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The Covid-19 shock on a low-carbon grid: Evidence from the nordics

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ABSTRACT

I investigate how the Covid-19 epidemic affected consumption and prices in a part of the Nordic electricity market that has a high penetration of intermittent renewable energy: Denmark and the southernmost part of Sweden. In sharp contrast to studies of other regions, I find no overall drop in consumption in this region. However, the distribution of consumption shifted away from peak hours. Nonetheless, prices dropped significantly, with a decline that started well before the imposition of societal restrictions in Denmark. Periods where wind power covered all of local load saw prices collapse towards zero with little variance under the Covid-19 epidemic. The results have important policy implications. Energy-only markets may fail to provide sufficient investment incentives for renewable energy when penetrations of such generation are already high. Policies and technologies that shift load from peak to non-peak times may further erode market incentives.

1. Introduction

The Covid-19 epidemic has led to a fundamental realigning of society in most economies and has had a substantial impact on most industries. The power industry and electricity markets are no exception. Electricity is an input into virtually all other industries as well as a major end-use commodity for households. The effects of the Covid-19 epidemic (which I will henceforth refer to as simply “the Epidemic”) were bound to be felt particularly quickly and strongly in electricity systems and markets.

Looking beyond the immediate challenges that Covid-19 has imposed on power markets, the most important challenge facing electricity systems and markets is the transition to low-carbon and renewable generation. With the current state of technology, much of this generation is forecast to come from intermittent generation sources–-primarily wind and photovoltaic solar power (IEA, 2020).

In this study I focus on the Nordic electricity market. The Nordic market is known for being generally efficient, well-run, and competitive. In particular, I consider the two Danish price areas and the southernmost Swedish price area that, taken as a whole, have some of the highest penetrations of intermittent generation – primarily wind power – in the world. More so, these price areas have little hydro power, with most of the non-intermittent generation consisting of thermal plants. In other words, the electricity system in this region looks like what the electricity systems in much of the rest of the world will look like in the next few decades under a successful energy transition: A high share of intermittent generation with residual thermal plants.

From the perspective of analyzing the effects of epidemic policy, this regions is also a useful case. Denmark imposed an early and stringent set of societal restrictions while Sweden did not.

This article seeks to explore both the immediate effects the Epidemic had on the Nordic electricity market, and also to use that shock to give insights into the future electricity grids that are expected to have lower supply elasticity in the form of high penetrations of intermittent energy, and higher demand elasticity in the form of more demand response.

The findings in this paper paint a nuanced picture. In stark contrast to findings from other parts of the world, I find no decrease in electricity consumption in the Danish price areas, and some weak evidence for a slight increase in consumption in the southern Swedish area when taking into account normal seasonal patterns. Though overall consumption did not decline, I document a notable shift in the distribution of consumption over the course of the day. Consumption tended to shift away from peak hours in the middle of the day and in the afternoon towards the other, traditionally non-peak hours. This shift is of interest in the long term development of the electricity system as it, in effect, simulates the shift of consumption from peak to non-peak that is the ultimate goal of various demand-response and “smart-grid” policies.

Despite little change in overall consumption, prices fell notably in the period, and prices began to fall well before societal restrictions were put in place in Denmark. Prices fell relatively more in the typically peak hours in the middle of the day and late afternoon. During the Epidemic, periods where renewable generation covered all or most of the local load

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were associated with prices collapsing close to zero and with little price-variability.

The frequency of negative prices also increased during the Epidemic, though this was not primarily associated with extremely high penetrations of wind power. Instead, this likely comes from the interaction with thermal plants, which face high ramping costs.

In section 2 I present theory as well as a review of the literature on electricity consumption under the Epidemic as well as other relevant literature. In section 3 I present the data used and give a short overview of the Nordic electricity market. In section 4 I provide an overview of the methodologies used in the article. In section 5 I present descriptive and model-based evidence for the effects of the Epidemic on consumption and prices. Section 5 concludes with a discussion of the results and suggestions for further research.

2. Theory and review of literature

Already a literature has grown around documenting the effects of the Epidemic on power markets. The most consistent finding across geographies is that the Covid-19 pandemic was associated with a dramatic fall in consumption. Beyer (2020) estimate a drop of 25% in energy consumption in India through an analysis of satellite imagery of night-time brightness. Fezzi and Fanghella (2020) find a short-run decline in electricity consumption of approximately 30% in Italy following lock-downs, and uses this to estimate the effect of lock-downs on a corresponding fall in Gross Domestic Product (GDP). In another study of Italy, Graf et al. (2020) estimate a fall in consumption of 20%. Multiple other studies from other regions also report significant falls in consumption, including from Canada (Leach et al., 2020), Spain (Santiago et al., 2021) and Brazil (Carvalho et al., 2020).

At the outset, the hypothesized steep fall in consumption served as a primary motivation for this research. With lower overall consumption, intermittent generation will tend to make up a higher proportion of the total electricity generated, since marginal costs of wind and solar power are close to zero and production from intermittent generators is generally highly price inelastic. In theory, periods of unusually low consumption and in turn a high total share of intermittent generation could be observed to learn about the functioning of electricity markets at such high penetrations.

Graf et al. (2020) explores a similar question of the interaction between the shock the Epidemic had on consumption and resulting high intermittent penetration. The authors take advantage of the drastic fall in electricity consumption in Italy to see how the market copes with a large share of intermittent energy. They find that though market prices fell, re-dispatch costs increased significantly.

The implications from this article build partly on the literature around the proper valuation of intermittent assets. Because intermittent generation is by definition non-dispatchable, then generation cannot actively respond to price signals and the intermittent generation assets will tend to receive on average lower prices for the electricity they produce compared to dispatchable generation assets (Joskow, 2011).

However, Hirth (2013) argues that intermittent generation will tend to receive a revenue flow at a rate that consistently diverges from the average electricity price as well. Hirth devises a "value factor" statistic in order to represent this divergence, where a value factor of one indicates that a technology is able to sell its electricity at the average electricity price in the market. Schmalensee (2016) finds that in a sample of generators across the United States, solar power had a value quotient of slightly more than one while wind power tended to have a value quotient of slightly less than one.

The finding that prices were pressed towards zero during periods of high wind power generation under the Epidemic suggests that both the average electricity price and the value factors of intermittent generation could be pressed down under high-penetration scenarios. This has some important implications for market incentives to invest in intermittent generation. In order for intermittent generation to consistently cover a significant amount of demand in the system, there will likely need to be a substantial amount of overbuilding of capacity–something that comes out of modeling scenarios almost as an obvious side-effect of intermittency (Clack et al., 2017).[1] Yet, after a certain level of penetration, it is not clear that energy-only markets provide the necessary incentives for further renewable investment. Thus policies such as capacity markets, green certificates and feed-in tariffs may need to be considered, even in the face of a continued fall in renewable generation costs.

3. Data, The Nordic electricity market and Covid-19 policy

3.1. The Nordic electricity market

The Nordic electricity market is one of the oldest deregulated electricity markets. The market has its origins in the deregulation of the Norwegian electricity system in the early 90's, and gradually expanded to include the entire Nordic region. The Nordic market is becoming increasingly integrated into the wider European electricity system. The market is widely considered to be well-run, competitive, and efficient.

The Nordic market is a zonal system, where the market is split up into fixed zones, where prices are geographically uniform within each zone. The main market mechanism is the day-ahead market, where upwards of 80% of total load is traded.[2] This market is organized around an auction mechanism. Suppliers submit a schedule for each hour of the following day indicating the amount of electricity they are willing to supply dependent on price. These schedules are aggregated to form a system-wide supply-curve.

In a similar manner, wholesale consumers submit a schedule of their bids from which an aggregated demand curve is created. From the intersection of these system-wide demand and supply curves, a system price is established that theoretically clears the market assuming the absence of any binding transmission constraints between areas.

Given the existence of congestion on the transmission network between price areas, the price in the area with a shortfall of electricity is increased and the price in the area with a surplus of electricity is decreased until all markets clear. Importantly, the flow of electricity between areas will always move from low price to high price areas.

In addition to the main day-ahead market, several short-term and balancing markets operate. Nord Pool runs a continuously traded intraday market where producers and wholesale consumers can trade up to an hour ahead of delivery. In addition, the national transmission system operators cooperate in running both manual and automatic reserve markets in order to maintain system balance at all times.

