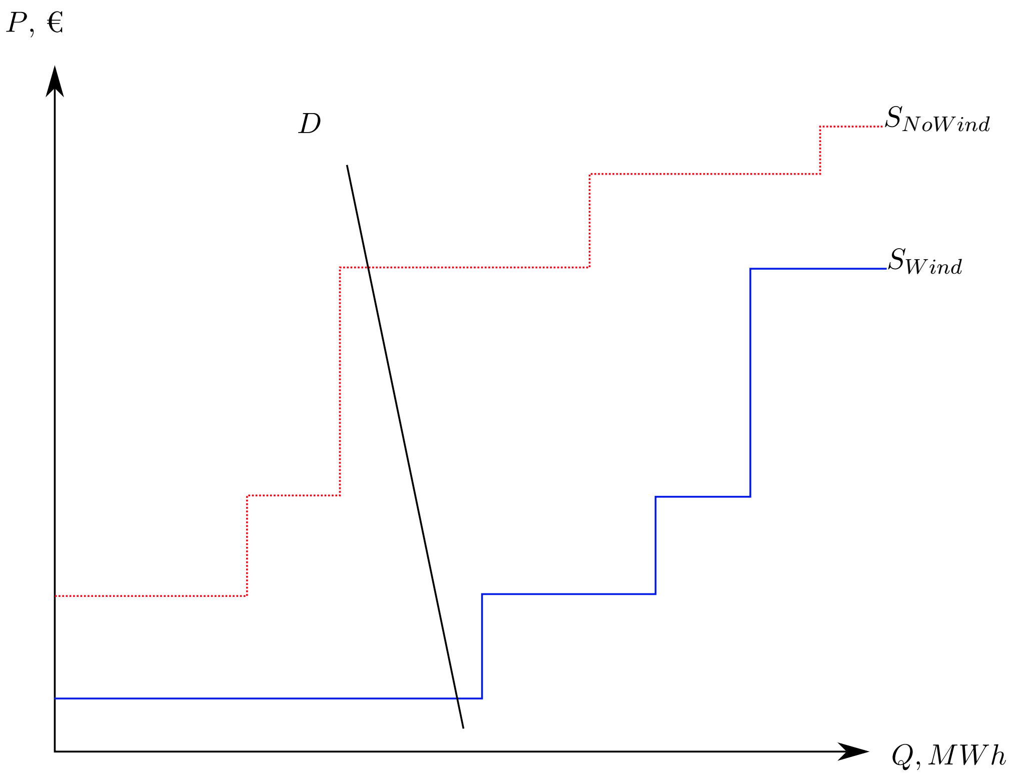
Electricity is supplied by different kinds of power plants that each has their own advantages in terms of when they can produce and how fast they reach an efficient production level. In most of Europe the common types of power include lignite, coal, gas, nuclear, solar, wind and hydro, ranged from the more emission intense to the least. The marginal cost of electricity from renewable sources is far less because almost no (costly) inputs are needed, but these typically require certain weather conditions outside the control of the supplier. Coal and lignite power plants have higher costs running and have to be running for a

[4] `https://www.nordpoolgroup.com/globalassets/download-center/annual-report/annual-report-nord-pool_2017.pdf`
[5] `https://en.energinet.dk`

while to reach efficient production, but do not rely on external parameters. These are typically used as a part of the base-load. The available production capacities and weather conditions thus shape the supply curve.

For each supplier it is optimal (at least in the short term) to ask for the marginal cost of producing electricity at a given point in time. This implies that the supply curve and thus the order in which generators are dispatched reflects the merit order. The merit order effect is illustrated below in figure 1. If the weather conditions are right, electricity from renewable sources are dispatched first - as illustrated by the blue supply curve, because they have marginal costs that are essentially zero, and only if not sufficient the other sources are utilized in the priority nuclear (imports only), gas, hard coal and lignite. If the share of renewables in the production capacity is large the supply curve is shifted to the right compared to the case of no renewables (S_{NoWind}).

Figure 1: Merit Order Effect



The marginal costs of electricity production from carbonizing plants are even higher in the EU where the supplier has to buy carbon dioxide emission quotas such that renewable and low-emission power production is prioritized.

In the case where the demand for electricity is particularly high, that is, at a peak then costs are also very high. The extra electricity generation is carried out by plants with high marginal costs. At peak the price is high enough to cover the costs from fossil fuels such as gas, oul, coal, and lignite. The last plants to be dispatched are thus all high emission - and has high economic and external costs cf. chapter 12 in Zweifel et al. (2017). Covering spikes in demand will remain problematic even if the share of renewable energy increases significantly. Demand side management may thus be relevant tools in transitioning to low emission electricity production. Most demand response mechanisms are intended to encourage shifts in consumption and thus reduce peak demand. Section 3.3 goes into greater details with demand. High prices does, however, also have some benefits - at least when it is set in a competitive market. It is when prices are high that producers can recover their capacity costs. Similarly the price serves as a signal to consumers of the state of the market. Price policies such as price caps may distort these mechanisms.

3.2.1. Market Integration

As mentioned in previous sections the European Energy Market has and is undergoing great changes in order to achieve what is considered a more efficient and thus well-functioning market. This is believed to be insured by inducing more competition in the energy sector - not just from ownership unbundling but also through freer movement of energy. This would imply that electricity is allowed to flow to where it is needed the most and from low-price regions to high-price regions. The end goal is thus a single, free (European) energy market with power production from the sources of the lowest possible merit order.

This is currently constrained by limited cross-grid transmission capacities. Depending on demand and supply on each side then a connecting capacity make up potential bottlenecks that can result in different prices. This is evident even for the relatively small market of Denmark where two price regions exists because the Great Belt Link has a capacity of 600 MW, which is too little for prices to fully converge.

Even though capacity constraints are still binding improved integration the Danish market is linked to the Northern European market. Trade happens at the electricity exchange 'Nord Pool'. Nord pool has already combined 13 markets; The Nordic countries, the Baltic countries, Germany, Austria, France, Belgium, the Netherlands and the UK. This and future integration implies that electricity prices in Denmark are under great influence from production conditions abroad. A low hydro reserve in Norway may thus increase Danish electricity prices and sunshine in Germany may vice versa lower prices.

Increased market integration means more harmonised prices and thus lower price volatility. Market integration can pose a solution to achieve an increased share of energy produced by intermittent renewable sources without increasing price volatility and uncertainty. Market integration allows for changes in the composition of the production capacities within the electrical grid to something more optimal where they complement each other. Danish wind energy is thus complemented very well by storaged hydro from Norway (Ambec and Crampes, 2012). This may become increasingly important as the EU is moving towards achieving its target of 50 percent renewable energy production in 2030 following the Paris Agreement.

3.3. Demand of electricity

It is often deemed more cost-efficient to reduce demand in periods of peak demand as opposed to dispatching high-merit generation plants. This can be prompted through demand responses defined as the resulting deviations from normal electricity consumption patterns in response to changes in the electricity price over time. These are often designed to induce lower consumption when demand is particularly high or when production from renewables is low (Albadi and El-Saadany, 2008). Examples include time-of-use tariffs, real time pricing and demand bidding. If implemented effectively they can benefit individuals through lower bills, but also the entire market by deferring or avoiding distribution and transmission upgrades, increasing reliability, reducing price volatility and improving the efficiency of the electricity market.

For demand responses to provide these benefits consumption must be price-sensitive. There are, however, many reasons why demand for electricity can be quite inelastic. If demand, as expected, turns out to be highly inelastic this either points to policies that try to change the demand curve itself or more centralized solutions where for instance the supply side of the market is targeted instead.

The market of electricity itself differs from most other markets as described above. The complexity of the market and its price formation in itself leads to consumers facing a higher price because the nature of the demand for electricity is of indirect character. Electricity demand, for retail and wholesale consumers alike, is shaped by the demand for the use of other appliances that require electricity to function.

This indirectness implies that less information on costs is available to the consumer at the time of consumption which makes responding difficult. In order to calculate the price of using an appliance knowledge of both electricity prices and how much each device uses is required. Elasticities thus answer the limits of using decentralized solutions to help the energy market to clear in an environmentally sustainable way.

In terms of demand of electricity there is an important distinction to make between residential and wholesale electricity consumers. But it is a common feature for both types of consumers that electricity is hard to replace. Much of firms' physical capital runs on electricity while the same applies for most household appliances needed for domestic production of food etc. Similarly society's reliance on electricity is increasing as more infrastructure is becoming digitized and moving away from fossil fuels. In other words, electricity is a necessity for economic growth and the functioning of developed and industrialized economies. Still, wholesale and retail consumers differ not only in how they enter into the market but also in the nature of their demand. The differences described in further detail below affect how flexible different consumer types are and thus why different elasticities are to be expected.

Demand for wholesale consumers

Wholesale consumers enter into the wholesale market themselves, as indicated, by their name. This implies that wholesale consumers can face real time prices or spot prices. Wholesale consumers thus have incentives to lower their consumption when it is costly to produce electricity as it reflects in higher prices. With the rare exception when price caps are binding, they can thus respond to the state of the market. Furthermore, firms are also mostly exempt from paying tariffs on their electricity.

For wholesale consumers electricity typically constitutes a great share of all costs. The possible cost reductions that monitoring of prices makes possible are non-negligible. This suggests that most wholesale consumers should be relatively more price sensitive than retail consumers.

On the other hand, firms are also subject to more restrictions in regards to when they operate as this is typically in business hours depending, of course, on the nature of the firm, such as what industry it operates in and how automatized its processes are. Similarly, firms can be required to deliver a product or a service subject to a contract or time-specific demand which does not allow firms to postpone production for too long.

Demand theory for retail consumers

Small scale consumers are more insulated from price fluctuations because they enter the energy market only through a middleman and contracts typically involve a fixed price per kWh albeit this may change in the future. New EU directives dictate that more billing options should be made available to retail consumers. One reason why most retail consumers are not settled hour-by-hour yet is that the physical infrastructure required (remotely read meters or smart meters) is either not widely installed or taken into effect. In fact, many demand responses rely on the consumer being able to inform themselves on the real time prices.

Even if residential consumers and small firms faced real-time prices, they might still not take them into account. One obvious limitation to the flexibility of demand is that demand responses require knowledge of prices at a given point in time. Furthermore it can be costly to take actions in order to reduce demand. Combined these factors may make it optimal for small consumers to not adhere to market signals except when prices are extremely high (Wolak, 2011), which could be due to the introduction of price based mechanisms such as a time-of-use tariff. This implies that many consumers have to rely on behavioral rules when deciding how much energy to consume cf. Kirschen (2003).

Another aspect has to do with how electricity is regarded as a good. Kirschen (2003) points to the fact that electricity is regarded as a good that is indispensable and essential to quality of life. It has always been marketed as easily accessible in terms of usage and availability although this may not genuinely be the case.

Residential consumers should be more flexible than industrial in at least one aspect: They are better able to forego some consumption. While some consumption is postponed usage of other appliances constitutes foregone consumption instead. Examples of foregone consumption include lighting and entertainment related electricity use.

Tariffs constitute a considerable share of the electricity bill for residential consumers as described in section 3.1. When fixed tariffs are very large they may overshadow any price fluctuations and thus make it more difficult for residential consumers to adjust their consumption. Tariffs and taxes, unless Pigouvian, are distortionary because prices serve as the suppliers' main signal of the true cost of production at a given point in time.

This all adds up to an expected weak elasticity for retail consumers. At least in the absence of hour-by-hour prices with salient price signalling.

4. Data and variables

We have scraped most of our data from various web sources in respect of the terms of use. The descriptive statistics for the main variables are shown in table 1 and described in further detail in the remainder of this section.