Fig. 1 shows a snapshot of the southern portion of the Nordic electricity market. In this article, I focus on the three southernmost price areas seen in the figure. The area DK1 comprises the western part of Denmark–mainly the peninsula of Jutland and the island of Funen. This price area contains the large majority of the wind power in Denmark. DK2 is composed of the eastern part of Denmark, primarily the island of Zealand and includes the Copenhagen metropolitan area and in turn the majority of electricity consumption in Denmark.

SE4 comprises the southernmost part of Sweden. Malmö is the largest metropolitan area in the region, and Malmö has close economic links to the Copenhagen metropolitan area by way of the Øresund bridge, which allows for travel between the cities by train, bus and car–often in under an hour.

Importantly, there is no significant amount of hydro power with reservoirs in the Danish or southern Swedish area; this is in contrast to the Norwegian and northern Swedish price areas that have substantial hydro power generation. Such hydro power generation provides a high degree of flexibility to a system both because generation can be ramped

[1] I thank Eric Hittinger for an enlightening discussion on this point.

[2] https://ec.europa.eu/energy/sites/ener/files/documents/overview_of_european_electricity_markets.pdf.

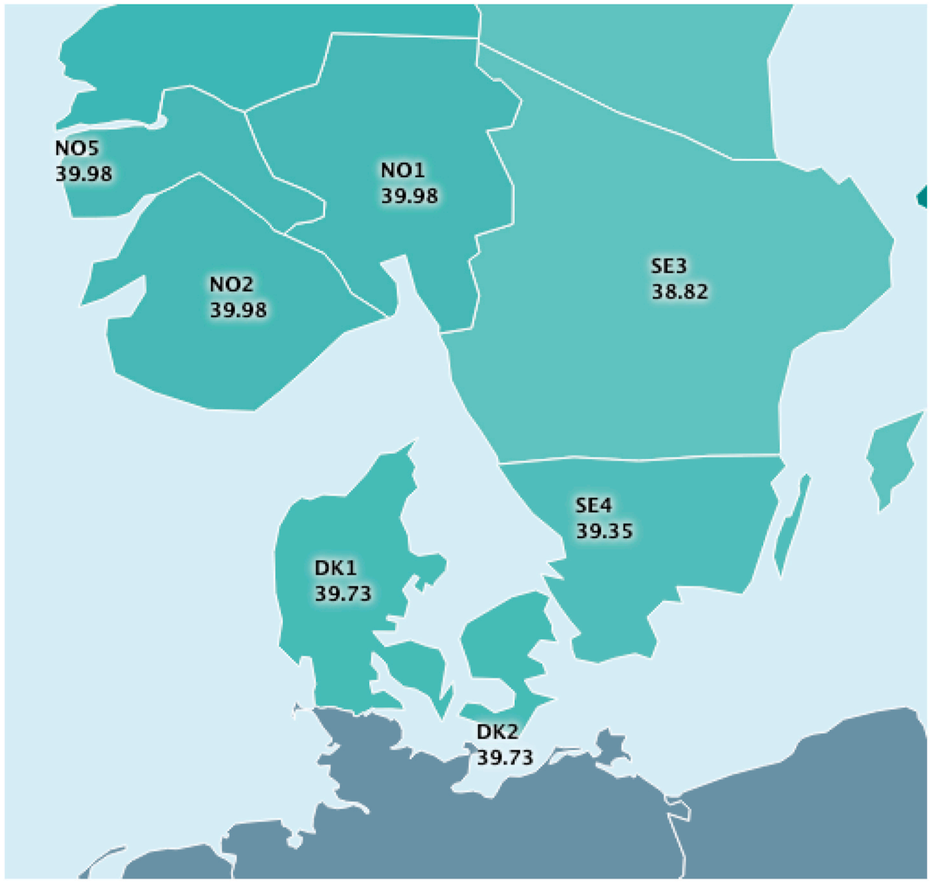

Fig. 1. A snapshot of the southern portion of the Nordic electricity market with prices shown in each price area. This study analyzes pricing and consumption in the two Danish areas, DK1 and DK2 as well as the southern-most Swedish area, SE4.
Source: Nord Pool Group

up and down very quickly and without significant ramping costs,[3] and because the hydro power plants can store energy in the form of water in reservoirs. The Danish and southern-Swedish area do have access to these resources to the extent that transmission capacity is available, and thus the state of transmission congestion becomes an important variable to consider.

Fig. 2 shows the shares of total yearly electricity generation by source from 2015 through 2020. As can be seen, in DK1 the combination of intermittent generation–primarily offshore and onshore wind power–made up more than 60 percent of total generation in the area in both 2019 and 2020. The share of generation coming from intermittent generation in the DK2 area has also been rising, and reached approximately 50 percent of total generation in 2020. The remaining generation consists primarily of thermal plants–mostly natural gas–and Combined Heat and Power (CHP) plants. CHP plants both generate electricity–-through burning gas, biomass and municipal waste; as well as heat for district heating systems, which are common in Danish cities.

The Swedish Transmission System Operator only provides a detailed break-down of generation per price area for the year 2020. In SE4, wind made up approximately 64% of total generation in the area, and solar provided a marginal 2%. The remainder of local production comes from small-scale hydro (20%) and thermal plants (14%). It should be noted that all of Sweden's remaining nuclear power plants are located in the bordering SE3 price area, and that the SE4 area imports a large amount of electricity from this area.

3.2. Covid-19 policy in scandinavia

On March 12th Denmark's prime minister announced sweeping closures and restrictions in order to limit the spread of Covid-19. This included the closure of all pre-schools, primary- and secondary schools as well as higher educational institutions. Workplaces deemed to be non-essential were also closed, and workers instructed to work from home. International travel restrictions were put in place and border controls established (Conyon et al., 2020; Juranek and Zoutman, 2020). Denmark was the first of the Nordic countries to implement such policies, but Norway followed with similar policies the following day. Finland waited until March 28th before implementing full restrictions. None of the Nordic countries implemented full stay-at-home orders.

In contrast to Denmark, Norway and Finland; Sweden resisted implementing widespread and severe closures and restrictions. Instead, the government put in place social distancing guidelines and on March 28th implemented restrictions on gatherings of more than 50 people as well as restrictions on visiting nursing homes. Otherwise, schools remained largely open, and it was left to individual workplaces to decide on whether to close and have workers work from home.

Of interest for understanding some of the results presented in this article, the international travel restrictions Denmark put in place also included controls on the Øresund bridge connecting the metropolitan areas of Malmö in southern Sweden with the Copenhagen metropolitan region. Travelers had to provide a valid reason for entering Denmark–though working in Denmark was considered to be such a valid

[3] It should be noted, that while there are few engineering-related ramping costs, hydro power producers often need to meet some minimum requirements for production in order to assure adequate down-stream flow for environmental reasons.

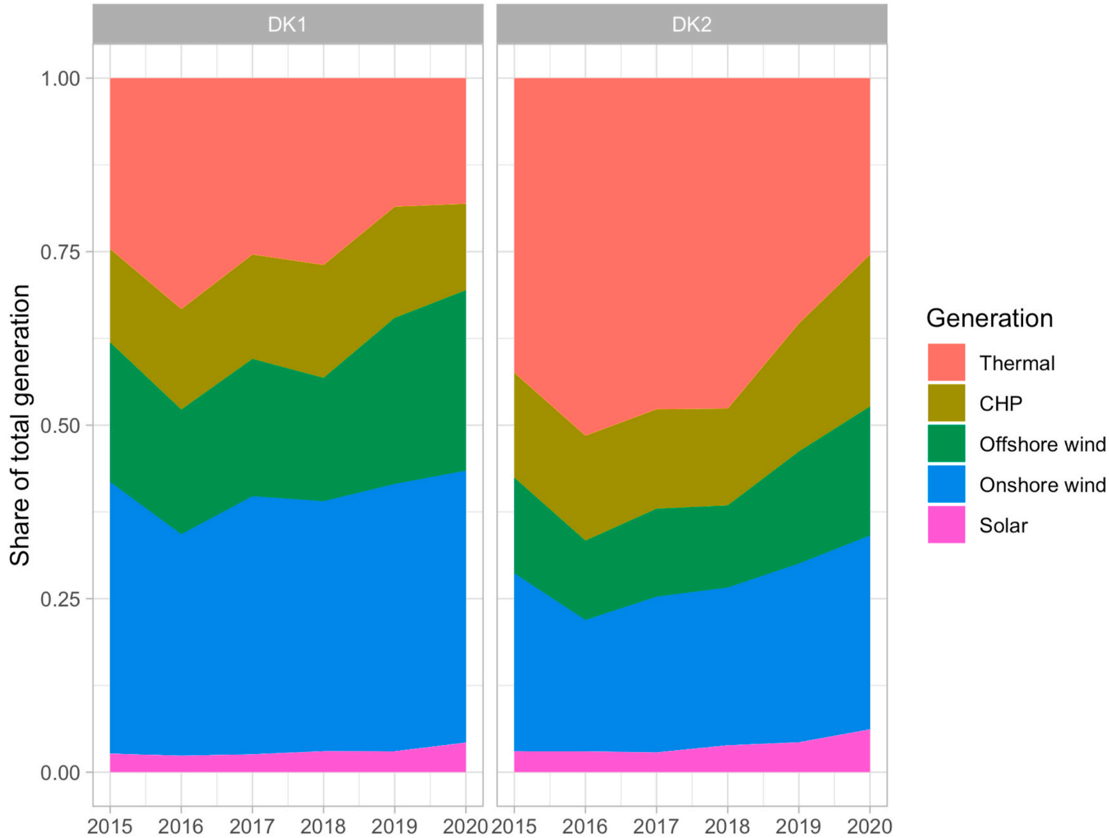

Fig. 2. The share of electricity generation in the two Danish price areas: DK1 and DK2 by technology. CHP stands for Combined Heat and Power plants.

reason. Danish citizens were also allowed to cross the border.

As of the end of the year in 2020, Denmark, with a population of approximately 5.8 million people, had recorded a total of 1024 deaths directly attributed to Covid-19. Sweden, with a population of approximately 10 million people, had recorded a total of 7824 deaths directly attributed to Covid-19.[4]

3.3. Data

In this article I make use of hourly data on prices, consumption, and wind power production between the 1st of January 2018 through the 1st of December 2020. Data is openly available from the website of the market operator, Nord Pool Group.[5] The cleaned and formatted data used in this analysis is available upon request.

In the article, I create a series called *Net Consumption*, which is defined as the difference between consumption in an area and wind power produced in that area (Eq. (1)). It can be interpreted as the total amount of local load that must be met by non-wind generation. A net consumption of 0 or below indicates that all load is met by local wind power production.

$$NC_t = C_t - wind_t \tag{1}$$

4. Methodology

4.1. Modeling consumption

Given the all-encompassing and–at the time of this writing–ongoing economic and societal shock caused by the Epidemic, my approach in this article is explicitly exploratory and descriptive. In contrast to an approach that attempts to estimate or identify a particular marginal or conditional effect, my approach will necessarily lead to more questions than answers.

Given the large falls in consumption documented in other countries, I rely to a certain extent on visualizations to show the lack of such large movements in the Danish and southern Swedish price areas. In addition, I confirm the findings by using some relatively simple ARIMA-type time series models.

Consumption and price data at an hourly and daily frequency are subject to high amounts of variance, thus in the visualizations I use smoothing techniques to more clearly show the underlying trend in the series. Depending on the frequency of the data, I use two such smoothing techniques. For daily data, Local Polynomial Regression Fitting (Loess) takes a weighted regression of the data at any given point in order to create a continuous smoothed curve (James et al., 2013). Loess often provides a good fit to most data, but is computationally expensive, thus for the hourly data I use cubic regression splines to create smoothed curves. With cubic regression splines, the series is divided into an optimal number of sections where a cubic regression is fitted. The sections, called basis functions, are then tied together at “knots” in order to create a single smoothed function over the range of data (James et al., 2013).

A major potential source of bias and incorrect interpretation is the considerable seasonal variation in the consumption data. For hourly data, there is daily, weekly and yearly seasonality. In order to formally estimate the effect of the lockdown, seasonality needs to be controlled for. A straight-forward way of doing this is to first sum up the hourly consumption data to daily-values and then difference the data with a comparable day in the previous year. For 2020 data, this will involve differencing by 364 days so that Mondays are compared with Mondays, Tuesdays with Tuesdays, and so forth. Thus the differenced consumption

[4] Data is obtained from the University of Washington Institute for Heath Metrics and Evaluation https://covid19.healthdata.org/.

[5] https://www.nordpoolgroup.com/historical-market-data/.

can be written as in equation (2). Here C_t^i represents consumption in period t and area i and dC_t^i represents the difference in consumption for day t and area i compared to the same day the previous year (364 days prior).

$$dC_t^i = C_t^i - C_{t-364}^i \tag{2}$$

The following three regression models (Eqs. (3), (4) and (5)) are run, one for each of the areas DK1, DK2 and SE4 to estimate the effect of the Epidemic-related restrictions.

$$dC_t^{DK1} = \alpha + corona_t + \eta_t^{DK1} \tag{3}$$

$$dC_t^{DK2} = \alpha + corona_t + \eta_t^{DK1} \tag{4}$$

$$dC_t^{SE4} = \alpha + corona_t + \eta_t^{SE4} \tag{5}$$

In these equations, the variables $\{dC_t^{DK1}, dC_t^{DK2}, dC_t^{SE4}\}$ represent the yearly difference in consumption in the respective price area. The α terms represent intercepts, the η_t terms are error terms and $corona_t$ represents an indicator variable that is equal to 1 starting with and including the start of the period of restrictions in Denmark on March 12th and up to but not including the 1st of June, after which restrictions were gradually lifted.

The dynamics in the error terms are modeled explicitly in order to take into account serial correlation (Hyndman and Athanasopoulos, 2019). In particular the error terms, $\{\eta_t^{DK1}, \eta_t^{DK2}, \eta_t^{SE4}\}$ from the three equations above are modeled as shown in equation 6 through 8. These specifications were chosen in order to maximize the fit of the model, as measured by minimizing Akaike Information Criteria (AIC). The $\{\eta_{t-1}, \eta_{t-2}, \ldots\}$ represent autoregressive terms (AR) with corresponding coefficients $\{\beta_1, \beta_2, \ldots.\}$ while the $\{\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\}$ represent moving average terms with corresponding coefficients $\{\sigma_1, \sigma_2, \ldots\}$.

$$\eta_t^{DK1} = \beta_1^{DK1}\eta_{t-1}^{DK1} + \beta_2^{DK1}\eta_{t-2}^{DK1} + \beta_3^{DK1}\eta_{t-3}^{DK1} + \beta_4^{DK4}\eta_{t-4}^{DK1} + \beta_5^{DK4}\eta_{t-5}^{DK1} + \beta_7^{DK1}\eta_{t-7}^{DK1} + \varepsilon_t^{DK1} \tag{6}$$

$$\begin{aligned}\eta_t^{DK2} &= \beta_1^{DK2}\eta_{t-1}^{DK2} + \beta_2^{DK2}\eta_{t-2}^{DK2} + \beta_3^{DK2}\eta_{t-3}^{DK2} \\ &+\beta_4^{DK2}\eta_{t-4}^{DK2} + \varepsilon_t^{DK2} + \sigma_1^{DK2}\varepsilon_{t-1}^{DK2} + \sigma_2^{DK2}\varepsilon_{t-2}^{DK2} + \sigma_7^{DK2}\varepsilon_{t-7}^{DK2}\end{aligned} \tag{7}$$

$$\eta_t^{SE4} = \beta_1^{SE4}\eta_{t-1}^{SE4} + \beta_2^{SE4}\eta_{t-2}^{SE4} + \varepsilon_t^{SE4} + \sigma_{14}^{SE4}\varepsilon_{t-14}^{SE4} \tag{8}$$

Even if the Epidemic was not associated with any decline in total daily electricity consumption in the Danish and southern Swedish price areas, it could still lead to a significant change in the distribution of consumption over the course of the day, as the normal daily routines among the populace likely changed. To estimate this potential redistribution of consumption between hours, data with hourly frequency is needed. However, year-over-year differencing on hourly data becomes cumbersome, and subject to even larger amounts of variance in the resulting series.

Instead, STL (Seasonal and Trend Decomposition using Loess) is used in order to remove the deterministic (yearly and weekly seasonality) components of the series (Cleveland et al., 1990). The core idea behind STL is to decompose a given series into three components: trend, seasons and error term. The seasonally adjusted series consists of the trend plus error term. This decomposition is done through the application of Loess smoothed curves. STL decomposition has several advantages over other common seasonal adjustment algorithms, including being able to model any frequency of seasonality and allowing the seasonality to change over time (Hyndman and Athanasopoulos, 2019). Fig. 3 shows the component parts of the DK1 consumption series after the application of the STL decomposition for the year 2020.