Table 1: Descriptive statistics

	mean	sd	min	p50	max
Wholesale electricity consumption, MWh	41.92935	92.16819	.082169	7.644501	757.5571
Retail electricity consumption, MWh	34.7628	80.92455	0	7.593214	906.3964
Number of wholesale meters	1113.68	2659.874	15	210.5	17674
Number of retail meters	68474.39	160277.3	1080	16564.5	1006061
- of which flex-settled	4836.807	39416.33	0	0	596267
- of which residual	63637.58	146395.8	974	16106	998864
Electricity spot price, DKK/MWh	253.3359	108.2735	-398.61	235.17	1898.9
Wind power prognosis for DK1, GWh	1.225359	.9221094	0	1.002	3.973
Wind power prognosis for DK2, GWh	.3266759	.2702798	0	.249	1.084
Wind power prognosis for Sweden, GWh	1.862874	1.118507	.062	1.668	5.84
Price region DK1 (Western Denmark)	.8125	.3903125	0	1	1
Share time-of-use tariff (Radius only)	.000155	.0084536	0	0	.5926748
Temperature	9.116639	6.923547	-11.9	8.8	31.4
Daytime	.5135255	.4857338	0	.6666667	1
Time trend	547.4559	316.4119	0	547	1095
Holiday (not in a weekend)	.0437643	.2045702	0	0	1
Observations	1,262,400				

For estimation purposes we log-transform electricity consumption, the number of electricity meters, and the electricity spot price. This furthermore allows us to interpret parameter estimates as elasticities/semi-elasticities. Before taking the natural logarithm the variables are censored with 1 as the lower bound whereby we loose some information as the spot price is negative for a few instances due to surplus wind power production.

4.1. Grid-level consumption

The Danish Transmission System Operator (TSO), Energinet provides public access to hourly aggregated consumption data[6] since January 2016 for each grid company grouped by hourly-settled consumption, flex settled consumption, and residual consumption. This allows us to distinguish between wholesale and retail consumption. Hourly-settled consumption consists of all firms with an annual electricity consumption of at least 100,000 kWh.

Flex-settled consumption was introduced in January 2018 such that households and small firms can opt to have their electricity consumption settled more flexibly for example according to real time electricity prices. Though installation of smart meters to enable flex-settling is only being introduced gradually, this allows a portion of residential consumers and small firms to better respond to price changes at an hourly rather than a yearly or quarterly basis.

The residual consumption is the remaining retail electricity consumption for which flex-settling is not used and thus includes all households and small firms till December 1 2017 and throughout the majority of 2018 as well.

As shown in figure 2 and 3 wholesale and retail consumption follows clear patterns not only within the day but also between days and across the year. That is, wholesale consumption is at its lowest on weekends, bank holidays and during the summer holiday while retail consumption peaks in the hours 5-7 PM (from here on written as hours 17-19) and half of the year during the winter.

For each grid we include the number of metering points[7] by each of the three consumer categories. This data is monthly by the 1$^{\text{st}}$ of the month. For studies on state-level data it is likewise common to control for size (Burke and Abayasekara, 2017).

The landscape of grid companies has changed drastically. From consisting of 74 grid companies by early 2016, only 56 grid companies remained by the end of 2018 (see figure 7 in appendix A). We remove the two grids with less than 10 metering points and the six grids with no wholesale consumption, which leaves us with 48 grids of which no less than 39 are located in Western Denmark. For a merged grid company we apply the sum of

[6]Scraped from energidataservice.dk/en/dataset/consumptionpergridarea using their transparent API via SQL statements.

[7]Received from Energinet after request.

each of the grids included in the future merge to all prior month as described further in appendix A.

Figure 2: Mean electricity consumption by hour and type

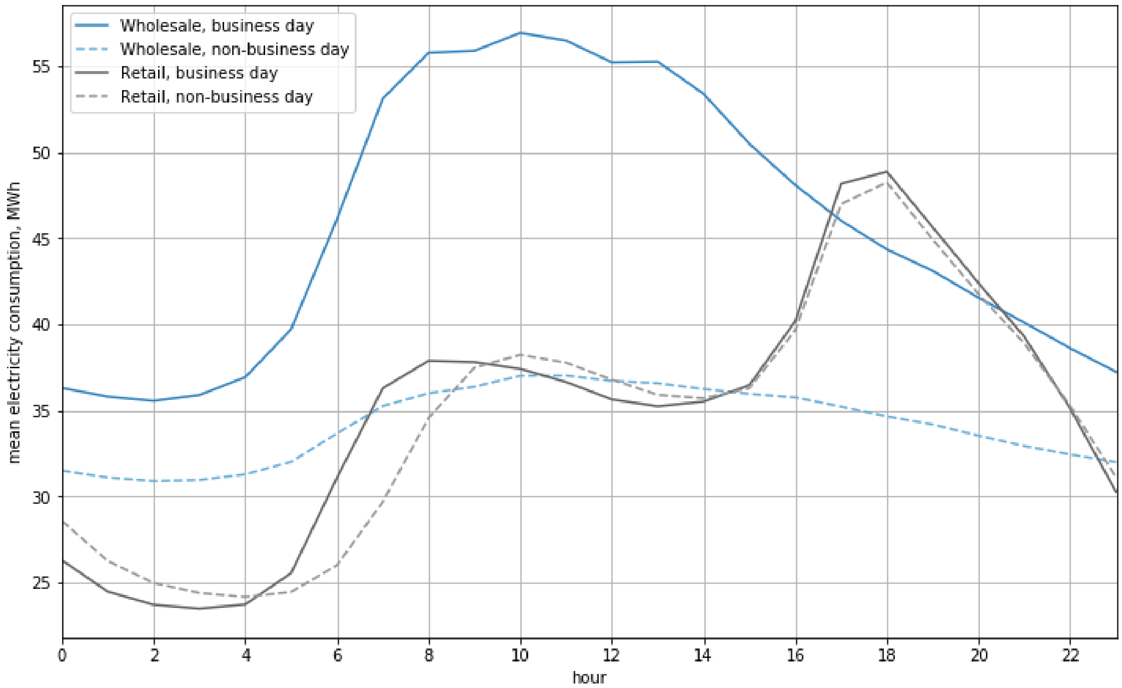
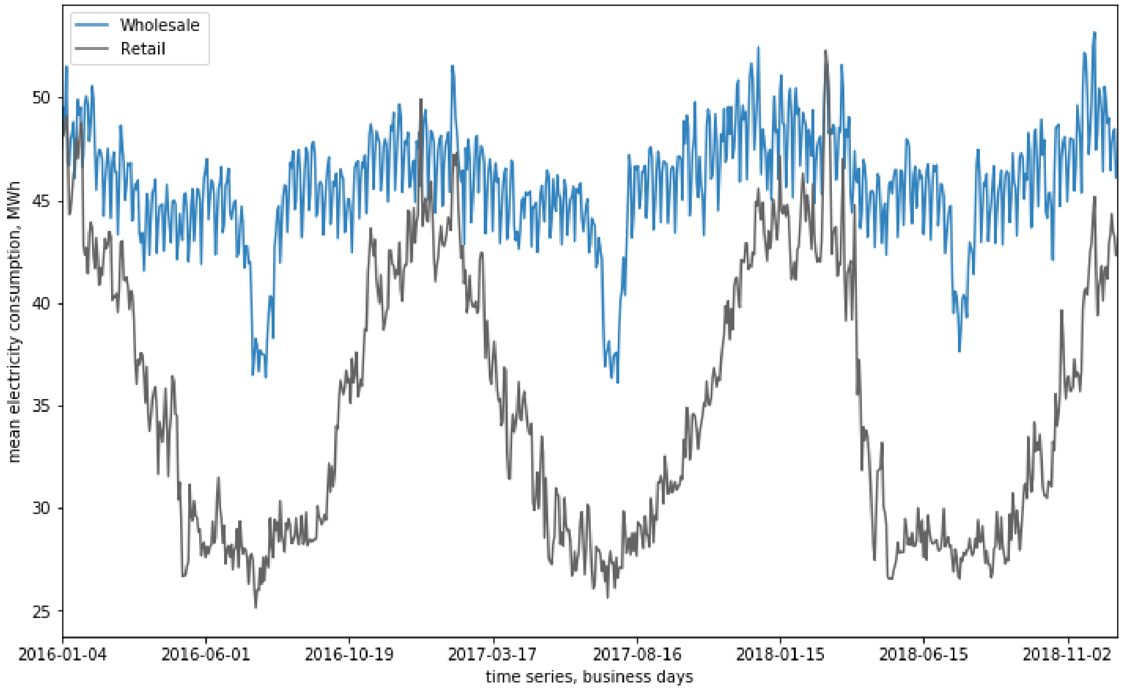


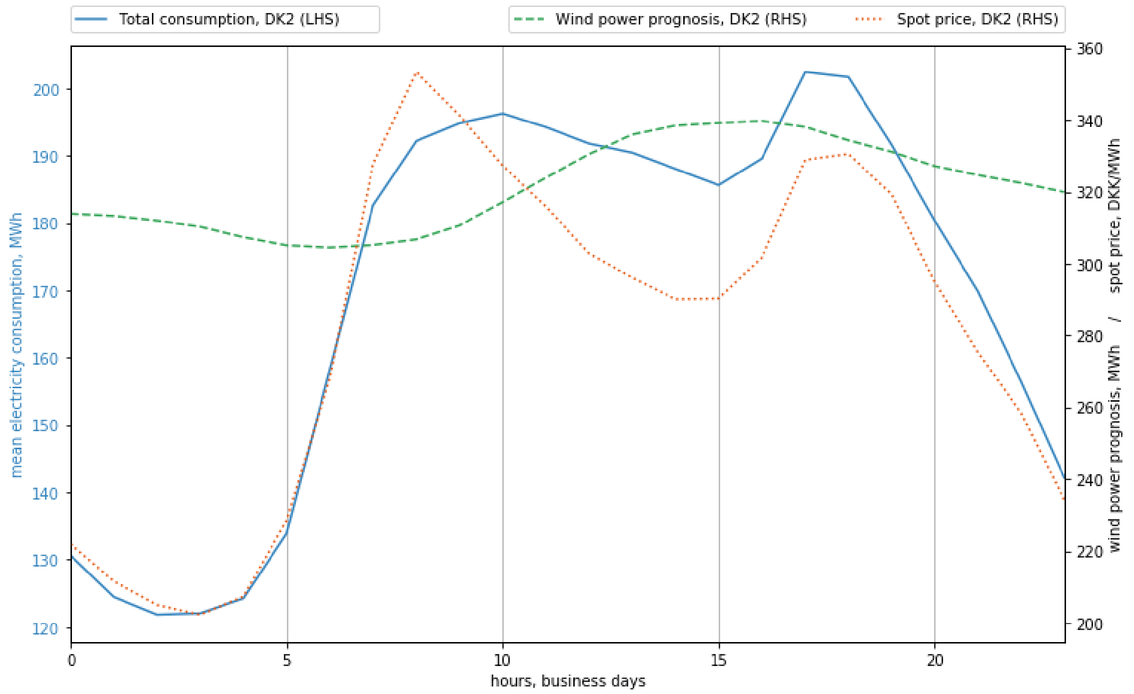
Figure 3: Time series for mean electricity consumption (business days)



4.2. Spot market prices and wind power prognosis

We include the hour-by-hour spot market price on the day-ahead-market for the price region DK1 (Western Denmark) or DK2 (Eastern Denmark) depending on where the grid company is located (see section 3). An important factor for the spot price on the day-ahead-market is the hour-by-hour wind power prognosis for the following day.[8] While being less volatile than wind power production, price is nonetheless highly volatile from day to day while having increased in 2018 as illustrated by the time series in figure 8 and 9 (appendix B).