The seasonally adjusted series for the three areas are shown in Fig. 4. Augmented Dickey-Fuller tests are run and reject the null hypothesis of a unit root for all three series.

Using the seasonal adjusted consumption data, regressions are run that can be represented by equation (9). The seasonally adjusted consumption in a given hour, t, in an area i ($i \in \{DK1, DK2, andSE4\}$), is represented by $C_t^{i,SA}$ $corona_t$ again represents the indicator variable for the period of time associated with the most stringent restrictions. $\mathbf{I_H}$ represents a vector of 24 h-dummies. The term $corona_t \times \mathbf{I_H}$ represents the vector of interaction variables, and the coefficients on these variables are the coefficients of interest. They represent the average effect on consumption per hour in the Corona period relative to the overall effect on consumption in the period.

$$C_t^{i,SA} = corona_t + \mathbf{I_H} + corona_t \times \mathbf{I_H} + \eta_t^i \tag{9}$$

The error terms are modeled dynamically as shown in equation (10).

$$\eta_t^i = \beta_1^i \eta_{t-1}^i + \beta_2^i \eta_{t-24}^i + \varepsilon_t^i \tag{10}$$

4.2. Modeling prices

Clearly, consumption and prices are closely related, but there are reasons to believe that the behavior of prices and consumption could diverge under the Epidemic. The Nordic day-ahead market is a purely physical market, but it can nonetheless be more forward looking than other similar markets due to the large amounts of hydro power with reservoirs located in Norway and northern Sweden. The largest of the reservoirs have storage capacities that allow them to arbitrage production over seasons and even years.

Looking at how the distribution of prices changed may be more informative than mean statistics. Therefore, I will initially look at the empirical distribution of prices. Because of the strong seasonal patterns in the consumption of electricity, simply looking at the distribution of prices before and after the imposition of restrictions will not accurately represent the effects of the Epidemic.

Time series models are used to formally confirm the impressions from the figures. The three price areas are treated as a single unit in this analysis, and thus the data is aggregated to a single observation per time period, where the net consumption variable is summed across areas and the price variable is expressed as the mean across the areas.

The regression can be expressed as in equations (11) and (12). Here $netConsumption_t$ refers to net consumption (consumption less wind power). The variable is scaled to be in GWh in order to make interpreting coefficients simpler. To get a sense of scale, the mean hourly consumption level for the three areas in total is about 6.5 GWh.

$$p_t = \delta_1 netConsumption_t + \delta_2 corona_t + \delta_3 fullWind_t + \delta_4 corona_t \times fullWind_t + \boldsymbol{\theta}\mathbf{I_H} + \boldsymbol{\zeta}\mathbf{I_{dow}} + \eta_t \tag{11}$$

$$\eta_t = \beta_1\eta_{t-1} + \cdots + \beta_{10}\eta_{t-10} + \beta_{24}\eta_{t-24} + \varepsilon_t \tag{12}$$

The variable $corona_t$ is as defined previously, with a corresponding coefficient δ_2. The variable $fullWind_t$ represents an indicator variable for whether wind power covered all of the total load in a certain hour for the entire 3-area region. The coefficient, δ_1, on this variable will then represent a shift in price relative to the linear relationship captured by the net Consumption variable for periods where wind power covers all of the load. In addition, an interaction variable, $corona_t \times fullWind_t$, is included, which represents any extra shift for periods where wind power covers all of the load during the Epidemic. δ_4 is the coefficient on the interaction term.

I_H and I_{dow} represent vectors of variables indicating hours of the day and days of the week. Notice that there is no separate intercept term in the regression so that each of the hourly dummies can be interpreted as a unique hourly intercept. As in the time series regressions for consumption, the dynamics are modeled in the error term, η_t. Through a process of maximizing the goodness of fit of the model (minimizing AIC), a specification with an AR order of 10 (η_{t-1} through η_{t-10}) terms and one

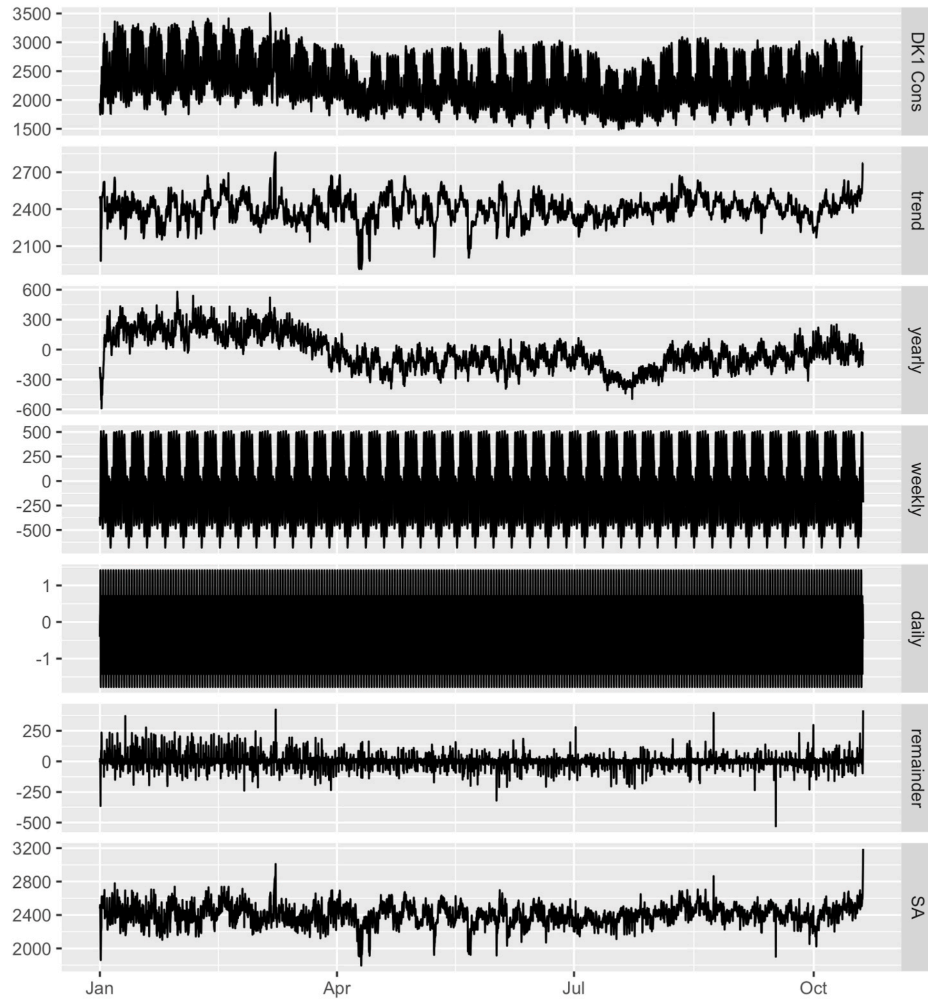

Fig. 3. Components of the STL seasonal adjustment model for consumption in the DK1 area for the year 2020.

seasonal (hourly) AR term (η_{t-24}) is chosen. ε_t represents the remaining, serial correlation adjusted error term.

I also investigate how the distribution of prices over the hours of the day changed during the Epidemic. Time series regressions are run as shown in equations (13) and (14). These equations are nearly identical to that presented in equations (11) and (12), but where a set of terms $\boldsymbol{\theta}_2^{\mathbf{H}}\mathbf{corona_t} \times \mathbf{I_H}$ are added. These represents an interaction effect of the hour-of-the-day indicator variables (with the first hour of the day left out as a comparison) with the indicator variable, $corona_t$.

$$p_t = \delta_1 netConsumption_t + \delta_2 corona_t + \delta_3 fullWind_t + \delta_4 corona_t \times fullWind_t + \boldsymbol{\theta}\mathbf{I_H} + \boldsymbol{\zeta}\mathbf{I_{dow}} + \boldsymbol{\theta}_2^{\mathbf{H}}\mathbf{corona_t} \times \mathbf{I_H} + \eta_t \quad (13)$$

$$\eta_t = \beta_1\eta_{t-1} + \cdots + \beta_{10}\eta_{t-10} + \beta_{24}\eta_{t-24} + \varepsilon_t \quad (14)$$

4.3. Software and replication

The open source statistical programming language R was used for all analyses in this article (R Core Team, 2019). The figures were created using the R package *ggplot2* (Wickham, 2016). The time series regressions were run using the *ARIMA* command found in the *fable* package (Hyndman and Athanasopoulos, 2019). The data used in this analysis as well as the code are available upon request.