Figure 4: Total consumption, wind power and spot price by hour (business days)



The wind power prognosis first and foremost takes into account weather forecasts in relation to the positions and capacity of windmills but also takes into account the expected demand as some wind mills can possibly be turned off if the expected price is too low. However, except for a slight peak in the afternoon and evening that is more likely due to sea and land breezes, wind power does not seem to care much for consumption patterns during the day (figure 4 for DK2 and 10 for DK1) and especially not across weekdays (figure 11).

On the contrary, the daily pattern of the spot price on average follows the pattern of

[8]'Elspot prices' and 'Wind power prognosis' by price region and year is updated daily after 2PM by Nord Pool and downloadable at nordpoolgroup.com/historical-market-data

demand by and large. The biggest gap between price and total consumption seen in figure 4 occurs during the afternoon where the low price relative to demand could possibly be explained by the higher wind power production.

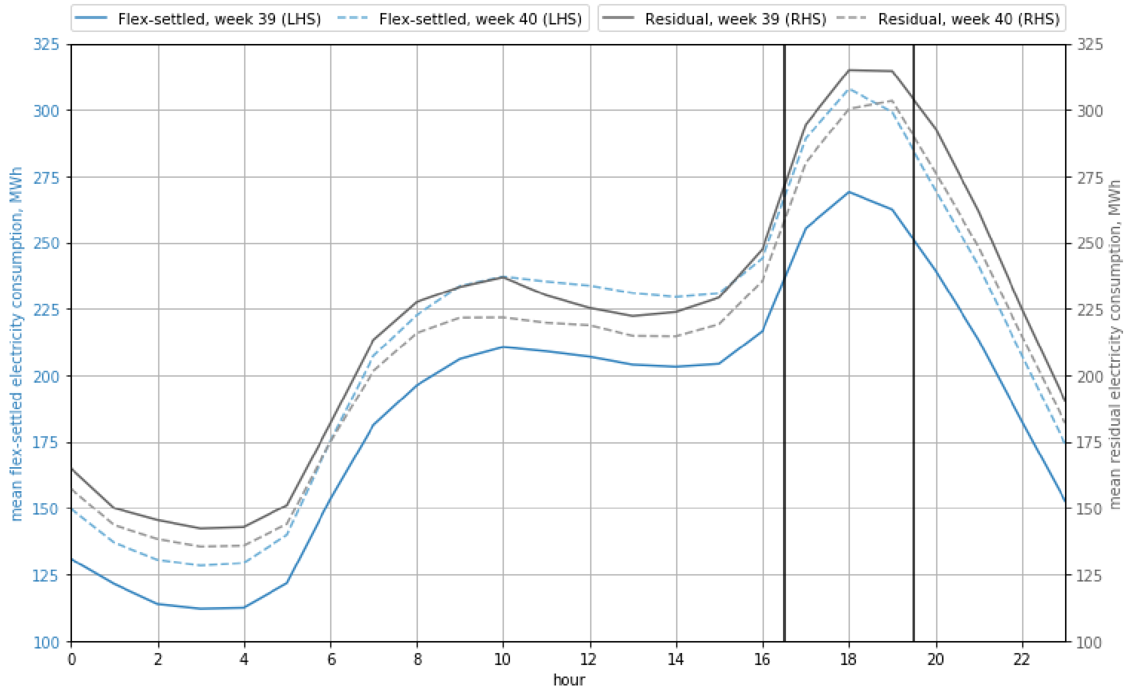
4.3. Time-of-use tariff

Since December 2017 grid companies have been allowed to introduce time-of-use tariff (TOUT) for retail consumption in order to send signals to encourage shifts of flexible tasks away from the peak hours around dinnertime. Two of the bigger grid companies have already introduced TOUT for the peak-hours 17-19 for the months October-March in which electricity consumption is also higher due to the lack of daylight. While Konstant initially only runs an experiment for a smaller group of flex-settled consumers, Radius is introducing a full-scale TOUT scheme while exchanging the old prepayment meters with smart meters for the 600,000 retail customers in the Copenhagen metropolitan area.[9]

The variable for the TOUT represents the share of retail customers in Radius possibly being exposed to the tariff. As seen in figure 5 and table 1 the share increases throughout the period and ends near 60 percent in December 2018. The concept of aggregate data makes it difficult to demarcate changes in behavior from changes in composition. In figure 5 we try to investigate the discontinuity around October 1 2018 as week 39 is in September and week 40 is in October. From a graphical inspection no clear response to the TOUT stands out, except that flex-settled consumers have higher consumption during the day and residual consumers during the night which might be due to sociodemographic differences between the areas with smart meters and those where it has yet to be implemented.

[9] See ing.dk/artikel/nu-loebes-fleksible-elforbrug-omsider-gang-209251 (Danish).

Figure 5: Flex-settled and residual consumption by week (Radius, 2018)



4.4. Weather data

The outside temperature is directly relevant to the extent that electrical heaters or air conditioning is used (Lijesen, 2007; Vesterberg et al., 2014). As the electricity consumption ceteris paribus is expected to be higher for both low-end and high-end temperatures, we let the effect of temperature enter as a 2^{nd} order polynomial in the estimation of electricity consumption.[10]

Lighting is used more in the absence of daylight. Therefore, an indicator for daytime is included such that $daytime = 1$ for hours between sunrise and sunset and e.g. $daytime = 0.25$ for $hour = 7$ if sunrise was a quarter past 7.[11]

Taking advantage of the population density in Denmark, temperature and daytime are only scraped for the two most populous municipalities (Aarhus and Copenhagen) and then applied to all grid companies within their respective price regions.[12]

[10]Scraped via iterative lookups in the records of the Danish Meteorological Institute at dmi.dk/vejrarkiv/

[11]Sunrise and sunset are scraped for each date in the sample via iterative lookups at soltider.dk

[12]Temperature is for the municipalities of Aarhus and Copenhagen respectively while sunrise and sunset are for the City Hall Square in each of the two cites.

4.5. Time controls

Year dummies as well as a time trend indicating the number of days since January 1 2016 are included to account for economic growth (overall increases in electricity consumption), technological progress (decreases in electricity consumption per appliance) (Lijesen, 2007), or other compositional changes that can affect electricity consumption other than the number of meters.

Danish bank holidays and a few other common holidays with lower wholesale electricity consumption[13] are taken into account in order to do sample split regressions for business days and non-business days, the latter including the aforementioned holidays and weekends.

5. Empirical strategy

5.1. Baseline model

Our baseline model is a Random Effects (RE) model to be estimated using feasible Generalized Least Squares (fGLS) where electricity consumption e for grid company i at time t (date by hour) is given by:

$$\begin{aligned}\ln e_{it} &= \varepsilon \widehat{\ln p_{rt}} + \delta \ln n_{im} + \boldsymbol{w}'_{rt}\lambda \\ &\quad + \gamma\ days + \eta_{year} + \eta_{week} + \eta_{hour} \cdot \eta_{month} + \eta_{hour} \cdot \eta_{day} + c_i + u_{it}\end{aligned} \tag{5.1}$$

where p is the electricity spot price in price region r at time t, n is the number of meters at the beginning of the month m, $\boldsymbol{w}$ is a vector of weather variables for the given price region r at time t (see section 4.4). The time variables in the second line include the time trend *days* and the η's representing dummies for each year and each ISO week number, as well as dummies for hour of the day interacted with month and day of the week respectively. The composite error term consists of the grid-specific time-constant unobserved effect c_i that is treated as random and the idiosyncratic error u_{it}.

We use a log-log specification for electricity consumption, the spot price, and the number of meters as it allows us to model demand responses across grid areas of different size.

[13] January 2 (the day after New Year's Day), May 1 (International Workers' Day), Friday after Ascension Day, June 5 (Constitution Day), last Friday before Christmas, and the days between Christmas and New Year's. All holidays according to kalendersiden.dk

Furthermore, log-log is the more standard specification which allows for a more direct comparison to the results in other studies (Burke and Abayasekara, 2017). Other attractive properties include that the estimation provides the elasticity directly and prevents predicting non-positive electricity consumption. Furthermore, the specification reduces the impact of outliers and is found to reduce systematic patterns in the estimated residuals (Burke and Abayasekara, 2017).

5.2. Instrumenting for prices

To circumvent the simultaneity problem that higher expected consumption reflects in higher demand in the day-ahead-market which drives the spot price up, we instrument for the price using the wind-power production. This makes sense as the marginal cost of wind-power production is close to zero, such that a higher expected wind-power production will drive down the price due to the merit order effect as illustrated in figure 1. This inverse relationship is consistent with what we observe in our data as seen in figure 6 for DK1 and in figure 12 for DK2 (appendix B). This insinuates that it is a relevant instrument. The instrument is also likely to be a valid one; weather is exogenous and it seems unlikely that consumption of electricity responds to wind weather through other channels than through the price of electricity conditional on temperatures and daytimes. These assumptions are tested formally in section 6.3.

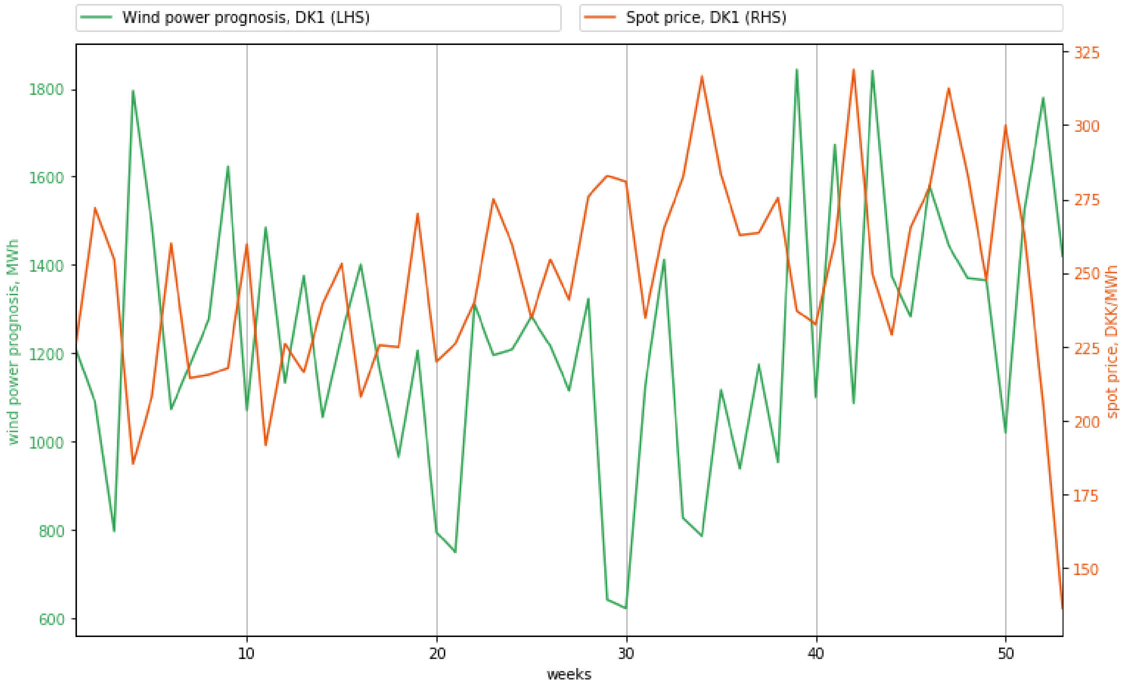
As the general level of wind power production is very different between the two price regions, we expect different slopes as well which we get by interacting it with dummies for each price region, thus, we estimate the reduced form for log price $\widehat{\ln p}$ in region r at time t by wind power prognosis *wind* for the same price region and time as well as using the same controls as in equation (5.1) though we expect the first-stage estimate $\widehat{\underline{\delta}}$ of the number of meters to be insignificant.