5. The effects of the epidemic on consumption and prices

5.1. Consumption

Fig. 5 shows the time series of local consumption in the three price areas DK1, DK2 and SE4. The vertical red line represents the start of the societal restrictions in Denmark on the 12th of March. The colored curves represent smoothed regression splines of the underlying consumption data, providing a clearer picture of the strong seasonal patterns in the data. While consumption is shown to decline following the imposition of societal restrictions, this decline is consistent with the overall seasonal pattern, thus the overall trend of consumption does not provide a reliable indicator of the effects of the Covid-19 restrictions on consumption.

Table 1 shows the results of the time series regressions of

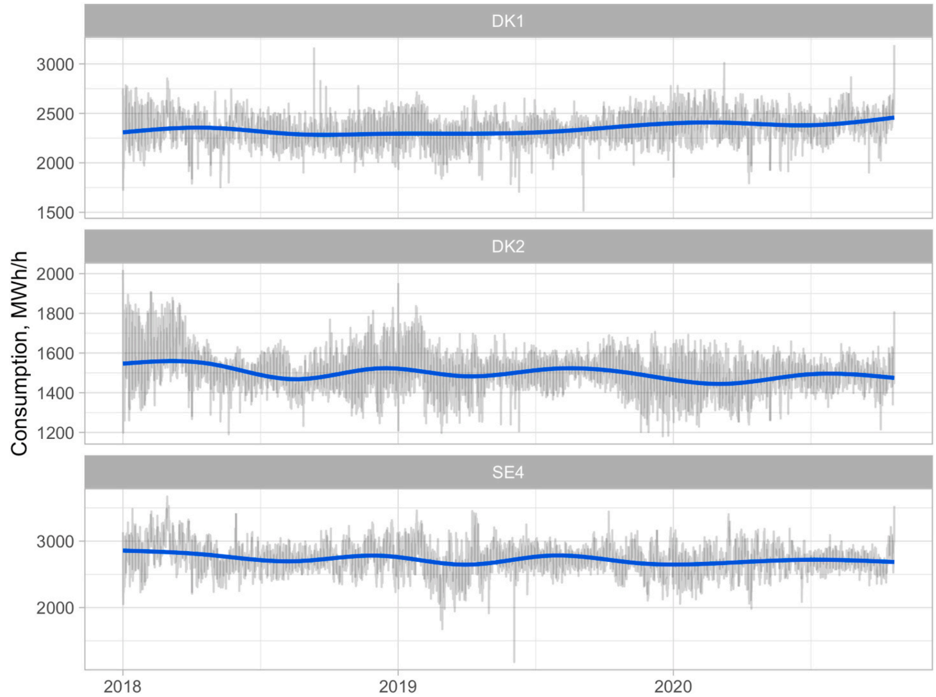

Fig. 4. Seasonally adjusted consumption for the three price areas DK1, DK2 and SE4. The blue line represents a Loess smoothed curve. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

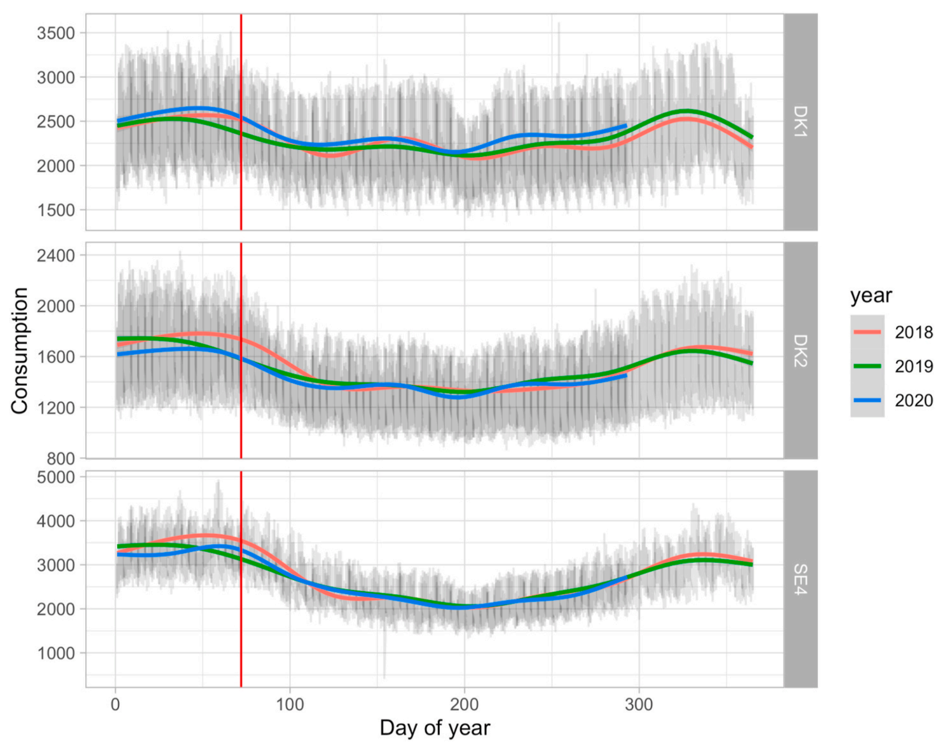

Fig. 5. The time series for local consumption in the DK1, DK2 and SE4 price areas. The red line is placed at March 12th, the date that Denmark announced its restrictions. The colored line represents a smoothed regression spline curve of consumption for each of the years 2018, 2019 and 2020. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

consumption with yearly differenced data. The label *corona* indicates the estimated coefficients on the indicator variable for the period with the most stringent societal restrictions. The labels for the coefficients on the autoregressive terms are ar1,ar2, and so on. The seasonal (weekly) autoregressive terms (autoregressive of order 7, 14, and so on) are labeled *sar*1 and *sar*2.

As we can see from Table 1, the coefficients on the $corona_t$ variable are all estimated to be slightly positive. However for the Danish price areas these are not estimated to be significantly different from zero. The coefficient for the Swedish price area is somewhat larger, but still not

Table 1
Estimated coefficients of the dynamic regression of consumption in the three price areas DK1, DK2 and SE4.

term	DK1	DK2	SE4
intercept		−1.98	−1.69
		(0.93)	(1.04)
		[0.03]	[0.10]
corona	1.82	1.64	2.83
	(3.22)	(2.16)	(2.61)
	[0.57]	[0.45]	[0.28]
ar1	−0.41	0.68	0.73
	(0.05)	(0.05)	(0.03)
	[0.00]	[0.00]	[0.00]
ar2	−0.43	−0.02	
	(0.05)	(0.06)	
	[0.00]	[0.72]	
ar3	−0.29	0.06	
	(0.05)	(0.06)	
	[0.00]	[0.36]	
ar4	−0.22	0.11	
	(0.05)	(0.05)	
	[0.00]	[0.04]	
ar5	−0.17		
	(0.05)		
	[0.00]		
sar1	−0.25	−0.11	0.07
	(0.05)	(0.05)	(0.04)
	[0.00]	[0.03]	[0.11]
sar2			0
			(0.04)
			[0.98]

White Standard errors in parenthesis.
P-values in square brackets.
Values of 0.00 indicates p-values of less than 0.005.

statistically significant at the 5% level. The overall interpretation is clear: Unlike results reported from other countries and regions, electricity consumption did not appear to make a sustained and substantial drop in these areas.

The results are robust to alternative methods for estimating a change in consumption. For example, instead of differencing, I can seasonally adjust the data using STL decomposition (as I do below with the hourly data) and then do a regression on the level data. Results are qualitatively the same: No significant change in consumption in Denmark and weak evidence for a slight increase in consumption in the southern Swedish area.

When the estimation is so simple and the starting hypothesis so stark (a steep drop in consumption), even a visual presentation of the data, as

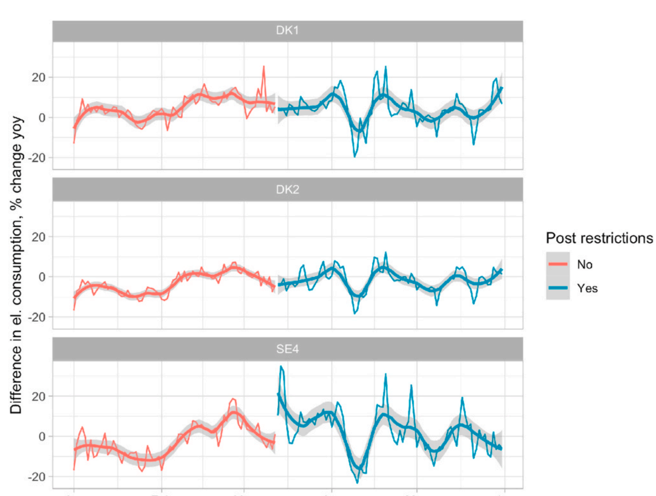

Fig. 6. Percentage change in electricity consumption, year-over-year with a Loess smoothed curve overlapped.