Thus, estimating electricity consumption by a Random Effects Instrumental Variables (REIV) estimation is a three-stage approach starting by estimating the reduced form for log price using a Generalized IV (GIV) estimator for the pooled sample (see subsection 5.4 below):

$$\begin{aligned} \ln p_{rt} = (\pi_1 DK1 + \pi_2 DK2) \cdot wind_{rt} + \underline{\delta} \ln n_{im} + \boldsymbol{w}_r' \underline{\lambda} \\ + \underline{\gamma}\ days + \underline{\eta_{year}} + \underline{\eta_{week}} + \underline{\eta_{hour} \cdot \eta_{month}} + \underline{\eta_{hour} \cdot \eta_{day}} + v_i \end{aligned} \tag{5.2}$$

Given a negative direction of $\hat{\pi}$, our log-level specification for spot price and wind power prognosis is an attempt to mimic the merit effects by ensuring that an increase in wind power has a larger effect on the spot price for low levels of wind power production and high prices while the effect diminishes as the price gets closer to zero for higher amounts of wind power.

Figure 6: Wind power prognosis and spot price by week (DK1)



An overproduction of wind power in one price region leads to transmission of cheap electricity to connected price regions, thus, as additional instruments we also consider the wind power prognosis for the other price region as well as for all of Sweden.

5.3. Effect of Time-of-use tariff

To estimate the effect of the time-of-use tariff (TOUT) (see subsection 4.3) the baseline specification (5.1) is estimated for the hours 17-19 solely for the grid company Radius using pooled 2SLS (P2SLS), thus, without the grid-area unobserved effect c_i but including a term for the effect of the TOUT:

$$\alpha \frac{nf_{month}}{nr_{month}} \tau_{year,month} \tag{5.3}$$

Where nf is the number of flex-settled meters by month, nr is the total number of meters for retail customers, and τ is a dummy for being in October-March after December 2017.

To isolate the effect of the TOUT we need to assume that residual consumers do not react to the tariff so their consumption, on the contrary, is assumed to follow the same hour-by-day, hour-by-month, and week patterns as in previous years and that the effects of year dummies and the time trend are evenly distributed across the year.

One weakness is that the monthly records for the number of flex-settled meters provides a lag which can result in an downward bias of $\widehat{\alpha}$ (if there is a negative effect of the tariff). This could possibly be improved by assuming a linear daily growth between nf_{month} and $nf_{month+1}$.

5.4. Random Effects estimation

Different candidates exists for panel data estimation with unobserved effects (Wooldridge, 2010). The simplest method is **pooled ordinary least squares (POLS)** and the corresponding **pooled two stage least squares** for instrumental variables (IV) estimation in he case of endogeneity issues, which we will use for one-grid estimations of our model (5.1). The number of meters is , however, the only grid-specific background variable we have available. Thus, for full-sample estimation it is likely that the presence of unobserved heterogeneity is not controlled for and therefore correlates with the set of controls such as having different industries or firm sizes regarding wholesale or different daily patterns for retail consumers. Even if the strict exogeneity condition holds:

$$cov(c_i, x_{it}) = 0 \tag{5.4}$$

then POLS would still result in serial correlation given that $c_i \neq 0$, which is present in the composite error for each time period i.e. $cov(c_i + u_{it}, c_i + u_{is}) = \sigma_c^2 > 0$. Though we would still need to handle the serial correlation, a first step is to note that we regardless of estimation technique would need to use cluster robust standard errors for the full-sample estimation.

Though it is a common way to handle serial correlation, we hardly consider the **first-difference (FD)** estimation as the great presence of heteroscedasticity in terms of seasonality and daily and weekly patterns with occasional holidays underlines that there is no obvious suggestion for the length of $t-s$ that would not violate the critical assumption of (5.4). Furthermore, we see no signs of electricity consumption acting as a unit root process in figure 2.

The consistent but somewhat inefficient approach is the **fixed effects (FE)** estimation as it does not assume strict exogeneity (5.4) due to performing a within transformation of all variables before estimating by POLS. Equivalently, **fixed effects instrumental variables (FEIV)** estimation is simply performed by within transforming both equation (5.1) and (5.2) and estimating this time-demeaned system by P2SLS. While the loss of time constant variables is a common flaw of FE estimation, we do not have any in our specification (5.1) except for c_i that causes the serial correlation.

A less extreme approach is the **random effects (RE)** estimator that first within-transform our model (5.1) to run a FE estimation in order to compute:

$$\widehat{\lambda} = 1 - \left(\frac{\sigma_u^2}{\sigma_u^2 + T\sigma_c^2} \right)^{\frac{1}{2}} \tag{5.5}$$

Next we use the stored size of $\widehat{\lambda}$ to estimate the quasi-time demeaned system by **feasible Generalized Least Squares (fGLS)** estimation where $\overline{\boldsymbol{x}_i}$ is a vector with the time-average for each regressor:

$$\begin{aligned} y_{it} - \widehat{\lambda}\overline{y_i} &= \beta_0 \left(1 - \widehat{\lambda}\right) + \beta_1 \left(\boldsymbol{x}_{it} - \widehat{\lambda}\overline{\boldsymbol{x}_i}\right) + \left(c_i - \widehat{\lambda}\overline{c_i}\right) + \left(u_{it} - \widehat{\lambda}\overline{u_i}\right) \\ &= \beta_0 \left(1 - \widehat{\lambda}\right) + \beta_1 \left(\boldsymbol{x}_{it} - \widehat{\lambda}\overline{\boldsymbol{x}_i}\right) + c_i \left(1 - \widehat{\lambda}\right) + u_{it} \end{aligned} \tag{5.6}$$

From equation (5.5) it is clear that the FE estimator (5.6) converges to the POLS estimator when unobserved heterogeneity is small, $\sigma_c^2 \to 0$ but goes towards the FE estimator when $T\sigma_c^2 \to \infty$. As $T = 26,300$ is an unusually large number of time periods we expect the term (5.5) to indeed go towards infinity given some presence of unobserved heterogeneity, $c_i \neq 0$. While the FE estimator never is efficient the RE estimator can be both consistent and efficient if c_i is not endogenous in which case the standard errors $se\left(\widehat{\beta_{RE}}\right) < se\left(\widehat{\beta_{FE}}\right)$, thus, in choosing RE over FE the strict exogeneity assumption (5.4) is critical and can be tested by the Hausman test statistic:

$$W = \frac{\left(\widehat{\beta_{RE}} = \widehat{\beta_{FE}}\right)^2}{var(\widehat{\beta_{RE}}) = var(\widehat{\beta_{FE}})} \overset{H_0}{\sim} \chi_1^2 \tag{5.7}$$

where the numerator is a measure for the consistency loss from choosing the RE over FE, and the denominator indicates the relative gains in efficiency from choosing RE over FE. Due to the high number of time periods T and compositional differences between grid areas in terms of socio-demographics and firm characteristics, we expect $\widehat{\lambda} \to 1$ in (5.5), and thus, we should not expect to be able to reject the Hausman test, meaning that RE is more efficient than FE estimation.

The **random effects instrumental variables (REIV)** estimator is a three-stage generalized IV (GIV) estimator where the first stages are basically the FEIV estimation for estimating the reduced form and $\widehat{\lambda}$ needed to perform a quasi-within-transformation of our model (5.1).

5.5. Robustness checks

Robustness of the elasticity for wholesale electricity demand in the peak-hours 11-15 is tested by splitting the sample by price region, year, and month to look for heterogeneous effects. Furthermore, we estimate the equation (5.1) for each grid area using P2SLS.

Likewise, we estimate the elasticity for retail electricity demand in the peak-hours 17-19 by price region and year, though consumers have no direct price incentive to react to hourly prices except for those that become flex-settled by 2018 and they actually change billing method to actually pay the spot market or real-time price that corresponds to hourly consumption.

Tests of the robustness of the effect of the TOUT is less straight forward. To reassure us that the constructed dummy constructed for Radius does not capture other effects, we try including the same dummy in the estimation of retail electricity demand for different grids, even though it functions as a pseudo variable we should expect to be zero as it only depends on the design of the TOUT for Radius and likewise the share of flex-settled meters in Radius.

6. Results and discussion

6.1. Results for wholesale

For wholesale consumers the baseline specification (5.1) is first estimated separately for each hour of the business day to identify peak, off-peak, and the shoulder hours. Based on these the peak-period is defined as the five consecutive hours 11-15 (11am-3pm) for all of which the estimated elasticity $\widehat{\varepsilon}$ is below $-.045$, while the off-peak period is defined as the five consecutive hours 00-04 (12am-4am) where $\widehat{\varepsilon}$ is greater than $-.030$. The hours on each side of these intervals are classified as shoulder periods. For non-business days none of these classifications are used because the estimated elasticities do not vary much, they are all of small magnitude ($\widehat{\varepsilon} \geq -.03$) and even insignificant for several hours of the day.

As we find there is almost no difference between the FE and RE estimates (appendix C.1) the Hausman statistic (5.7) is low enough that we clearly reject exogeneity of unobserved effects and use REIV for consistent and efficient estimation of the quasi-time-demeaned system of our model (5.1) and the reduced form (5.2).

For each of the above mentioned classifications table 2 show the REIV estimates of wholesale electricity consumption which is instrumented for by wind power prognosis for the same region. As can be noted from column 1 for the peak-hours 11-15 on business days, wholesale of electricity is estimated to decrease with almost 5 percent when the spot price doubles all other things equal. As seen in table 1 the overall standard deviation of 108 DKK is a deviation by 43 percent of mean price, thus an increase in the price by a full standard deviation would decrease electricity demand by 2 percent.

The difference between business and non-business days is quite outspoken; wholesale consumers are 1.5 times more responsive at peak on business-days compared to the average on non-business days.

Weather and daytime controls also have significant effect on wholesale consumption in the directions that should be expected. The effects of temperature translates into a 2$^{\text{nd}}$ order polynomial with the minimum electricity consumption at 7°C for peak hours on business days. All other things equal a decrease in the outdoor temperature from -3 to -4°C or an increase from 21 to 22°C tend to increase electricity consumption by 0.5 percent.

Table 2: log wholesale electricity consumption (REIV)

	(1) Peak: 11-15	(2) Off-peak: 00-04	(3) Shoulder	(4) Non-business day
	b/se	b/se	b/se	b/se
log spot price	-0.0484***	-0.0266***	-0.0333**	-0.0189*
	(0.0163)	(0.0094)	(0.0149)	(0.0099)
log wholesale meters	0.1578***	0.1422***	0.1255***	0.1424***
	(0.0375)	(0.0399)	(0.0332)	(0.0375)
Temperature	-0.0036***	-0.0014**	-0.0022***	-0.0038***
	(0.0008)	(0.0006)	(0.0004)	(0.0006)
Temperature squared	0.0002***	0.0001***	0.0001***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Daytime			0.0198***	0.0966***
			(0.0052)	(0.0085)
Time variables	Yes	Yes	Yes	Yes
R^2 within	0.3614	0.1576	0.5797	0.1414
R^2 between	0.9492	0.9140	0.9375	0.9250
Number of groups	48	48	48	48
Obs. per group	3,675	3,675	13,178	8,660

Robust Robust standard errors are clustered at grid level and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Log spot price is instrumented for by wind power prognosis for the same region.

6.2. Results for retail consumption

The REIV estimation of (5.1) for the retail electricity consumption of the small companies and households is reported below in table 3. Though small, our expectations for the size of the price elasticity are exceeded by the the estimation results.

Pooling across all 1,096 days we find that a 100 percent increase in the spot price causes a decrease in consumption of about 2.8 percent - which appears to be driven by reductions on business days. This is despite that for two of the three years none of the consumers pay the spot market price and the last year it is only offered as an option for a minority. Thus, it is a relatively surprising how responsive the consumption of households and small firms are compared to that of wholesale consumers.