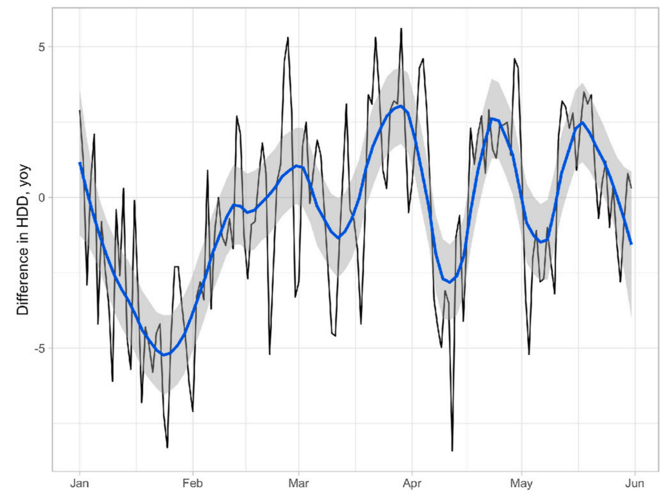

Fig. 7. Year-over-year change in Heating Degree Days, Copenhagen, DK.

in Fig. 6 provides substantial evidence for the result of no significant fall in electricity consumption. The figure shows the percentage change in consumption compared to the year earlier, with the post-restriction period colored in green. The overlayed line represents a Loess smoothed curve. No clear trend of lower electricity consumption is apparent following the imposition of societal restrictions in Denmark. Fig. 7 shows year-over-year temperature changes in Copenhagen in the form of heating degree days (HDD). Heating degree days measure the number of degrees Celsius under a certain base temperature–in this case 15.5 degrees–in days. Thus if a day has 2 HDD, then it had an average temperature of 13.5° over that day. The change in HDD in the period around the imposition of restrictions was close to zero, thus temperature changes are unlikely to be hiding any underlying change in overall consumption. Temperature does appear to explain the notable fall in consumption apparent in the first half of April.

It can appear as if electricity consumption had a modest jump in Sweden. However, the year-over-year change in the consumption series for Sweden exhibits a high degree of variance and sharp jumps. In other words, the jump in consumption compared to the year earlier could very well have been a coincidence.

However, given the geography and differing Covid-19 policies between Denmark and Sweden, a plausible story does emerge for higher consumption in the SE4 area. As noted, the major urban center in the SE4 area is the city of Malmö, which in turn lies directly on the other side of the Øresund Straight from Copenhagen. The two cities are connected by a bridge serving car-traffic and commuter trains and buses.

The two cities are often considered to have a common job market, with many workers commuting across the bridge on a daily basis.[6] The Copenhagen metropolitan area is by far the larger and more dynamic of the two economies, and among other things, home prices tend to be more expensive on the Danish side of the bridge, thus there tends to be far more people that commute from Sweden to Denmark compared to the opposite.

When restrictions came into place in Denmark, commuters to Copenhagen who live in Sweden had to stay at home, potentially leading to a net-increase in Swedish electricity consumption. The opposite effect–a disturbance of commuting from Denmark to Sweden–would be expected to be smaller in magnitude both because there are substantially fewer such commuters, and because Swedish businesses, to a much

[6] Readers interested in a popular culture depiction of the social and economic connections between these two metropolitan areas, as well as a portrayal of common Danish and Swedish stereotypes, are encouraged to see the excellent Nordic-Noir TV series "The Bridge".

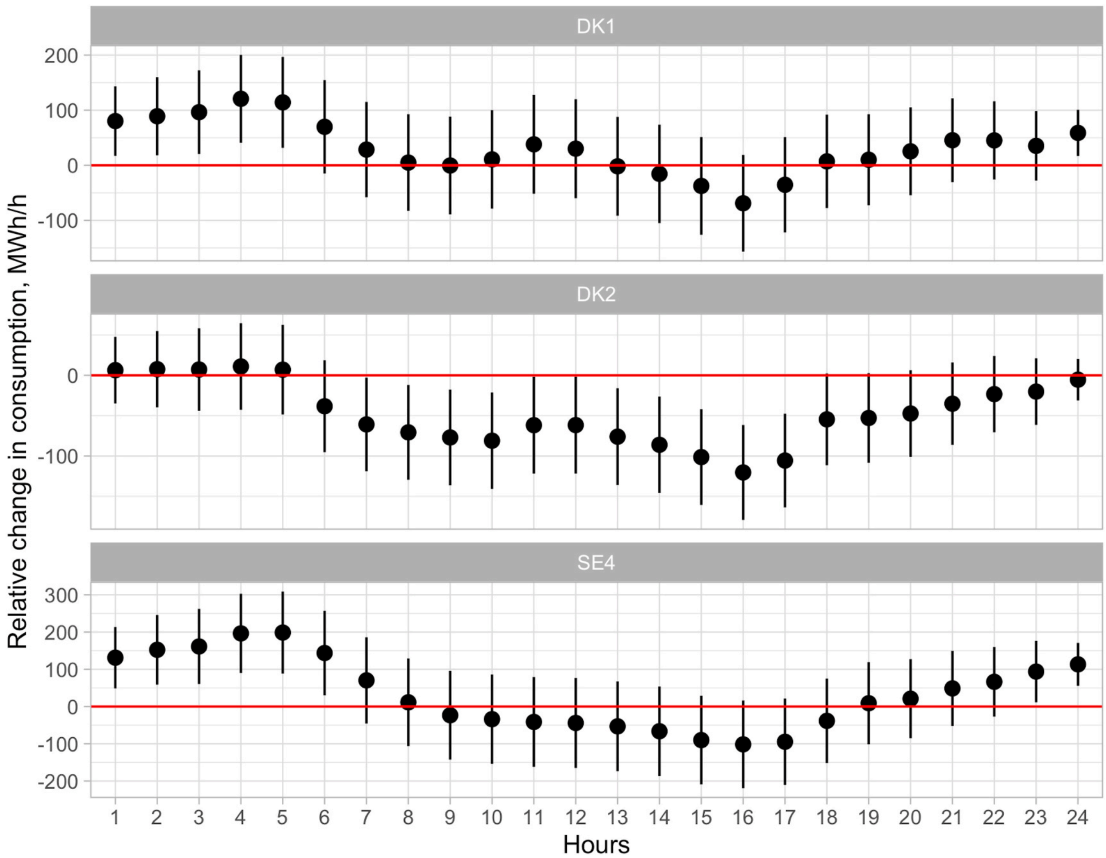

Fig. 8. Relative change in the distribution of consumption over the day by hour. The black dots represent the point estimates of the estimation while the lines represent 95% confidence intervals.

larger extent, stayed open.

Finally, the result of little change in consumption seems to hold in other parts of the Nordics. Preliminary analysis of Norwegian data also indicates little to no fall in consumption taking into account seasonal patterns (See appendix).

Even though there was little overall change in total daily consumption, the time series regressions using hourly data suggests that there was a substantial shift in the distribution of consumption over the course of the data. The results for the interaction terms between the hourly and corona indicator variables are shown in Fig. 8.

The individual coefficients on each hour are likely to be less informative than the overall relative position of the coefficients. The general impression is of a shift of consumption away from typically peak periods in the middle of the day. In particular, a notable drop in consumption appears to happen in the afternoon in the hours 15–17. In normal times, this is the period where many workers arrive home from work, turn on lights, ovens and other appliances and perhaps turn up the heat. The exact patterns appear somewhat different between the three price areas, though this is to be expected given the uncertainty in the models as indicated by the confidence bans.

While overall consumption at a daily level did not drop in this region, there was nonetheless a change of consumption from peak to non-peak. Interestingly, this is the type of shift in consumption that is foreseen with the integration of greater amounts of "smart grid" and demand-response technologies and the proper policies to encourage their adoption.

The shift in the distribution of consumption may have an effect on pricing in the market. More so, this shift in consumption patterns will also likely have interacting effects with the daily pattern of intermittent generation. I explore these implications in the following subsection.

5.2. Electricity prices, the distribution of prices and intermittent generation under Covid-19

Fig. 9 shows electricity prices on the day-ahead market averaged over the three price areas by year. The underlying hourly series is shown in the background, with a smoothed curve–calculated by a cubic regression spline–superimposed to more clearly see shifts in the mean price. The first purple vertical line represents March 12th, when strict regulations were put into place in Denmark. The second purple line represents June 1st, which is an approximate starting point for the gradual easing of societal restrictions.

Following the imposition of restrictions, prices are visibly lower in 2020 compared to previous years. Though prices started dropping well ahead of the imposition of restrictions. This is consistent with the market foreseeing lower future prices due to the Epidemic. The outbreak of the virus in China became widely reported in January and the first confirmed case in Italy were reported in mid-February.

Fig. 10 shows the empirical density functions of prices in the three price areas during the period with the highest restrictions (12th of March to 1st of June), compared to the pre-lockdown densities. The figure clearly shows a shift of the median of the distribution towards the right. More so, it appears the density post-lockdown has a more pronounced left-skew–that is, prices near and even below zero make up a proportionally larger part of the distribution, and the distribution has a clear bi-modal shape. A substantial proportion of the prices also appear to be negative in the Corona period.

Plausibly, the shift in the distribution of prices could be explained by the strong seasonal patterns of electricity consumption. However, in the bottom two facets of Fig. 10 I show the distribution of prices in the period March 13th through June 1st in 2018 and 2019. If anything both the modal shift to the left and the increased left-skew become more

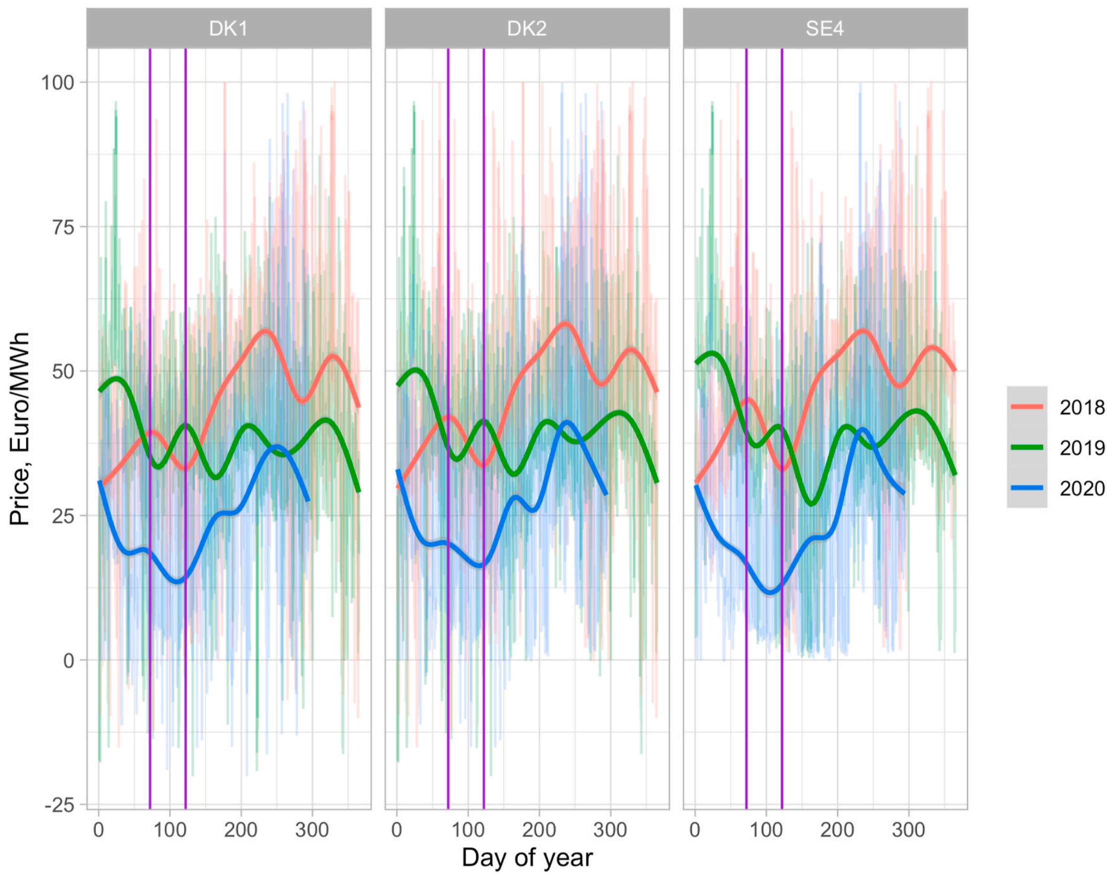

Fig. 9. Prices for electricity averaged over the three price areas. The underlying hourly data is in the background. A smoothed curve, calculated by a cubic regression spline, is overlayed in order to show the overall trend. The red line represents 2018, the green 2019 and the blue 2020. The first vertical purple line represents March 12th. The second represents June 1st. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

prominent when comparing to the distributions of prices in similar periods in the prior years.

In order to get a sense of the relationship between consumption, wind power and prices, in Fig. 11 I show a scatter plot of net consumption–consumption less wind power–for the aggregated price area composed of DK1, DK2 and SE4 and the mean price in these three price areas. The left-panel shows data pre-Epidemic. There is a clear negative relationship between net consumption and prices, however the price level remains positive in periods where wind power covers most or all of local consumption–that is, where net consumption is close to or below zero. However, during the Epidemic, prices at times where wind power covers most of consumption collapses to near zero.

As noted, the most direct explanation for why prices drop close to zero when wind power covers most of consumption is that the marginal cost of wind is close to zero, and that in a competitive electricity market, producers will have an incentive to bid in their marginal costs. Yet, Fig. 10 indicates that this explanation is incomplete, as prices appear to be significantly above zero pre-Epidemic, while only collapsing to the marginal cost of wind power post-pandemic.

The more complete explanation includes the extra dynamics introduced by the large amounts of hydro power in the neighboring Nordic price areas–primarily in Norway and norther Sweden. Even when wind power covers all of the local consumption, if there is available transmission capacity, then prices will converge to the marginal cost established by the hydro power-dominated price area, which should be equal to the shadow price of storage in the reservoir (Forsund, 2015). Intuitively, the marginal cost of a hydro power plant with a storage magazine is the opportunity cost of producing at a later time with potentially higher prices.

The effect of the Epidemic was potentially to lower demand across time periods so that the marginal cost of hydro power (the shadow price of storage) also collapsed to zero during periods with heavy amounts of wind power.

The first column of Table 2, labeled Price Model I, shows estimated coefficients from the time series regressions as described by equations (11) and (12). The coefficient on net consumption, labeled *netConsumption*, is estimated to be approximately 3.1. That can be interpreted to mean that all else equal, a 1 GW increase in net consumption leads to a 3.1 EUR/MWh increase in the electricity price. Neither the coefficient on the Epidemic indicator variable, labeled *corona*, nor the coefficient on the $fullWind_t$ indicator was significantly different from zero. This can be interpreted as neither variable contributing to explaining price beyond what information is already included in the variable for net consumption. These results should perhaps be interpreted with care. As we saw earlier, prices began to decline well before the imposition of restrictions on March the 12th.

Importantly, however, the interaction effect between the $fullWind_t$ and $corona_t$ variables, labeled *corona*: *fullWind* is estimated to be both statistically and economically significant with a coefficient of approximately -2.39. That is to say, that during the period of societal restrictions, prices were about -2.4 EUR/MWh lower during periods where wind power covered all of the load, compared to what would be expected based on the linear net consumption relationship. This result is in line with what we observe from Fig. 11, where it appears prices collapse during the Corona period when wind power covers all of load.