Reversely, one possible explanation for why we do not capture a much higher elasticity for wholesale consumption, could be that the estimations are blurred by wholesale consumers dragging the result in different direction as they are much less homogeneous than retail consumers. This would be in line with the smaller magnitude of the standard errors of the estimated elasticity for retail consumers.

There is a relatively large consumption decrease associated with *daytime* where being before sunset implies a decrease in consumption of about 4 percent. This can be due to many non-electricity consuming leisure activities are weather and light dependent. On that note, a possible downward bias of $\widehat{\varepsilon}$ that could help explain the significant price elasticity of retail consumption would be if an unobserved variable such as sunshine correlates positively with wind power while leading to lower electricity consumption.

Table 3: log retail electricity consumption by region, hours 17-19 (REIV)

	(1) All b/se	(2) Business day b/se	(3) Non-business day b/se	(4) DK1 b/se	(5) DK2 b/se
log spot price	-0.0275***	-0.0354***	-0.0041	-0.0292***	-0.0305***
	(0.0056)	(0.0059)	(0.0061)	(0.0061)	(0.0092)
Share time-of-use tariff	-0.0406***	-0.0350***	-0.0558***		-0.0069
	(0.0101)	(0.0110)	(0.0086)		(0.0148)
Oct-Mar (Radius only)	0.0517***	0.0531***	0.0483***		0.0204
	(0.0119)	(0.0117)	(0.0123)		(0.0190)
log retail meters	0.9077***	0.9253***	0.9545***	0.8960***	1.0056***
	(0.0376)	(0.0351)	(0.0275)	(0.0369)	(0.0340)
Temperature	-0.0035***	-0.0046***	-0.0043***	-0.0039***	-0.0037***
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0007)
Temperature squared	0.0001***	0.0001***	0.0001**	0.0001***	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Daytime	-0.0409***	-0.0449***	-0.0230***	-0.0338***	-0.0582***
	(0.0030)	(0.0030)	(0.0032)	(0.0018)	(0.0040)
Time variables	Yes	Yes	Yes	Yes	Yes
R^2 within	0.8086	0.8152	0.8181	0.7923	0.8866
R^2 between	0.9930	0.9933	0.9922	0.9927	0.9963
Number of groups	48	48	48	39	9
Obs. per group	3,288	2,205	1,083	3,288	3,288

Robust Robust standard errors are clustered at grid level and reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Log spot price is instrumented for by wind power prognosis for the same region.

6.2.1. Results for Radius

We examine the grid company Radius separately. Radius operates in the Copenhagen metropolitan area and since December 2017 its flex-settled customers (households and small companies) are charged a Time-of-Use (TOU) tariff of 0.835 DKK (0.112 EUR) for the hours 17-19 from October until March and 0.3236 DKK (0.043 EUR) otherwise. Table 4 shows pooled 2SLS estimates of electricity consumption for households and small companies in Radius for the hours 17, 18, and 19.

The estimated effect of this tariff is found to be a decrease in electricity demand of 2.2 percent for the hours when it is relevant. However, on business days the smaller effect of 1.4 percent is only statistically significant at the 10% level while the decrease is no less than 4.1 percent on non-business days where it can be easier to alter consumption patterns simply because there are more non-work hours free to shift consumption to.

Table 4: log retail electricity consumption in Radius, hours 17-19 (P2SLS)

	(1) All days b/se	(2) Business days b/se	(3) Non-business days b/se
log spot price	-0.0184**	-0.0251***	0.0061
	(0.0076)	(0.0081)	(0.0179)
Share time-of-use tariff	-0.0219***	-0.0137*	-0.0408**
	(0.0081)	(0.0080)	(0.0174)
log retail meters	-1.6012*	-1.2889	0.3618
	(0.8606)	(0.9208)	(1.6832)
Temperature	-0.0029***	-0.0040***	-0.0026**
	(0.0006)	(0.0007)	(0.0013)
Temperature squared	0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)
Daytime	-0.0450***	-0.0450***	-0.0250
	(0.0104)	(0.0108)	(0.0198)
Time variables	Yes	Yes	Yes
Adj. R^2	0.9462	0.9587	0.9297
Observations	3,288	2,205	1,083

Robust Robust Robust standard errors are clustered at grid level and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Log spot price is instrumented using the wind power prognosis.

6.3. The validity of instrumenting

All our statistical test results are reported in appendix C. As they are first and foremost regarding the validity of instrumenting for the log spot price by wind power prognosis we choose to do the tests based on POLS and P2SLS procedures separately for the biggest grid company in each price region as more elaborate test methods are developed and implemented into the core of Stata for these techniques compared to RE and REIV procedures (StataCorp, 2017).

For single-grid estimations we use robust standard errors as well, as the simultaneous Breusch-Pagan / Cook-Weisberg test for heteroskedasticity clearly rejects the H_0 of homoscedasticity ($p = 0.000$). However, specifically for Radius in DK2 the Bonferroni-adjusted p-values for price, number of wholesale meters, and temperature are ~ 1, showing that they are quite homoscedastic while heteroscedasticity is caused by seasonality and daily patterns. (appendix C.2).

Different specifications for the reduced form estimation of log spot price can be seen in table 5 for DK1 and equivalently in table 8 in appendix C.3 for DK2. The clear relevance of wind power prognosis in the same region as an instruments for the spot price stands out. Not only due to the high significance of the estimate in column for (3) but even more so from the great reduction in the adjusted R^2 value by .09 for DK1 and .07 for DK2 when having omitted wind power prognosis in column (4) relative to column (3).

Though the effect of a given absolute change in the wind power prognosis is almost 3 times as high for DK2, this is more than offset by both the mean and standard deviation of wind power prognosis $3\frac{1}{2}$ times higher for DK1 (table 1).

The t-tests and F-tests deem the wind power prognosis for DK2 to be a relevant instrument for the log spot price in DK1. On the contrary, the capacity constraints of the Great Belt Link becomes clear as the wind power prognosis for DK1 is not significant for the log spot price in DK2 while the wind power prognosis for Sweden is. The robust test of the first stage in Stata likewise clearly reject that either of the instruments are weak (StataCorp, 2017). However, the adjusted R^2 value barely decreases when omitting the second instrument in going from column (2) to (3), that is, they do not carry any noteworthy explanatory power.

Table 5: Reduced form of log spot price for DK1, business days, hours 11-15 (POLS)

	(1) 3 instruments	(2) DK1 and DK2	(3) DK1	(4) None
	b/se	b/se	b/se	b/se
Wind power prognosis same region	-0.0920***	-0.0951***	-0.1617***	
	(0.0137)	(0.0130)	(0.0079)	
Wind power prognosis other region	-0.2727***	-0.2724***		
	(0.0478)	(0.0479)		
Wind power prognosis for Sweden	-0.0048			
	(0.0057)			
log wholesale meters	-0.6420	-0.6021	-1.0020	-2.1420**
	(0.9546)	(0.9505)	(0.9144)	(0.9763)
Temperature	-0.0236***	-0.0238***	-0.0235***	-0.0357***
	(0.0033)	(0.0033)	(0.0034)	(0.0039)
Temperature squared	0.0008***	0.0008***	0.0008***	0.0014***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Time variables	Yes	Yes	Yes	Yes
Adj. R^2	0.4604	0.4605	0.4550	0.3666
Observations	3,675	3,675	3,675	3,675

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Similarly, Wooldridge's robust score test as well as the robust regression-based test show that log spot price is endogenous when instrumenting by wind power prognosis in the other region (for DK1) or wind power prognosis for Sweden (for DK2) respectively both when using the instrument on its own or jointly with wind power prognosis in the same region. However, Wooldridge's heteroscedasticity-robust score test of overidentifying restrictions is barely rejected for DK1 and clearly rejected for DK2 (appendix C.4) (StataCorp, 2017).

Thus, due to our observation that neither wind power prognosis for the other region nor for Sweden carries explanatory power in the reduced form estimation of the log spot price, we conclude that our model would be misspecified, namely overspecified, if we included more instruments than the wind power prognosis for the same region.

6.4. Heterogeneity and robustness

We conduct a number of additional estimations to evaluate the robustness of the above results. Checks for wholesale consumption are included in appendix D, while those for retail are reported in appendix E. We estimate sample split results of our specification (5.1) by the two price regions and for each year.

For wholesale consumption estimates are reported in table 11. It appears that the overall response is likely to be driven by DK1 (Western Denmark) whereas estimates for DK2 are small and insignificant. It should, however, be noted that there are only 9 grid companies in DK2 which may boost the grid-clustered standard errors upwards. Also the 9 companies enter with equal weight even though the price region is clearly dominated by Radius and Cerius as is evident from appendix A.

Results are, however, quite robust across years. Here we cannot reject that estimates differ. By considering the five largest grid-areas (in terms of the number of meters) separately in table 12. Here estimates differ quite significantly which suggests there are some unobservable heterogenous characteristics that can explain the different responses to price changes. For example the estimated elasticity for Cerius, albeit small in magnitude, is significantly positive for which we can think of no other reason than omitted variable bias.

For retail consumption there is no difference in the price elasticity between the price regions (table 3). Though we would expect the elasticity to be higher in 2018 compared to 2016, this is not the case, however being significantly smaller in 2017 (table 13). While not being our preferred specification for estimating the effect of the TOUT as the only control for grid-specific consumption patterns is the dummy for being in the months October-March and grid company Radius. For the full sample and split by business day and non-business day the estimated effect of the TOUT use is nonetheless significant and of greater magnitude which shows some robustness (table 3).

On the contrary, including the Radius-specific dummy (5.3) to the estimation for each of the 47 other grids yields disappointing though not too surprising results, as the pseudo "effect" is significant and even higher for many of the other grid companies.[14] Taking another look at this variable, except for only being activated for the winter half of the year it is constructed as the share of flex-settled retail consumers in Radius which follow an almost linear growth of .05 per month throughout 2018, thus it will simply act as a time trend, but ignoring the summer half of the year for which consumption faces a huge slope.

Our overall estimates of the price elasticity for wholesale and retail consumption remain

[14]github.com/thornoe/energy/blob/master/results/r_grids_DK1.md
github.com/thornoe/energy/blob/master/results/r_grids_DK2.md

largely robust, but also motivates a closer look at more disaggregated data to examine the drivers of the observed heterogeneities.

6.5. Discussion

Our estimates are bigger than those obtained by Lijesen (2007) but around the same size as Wolak and Patrick (2001) finds for 5 of the 6 most elastic industries. Part of this difference has to do with limited access to disaggregated high frequency data. Although estimates are statistically significant their economic significance is more limited. They all point to a quite inelastic electricity demand even for the most elastic part of the market. This suggests that the prospects of using decentralized interventions such as demand response programs are limited. From the small estimated effect on the time-of-use tariff in Radius similar conclusions can be conjectured. Prices does, however, rise quite dramatically during hours of peak demand. Thus, rather small decreases in consumption can still matter.

Oddly enough, the time-of-use tariff did seem to have an effect outside of the area that was actually affected by the tariff. This could be a response from an increasing awareness that electricity demand and thus emissions from production are high in the peak period. Likewise, awareness about the fact that electricity supply largely relies on coal power when the wind is calm could be the driver of the general elasticity as few retail consumers actually pay an hourly price.

Even though people do not appear to respond much to electricity prices nor the TOUT this could simply be due to little available information. The tariff is applied grid wide, but its actual implementation (into billing contracts etc.) is left for the individual electricity providers to decide on. Thus, both information granted and actual exposure to the tariffs may vary significantly across providers. It could also simply be the case that people have not had enough time to adjust their behavior, which can be costly in terms of utility. Adjustment time may similarly also depend on the implementation of the program, this is the extent to which consumers were actually aware of the tariff introduction.

Even in the absence of large consumption changes there are still other advantages associated with demand responses such as real time pricing. Without load shedding the current system of limited exposure to price fluctuations is implicitly build to over-cater to peak demand which is harmful through greenhouse gas emissions and promotion of high-cost, non-competitive supply. Non-distorted prices makes up for this by better reflecting the current state of the market - at least in the absence of externalities.[15] When prices are high this encourages investments in energy efficient devices but it also makes electricity storage more profitable. Research and development of storage may, in the long run, make it feasible to rely purely on intermittent, renewable energy.

There could still be decentralized solutions to the issue of smoothing electricity consumption. One obvious solution would be to limit the number of contracts where consumers pay a fixed price and increase contracts with more flexible settlement. The EU are in the process of implementing a great deal of policies moving in this direction. There is, however, little empirical support of what difference implementation could make without the provision of additional information. Given that people have limited cognitive capacity it could be useful to provide cost examples of using a specific electrical device during peak compared to off-peak or shoulder periods. Another concern here is that this could also have the opposite effect if the price provided then is perceived as too small to matter rather than exacerbate prices. If people rely on heuristics this could likely be a "harmful" rule of thumb.

There is much experimental research devoted to looking into ways of getting people to conserve energy using non-standard economic tools because the standard tools does not appear to alter behavior. This paper highlights the importance of these results. Examples include Allcott (2011) where US consumers are informed about how their own consumption of energy compares to that of their neighbours which especially causes those with a relatively high consumption to adjust it to a level closer to that of their neighbours thereby conforming to social norms. This is also an argument in favour of decentralized solutions that focus on moving the demand curve itself rather than moving customers along it. Kirschen (2003) argues that electricity is perceived as necessary, but it may be needed to change the perception of what constitutes "normal consumption". From figure 3 we note that consumption is much lower in summer which reveals potential to reduce in wintertime as well despite higher requirements for electrical heating and lighting.

Another example is Saele and Grande (2011) where they use information in combination with a demand response mechanism. Authors find that costumers respond more than in other studies and conclude that it especially has potential for consumers with electrical heating which is not of much relevance to Denmark.

[15] In the presence of uninternalized, negative production externalities the problem of over-catering is exacerbated even more

All in all, demand responses may not be the most easily implemented and effects may not be big enough for them to stand alone. While these initiatives may be cost-effective there is limited evidence of persistent effects over time as Allcott and Rogers (2014) among others find that effects are decaying after treatment has ended.

6.5.1. Centralized solutions

Given how costly it can be for consumers to alter consumption behavior there may be a bigger need for more centralized solutions to the issue. One option could be to directly affect and alter the supplying capacities. Increased market integration may satisfy many of these requirements. In section 3.2.1 it is described how better integration in terms of greater connecting capacities across the current price regions could lead to less price volatility in spite of more reliance on intermittent renewables because of a more optimal energy mix. This corresponds to diversification of the generation portfolio. Expanding grid boundaries can make an electricity production that relies on intermittent renewable sources more stable. This almost corresponds to invest across a market index which diminishes individual risk from each producer. It would allow for complementary production capacities among the energy producers. Hydro and wind energy for example complement each other well; hydro can be deployed when the wind does not blow and then cheap wind power can be used to pump water reservoirs full again. Initiatives in this direction are already being taken at the European level with the 'Clean Energy for all Europeans' package consisting of 8 legislative acts and the renewable energy directive.

Technology has thus far prevented "smart" solutions but an increasing number of countries are rolling out smart meters that allow for integration into a smart grid. A smart meter can allow for remote metering, show current consumption and current prices. In similar fashion a smart device is one where its electricity consumption can be changed automatically in response to the electricity price. Biggar and Hesamzadeh (2014) reports how end-of-use consumers are committing to make their devices capable of being responsive to the real time prices. This implies more integration of retail consumers into the wholesale market which according to our results could be a way to induce a higher price elasticity. Smart grids can be advantageous by providing a feasible way to expand electricity storage. End-of-use owned storage units (such as electrical cars) that are already readily available could be integrated onto the grid and programmed to charge whenever renewable production prices exceeds demand. Owners could then opt to sell stored electricity when demand exceeds such production.

6.6. Possible extensions

A straightforward extension would be to look at the elasticity of aggregate consumption in each price region and not only on an unweighted average of the effects in grid companies of very different size. However, this would provide less efficient estimates due to the loss of nuances between grids. As the FE estimates are identical to the RE estimates, however less efficient, we could instead try to weight the FE estimates by the average number of wholesale meters in each grid.

A more cumbersome extension could be to include various observed grid-specific effects. However, precise identification might be less feasible as the boundaries of the grids often are not in line with municipality borders or other common statistical entities. The motivation being that one can expect a exists great variation in terms of size, distribution of retail customers (residential and commercial), and industry-commercial ratio of wholesale customer. Both between grid companies and over time within a grid.

A very tractable but hard-to-come-by extension would be to use micro data which would remove the bias from compositional changes in the presence of heterogeneous consumers. Similarly more detailed data would allow for an exploration of further heterogeneities in terms of who is more or less responsive to electricity prices. This would be useful for both the wholesale market where it could be interesting to look at heterogeneity across different industries while for the retail consumers it would be interesting to explore how age, gender, or educational level affects price responsiveness.

7. Conclusion

The electricity market is and has been undergoing great changes. The energy market and related policy areas are the subject of increasing political attention, in response to the climate crisis. If the electricity production is to become a zero-emission sector it is unlikely to happen without inducing changes in energy consumption behaviors. From a theoretical point of view there are many reasons to expect inelastic demand; there are few and no close substitutes, demand is indirect and it is deemed a necessary good. Still it constitutes a relatively big expense and prices can grow very high when production is low and demand is high so some response is still to be expected. We estimate hour-by-hour price elasticities for wholesale and retail consumers in Denmark to evaluate the prospects of using price tools to induce such adaptions in the consumption.

The hour-by-hour price elasticities of electricity consumption are estimated using hourly grid-area-level consumption data stretching from January 2016 to December, 2018. In order to obtain valid estimates we apply random effects instrumental variables (REIV) estimation. To overcome the problems of endogeneity from a regression of quantity and price, that are jointly determined, electricity prices are instrumented by wind power prognosis for the same region. Wind-power is unlikely to affect electricity consumption through other channels than via the price. Due to merit order effects and because wind power constitutes a significant share of Danish energy production this has great impact on electricity prices.

We obtain estimates that range between -0.019 and -0.048 for wholesale consumers, while the price responsiveness of retail consumers span from no response (zero-estimate) to -0.035 for retail consumers. All in all, consumption is largely inelastic and it holds that wholesale consumption is more price-responsive than retail consumption. This suggests that responsiveness is likely related to the degree of exposure to the real-time electricity price fluctuations. A separate though not as consistent analysis is conducted for the grid-company Radius where a time-of-use tariffs was gradually introduced since the end of 2017. Here we find a statistically significant, yet economically negligible reduction in electricity consumption from the tariff. This "first-inspection" of the tariff indicate that it may have been poorly implemented and/or that it is a poor policy tool. Our analysis point in the direction of more centralized solutions as necessary complements for establishing a more sustainable energy production and consumption.

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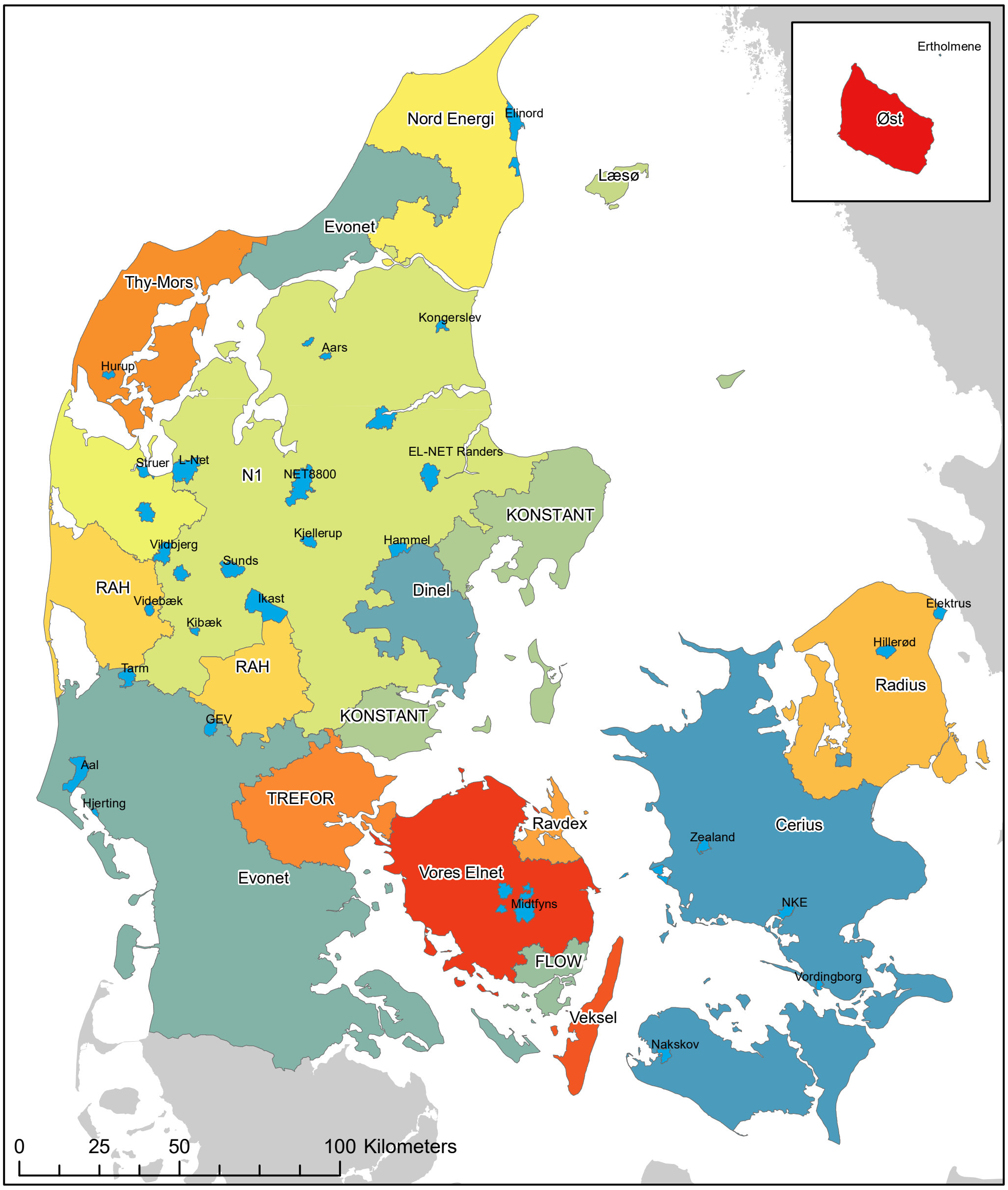
A. Grid companies

Figure 7: Grid companies in may 2019



Source: Danish Energy Agency (Energistyrelsen).

Mergers during 2016-2018:

- Nord Energi took over Taars by December 2017 and Hirtshals by January 2018.
- Læsø took over Hornum by October 2017.
- EnergiMidt merged with HEF, AKE, Bjerringbro, ELRO, EnergiMidt Vest, Borris, and Sdr. Felding by January 2018 and Nibe by April 2018, taking the name Eniig and later N1.
- Dinel was founded as a merge of Brabrand, Viby, GE, and Østjysk by April 17.
- SE took over VOS and Ærø by January 2018, later renaming to Evonet.
- RAH Net took over RAH Net 2 by December 2017 and MES Net by March 2018.

To distinguish the grid name from the parent company Nyfors, NRGI, Energi Fyn, and SEAS-NVE has renamed to Evonet, Konstant, Vores Elnet, and Cerius respectively.

B. Data for wind power prognosis and spot price

Figure 8: Wind power prognosis and spot price by date (Western Denmark)

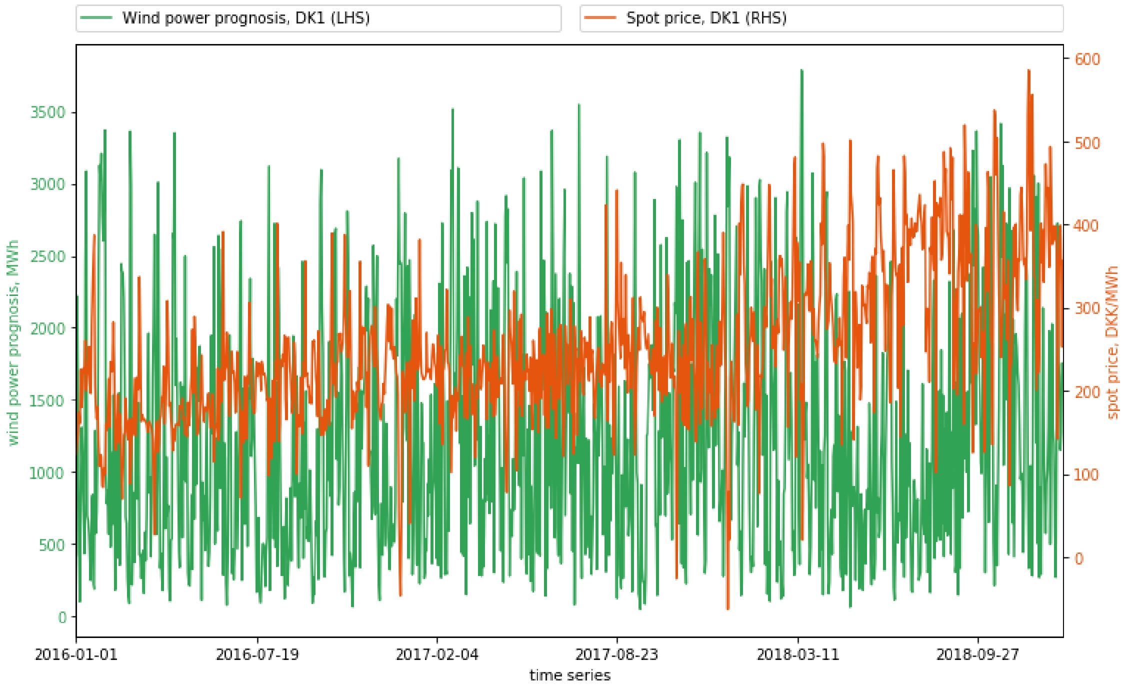
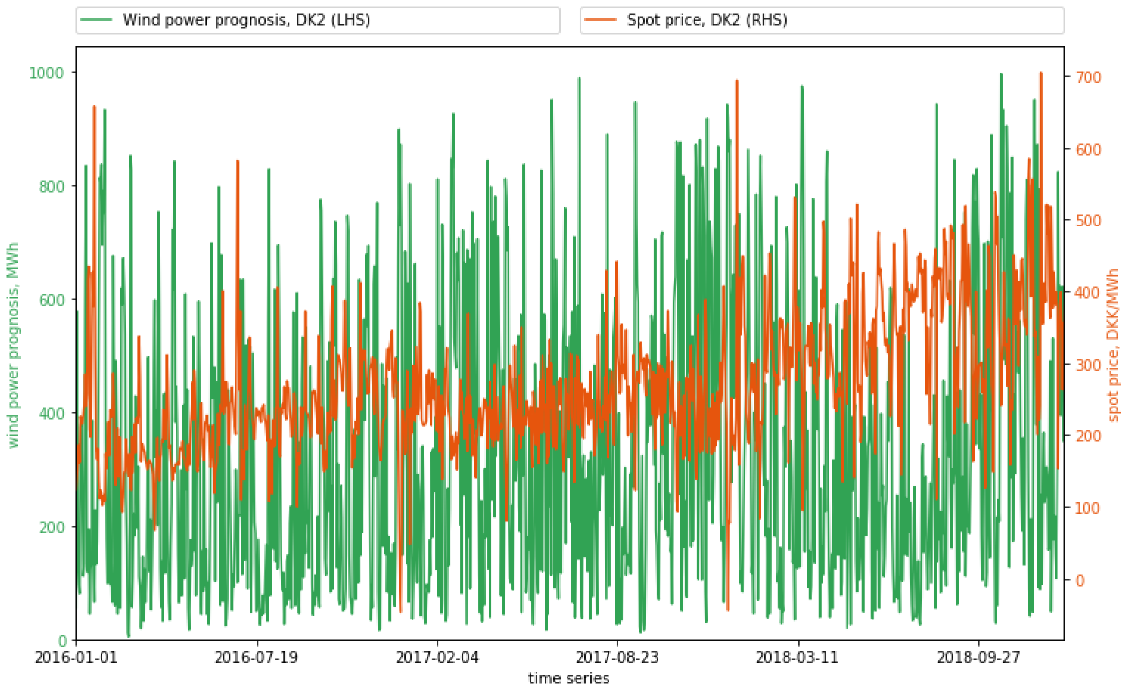


Figure 9: Wind power prognosis and spot price by date (Eastern Denmark)



B. Data for wind power prognosis and spot price

Figure 10: Wind power prognosis and spot price by hour (business days, Western Denmark)

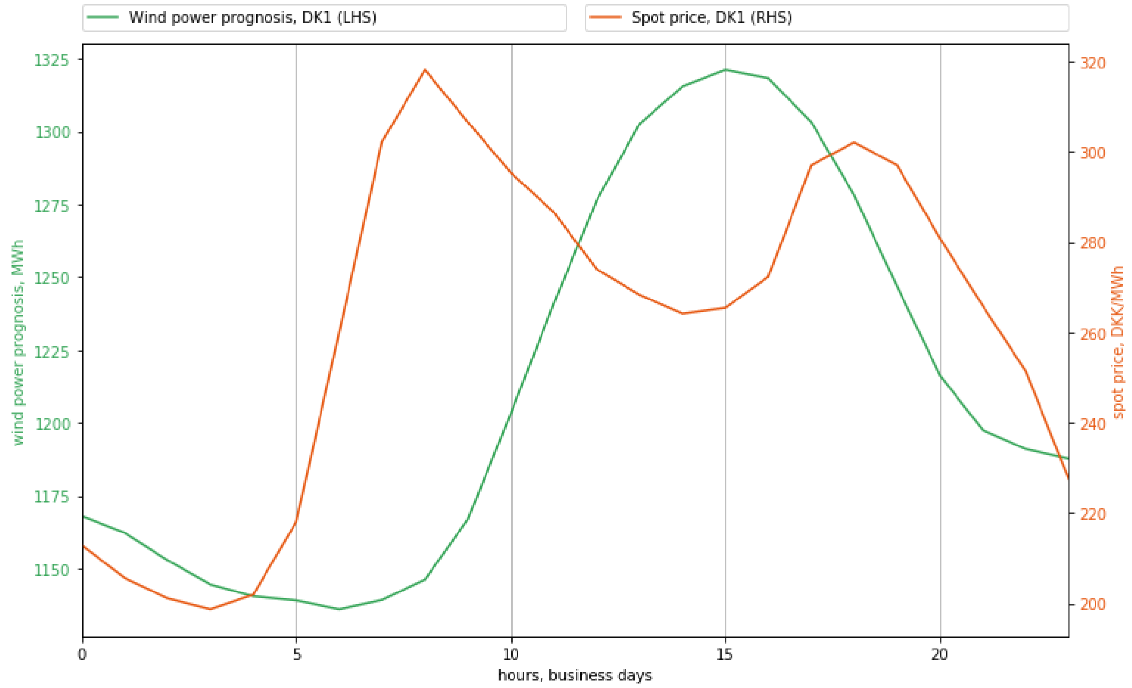


Figure 11: Wind power prognosis and spot price by weekday (Monday=1)

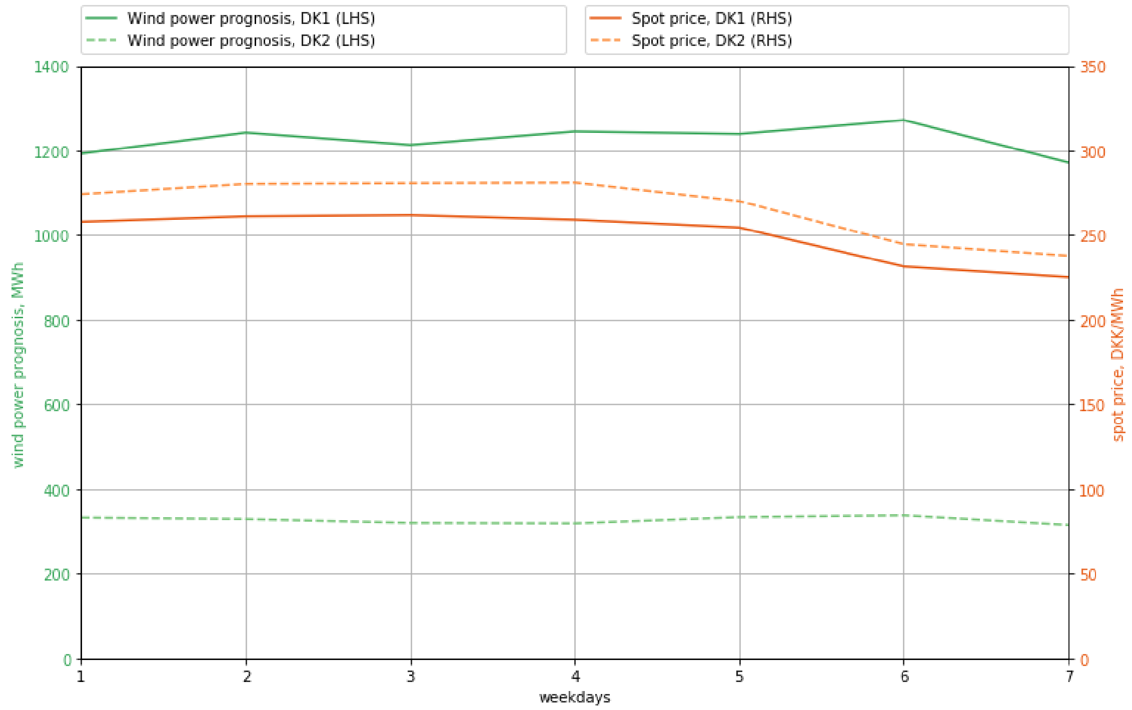
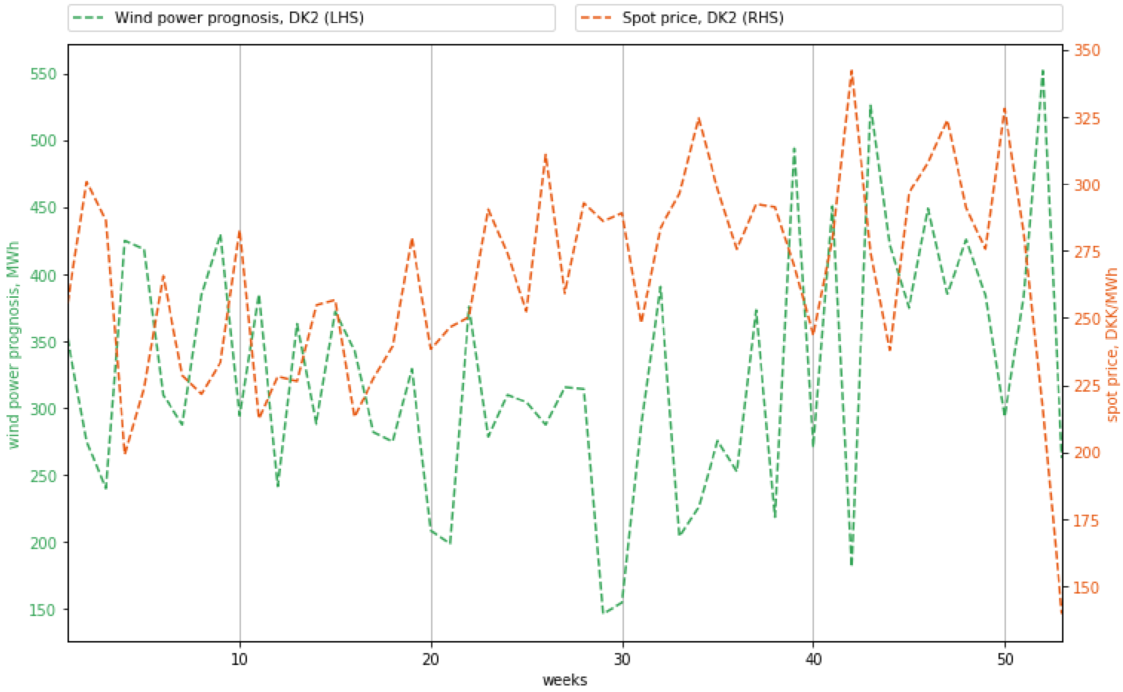


Figure 12: Wind power prognosis and spot price by week (Eastern Denmark)



C. Statistical tests

C.1. Hausman test for endogeneity of unobserved effects

Table 6: log wholesale electricity consumption, business days, hours 11-15 (FE, RE, FEIV, and REIV)

	(1) FE b/se	(2) RE b/se	(3) FEIV b/se	(4) REIV b/se
log spot price	-0.0096***	-0.0096	-0.0484***	-0.0484***
	(0.0028)	(.)	(0.0163)	(0.0163)
log wholesale meters	0.1318***	0.1566	0.1327***	0.1578***
	(0.0402)	(.)	(0.0401)	(0.0375)
Temperature	-0.0022***	-0.0022	-0.0036***	-0.0036***
	(0.0005)	(.)	(0.0008)	(0.0008)
Temperature squared	0.0001***	0.0001	0.0002***	0.0002***
	(0.0000)	(.)	(0.0000)	(0.0000)
Time variables	Yes	Yes	Yes	Yes
R^2 within	0.3686	0.3686	0.3612	0.3614
R^2 between	0.9485	0.9485	0.9494	0.9492
Number of groups	48	48	48	48
Obs. per group	3,675	3,675	3,675	3,675

Robust standard errors are clustered at grid level and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Log spot price is instrumented for by wind power prognosis for the same region.

C.2. Testing for homoscedasticity

For the estimations shown in table 7 the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity with Bonferroni-adjusted p-values can be seen for each variable at github.com/thornoe/energy/blob/master/results/ws_homoscedasticity_bp.md

Table 7: log wholesale electricity consumption by grid, business days, hours 11-15 (POLS)

	(1) 131: s.e.	(2) 131: robust s.e.	(3) 791: s.e.	(4) 791: robust s.e.
	b/se	b/se	b/se	b/se
log spot price	-0.0089***	-0.0089***	-0.0039***	-0.0039***
	(0.0014)	(0.0017)	(0.0010)	(0.0009)
log wholesale meters	0.5673***	0.5673***	-0.2972***	-0.2972***
	(0.0873)	(0.0864)	(0.0459)	(0.0426)
Temperature	-0.0034***	-0.0034***	-0.0041***	-0.0041***
	(0.0003)	(0.0004)	(0.0002)	(0.0003)
Temperature squared	0.0001***	0.0001***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Time variables	Yes	Yes	Yes	Yes
chi^2	1422.7		1154.4	
DF	134		134	
Adj. p-val	0.000		0.000	
R^2	0.881	0.881	0.868	0.868
Adj. R^2	0.876	0.876	0.863	0.863
Observations	3,675	3,675	3,675	3,675

(Robust) standard errors are reported in parentheses below each estimate. * p<0.10, ** p<0.05, *** p<0.01.

Grid number 131 is N1 (DK1) and grid number 791 is Radius (DK2).

C.3. Relevance of instrumenting (DK2)

Table 8: Reduced form of log spot price for DK2, business days, hours 11-15 (POLS)

	(1) 3 instruments b/se	(2) DK2 and SE b/se	(3) DK2 b/se	(4) None b/se
Wind power prognosis same region	-0.4562***	-0.4233***	-0.4663***	
	(0.0430)	(0.0277)	(0.0243)	
Wind power prognosis other region	0.0125			
	(0.0104)			
Wind power prognosis for Sweden	-0.0245***	-0.0221***		
	(0.0043)	(0.0041)		
log wholesale meters	-0.1164	-0.1435	-0.3372	0.1289
	(0.5918)	(0.5894)	(0.5900)	(0.6410)
Temperature	-0.0378***	-0.0377***	-0.0385***	-0.0451***
	(0.0033)	(0.0033)	(0.0033)	(0.0036)
Temperature squared	0.0012***	0.0012***	0.0012***	0.0016***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Time variables	Yes	Yes	Yes	Yes
Adj. R^2	0.4691	0.4691	0.4674	0.3979
Observations	3,675	3,675	3,675	3,675

Robust standard errors are reported in parentheses below each estimate. * p<0.10, ** p<0.05, *** p<0.01.

C.4. Testing for endogeneity and overidentifying restrictions

Table 9: log wholesale electricity consumption for N1 (DK1), business days, hours 11-15

	(1) POLS	(2) P2SLS, wp DK1	(3) P2SLS, wp DK2	(4) P2SLS, both
	b/se	b/se	b/se	b/se
log spot price	-0.0089***	-0.0347***	-0.0390***	-0.0366***
	(0.0017)	(0.0051)	(0.0052)	(0.0050)
log wholesale meters	0.5673***	0.5122***	0.5030***	0.5081***
	(0.0864)	(0.0894)	(0.0908)	(0.0899)
Temperature	-0.0034***	-0.0043***	-0.0045***	-0.0044***
	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Temperature squared	0.0001***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Time variables	Yes	Yes	Yes	Yes
Score test of exogeneity		33.4	46.3	41.0
p-val, exogeneity		0.0000	0.0000	0.0000
Regression-based F-statistic		34.7	48.1	43.1
p-val, regression-based		0.0000	0.0000	0.0000
Test of overidentifying restrictions				3.9
p-val, overidentifying restrictions				0.0481
Adj. R^2	0.8762	0.8649	0.8608	0.8632
Observations	3,675	3,675	3,675	3,675

Robust standard errors are reported in parentheses below each estimate. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 10: log wholesale electricity consumption for Radius (DK2), business days, hours 11-15

	(1) POLS	(2) P2SLS, wp DK2	(3) P2SLS, wp SE	(4) P2SLS, both
	b/se	b/se	b/se	b/se
log spot price	-0.0039***	-0.0347***	-0.0283***	-0.0096***
	(0.0009)	(0.0051)	(0.0070)	(0.0027)
log wholesale meters	-0.2972***	0.5122***	0.5258***	-0.2965***
	(0.0426)	(0.0894)	(0.0893)	(0.0422)
Temperature	-0.0041***	-0.0043***	-0.0041***	-0.0043***
	(0.0003)	(0.0005)	(0.0005)	(0.0003)
Temperature squared	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Time variables	Yes	Yes	Yes	Yes
Score test of exogeneity		33.4	8.5	5.0
p-val, exogeneity		0.0000	0.0036	0.0249
Regression-based F-statistic		34.7	8.3	4.8
p-val, regression-based		0.0000	0.0041	0.0286
Test of overidentifying restrictions				15.5
p-val, overidentifying restrictions				0.0001
Adj. R^2	0.8635	0.8649	0.8698	0.8622
Observations	3,675	3,675	3,675	3,675

Robust standard errors are reported in parentheses below each estimate. * p<0.10, ** p<0.05, *** p<0.01.

D. Robustness checks for wholesale consumption

Table 11: log wholesale electricity consumption by region/year, business days, hours 11-15 (REIV)

	(1) Western DK	(2) Eastern DK	(3) 2016	(4) 2017	(5) 2018
	b/se	b/se	b/se	b/se	b/se
log spot price	-0.0523***	-0.0064	-0.0454**	-0.0407***	-0.0562***
	(0.0188)	(0.0070)	(0.0184)	(0.0139)	(0.0151)
log wholesale meters	0.1496***	0.4145*	0.2042	0.3054***	0.4584***
	(0.0367)	(0.2297)	(0.1271)	(0.0794)	(0.1443)
Temperature	-0.0034***	-0.0036***	-0.0030***	-0.0021**	-0.0035***
	(0.0008)	(0.0005)	(0.0009)	(0.0010)	(0.0009)
Temperature squared	0.0002***	0.0001***	0.0001***	0.0001*	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Time variables	Yes	Yes	Yes	Yes	Yes
R^2 within	0.3847	0.3361	0.4017	0.3883	0.3547
R^2 between	0.9430	0.9886	0.9501	0.9464	0.9480
Number of groups	39	9	48	48	48
Obs. per group	3,675	3,675	1,235	1,225	1,215

Robust standard errors are clustered at grid level and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Log spot price is instrumented for by wind power prognosis for the same region.

Table 12: log wholesale electricity consumption by large grid areas, business days, hours 11-15 (P2SLS)

	(1) N1 (DK1)	(2) Konstant (DK1)	(3) Evonet (DK1)	(4) Cerius (DK2)	(5) Radius (DK2)
	b/se	b/se	b/se	b/se	b/se
log spot price	-0.0347***	-0.0082**	-0.0569***	0.0168***	-0.0114***
	(0.0051)	(0.0033)	(0.0051)	(0.0062)	(0.0028)
log wholesale meters	0.5122***	0.7768***	3.0910***	0.2486***	-0.2962***
	(0.0894)	(0.0399)	(0.5103)	(0.0786)	(0.0423)
Temperature	-0.0043***	-0.0023***	-0.0043***	-0.0017***	-0.0044***
	(0.0005)	(0.0003)	(0.0005)	(0.0005)	(0.0003)
Temperature squared	0.0002***	0.0001***	0.0002***	0.0001***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Time variables	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.8649	0.8125	0.8062	0.6474	0.8613
Observations	3,675	3,675	3,675	3,675	3,675

Robust standard errors are in parentheses below each estimate. * p<0.10, ** p<0.05, *** p<0.01.

Log spot price is instrumented for by wind power prognosis for the same region.

E. Robustness checks for retail consumption

Table 13: log retail electricity consumption by year, hours 17-19 (REIV)

	(1) Year 2016	(2) Year 2017	(3) Year
	b/se	b/se	b/se
log spot price	-0.0314***	-0.0117**	-0.0275***
	(0.0060)	(0.0048)	(0.0065)
log retail meters	1.0049***	1.0132***	1.0082***
	(0.0144)	(0.0268)	(0.0142)
Temperature	-0.0022***	-0.0013***	-0.0020***
	(0.0004)	(0.0004)	(0.0003)
Temperature squared	0.0000**	-0.0000	0.0000*
	(0.0000)	(0.0000)	(0.0000)
Daytime	-0.0321***	-0.0369***	-0.0380***
	(0.0029)	(0.0032)	(0.0039)
Share time-of-use tariff			0.0779***
			(0.0226)
Time variables	Yes	Yes	Yes
R^2 within	0.8503	0.8341	0.8108
R^2 between	0.9936	0.9930	0.9919
Number of groups	48	48	48
Obs. per group	1,098	1,095	1,095

Robust standard errors are clustered at grid level and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Log spot price is instrumented for by wind power prognosis for the same region.