The second column of Table 2, labeled Price Model II, shows results with the inclusion of the interaction variables between the Epidemic indicator variable and the hour indicators as described by equations (13) and (14). The coefficients on these interaction terms, $\widehat{\theta_2^H}$, which can be

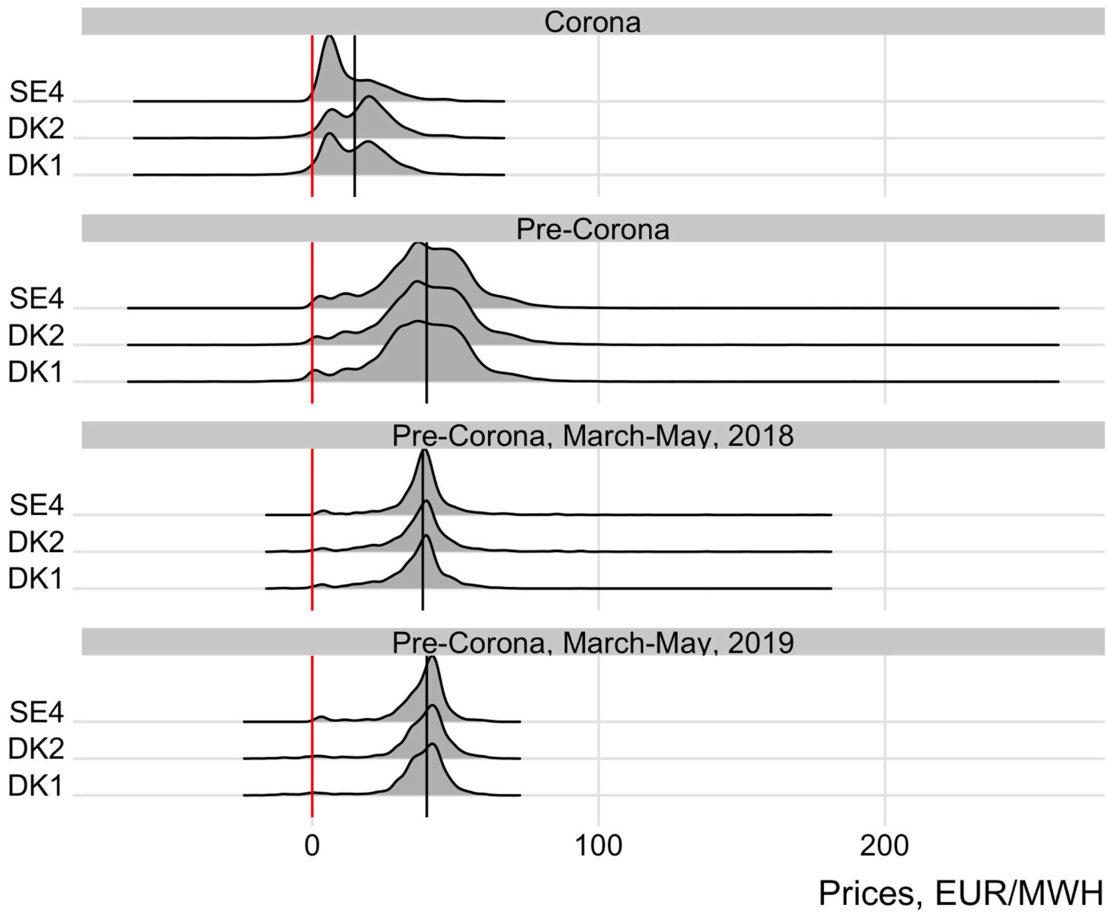

Fig. 10. The distribution of prices in the DK1, DK2 and SE4 price areas during the period with the tightest restrictions (March 13th to June 1st) compared to the pre-Corona distribution (January 2018 through March 12th). The bottom two facets show the distribution of prices in the period March 13th through June 1st in 2019 and 2018. The vertical black lines represent median values for each category.

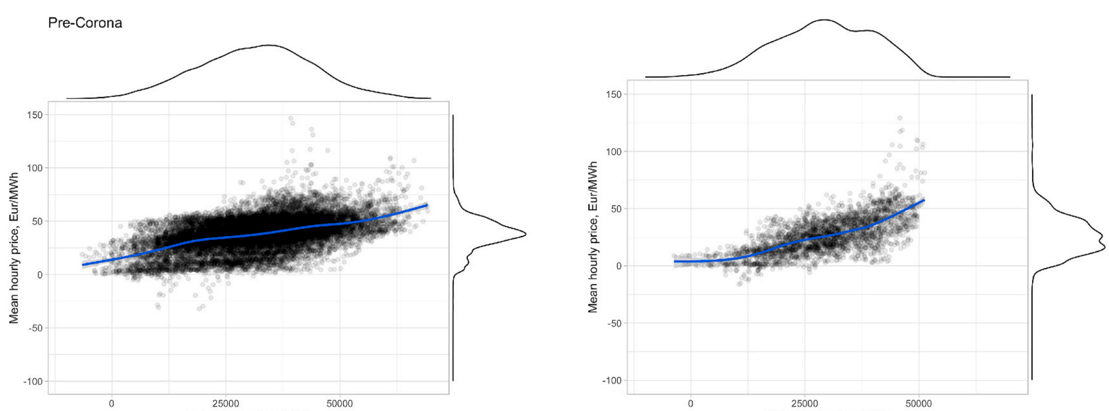

Fig. 11. The left-panel shows a plot of the hourly electricity price before the imposition of Epidemic-related societal restrictions, averaged over the three price areas against net consumption (consumption less wind power) summed over the three price areas. The right panel shows average hourly prices after the imposition of societal restrictions. Prices in periods with close-to or below zero net consumption appear to collapse towards zero.

interpreted as the change in the distribution of prices over the day under the imposition of societal restrictions are shown in Fig. 12. The bands represent 95% confidence intervals. As we can see, the distributive effects mirror those we saw earlier for the consumption pattern: Relative prices fell in the middle of the day, and especially in the late afternoon–around 17–18.

5.3. Negative prices

Referring back to Fig. 11, we can see that in both pre- and post-Epidemic periods, the incidence of negative prices is generally not at times where wind power covers all local consumption. Instead, negative prices tend to happen in periods where there is significant residual (thermal) power generation. This observation is in line with our understanding of how negative prices are formed in electricity markets.

Table 2
Estimated coefficients for dynamic time series regressions of price. The first column from the left shows results from a model where hourly and day-of-week indicator variables are included to control for seasonality, though the coefficients on these variables are not of interest and are thus not included for brevity. The second column includes interaction terms between the $corona_t$ variable and the hourly indicator variables. The estimated coefficients and confidence intervals for these interaction variables are displayed visually in Fig. 12.

term	Price Model I	Price Model II
corona	2.23	3.92
	(1.67)	(1.83)
	[0.18]	[0.03]
fullWind	0.58	0.56
	(0.85)	(0.85)
	[0.49]	[0.51]
netConsumption	3.12	3.1
	(0.09)	(0.09)
	[0.00]	[0.00]
corona:fullWind	−2.39	−2.43
	(1.91)	(1.91)
	[0.21]	[0.2]
ar1	1.1	1.1
	(0.01)	(0.01)
	[0.00]	[0.00]
ar2	−0.22	−0.22
	(0.01)	(0.01)
	[0.00]	[0.00]
ar3	0	0
	(0.01)	(0.01)
	[0.62]	[0.65]
ar4	−0.01	−0.01
	(0.01)	(0.01)
	[0.23]	[0.24]
ar5	0.04	0.04
	(0.01)	(0.01)
	[0.00]	[0.00]
ar6	−0.03	−0.03
	(0.01)	(0.01)
	[0.01]	[0.01]
ar7	0.03	0.03
	(0.01)	(0.01)
	[0.00]	[0.01]
ar8	0.02	0.02
	(0.01)	(0.01)
	[0.09]	[0.09]
ar9	−0.01	−0.01
	(0.01)	(0.01)
	[0.53]	[0.56]
ar10	0.05	0.05
	(0.01)	(0.01)
	[0.00]	[0.00]
sar1	0.24	0.23
	(0.01)	(0.01)
	[0.00]	[0.00]

White standard errors in parenthesis.
P-values in square brackets.

There are significant ramping constraints associated with production from thermal plants–starting and stopping such plants or even just reducing or increasing power output can take a significant amount of time and has significant costs. Operators of thermal plants are then typically constrained to submit block-bids for production–bidding in a certain amount of production over a block of hours. In periods with an overbalance of electricity, these operators may find it optimal to pay (a negative price) in order to continue to produce as long as the payments are lower than the cost that is imposed by the ramping constraint.

Fig. 13 shows another pattern associated with negative prices. In this figure, prices are plotted against net consumption conditional on whether there was congestion (1) or not (0) between the DK1 and the southernmost Norwegian area, NO2. The DK1 and NO2 price areas were chosen because major transmission cables connect these two areas. In the DK1 and DK2 price areas, negative prices happen exclusively during periods where there is congestion between the DK1 and the NO2 areas. Access to the flexible hydro power in Norway creates a price floor of zero for the Danish market.

This is not to say that wind power production has no bearing on the incidence of negative prices. At the margin, increased penetration of intermittent generation is likely to lead to more frequent negative prices. The reason is that a larger share of intermittent generation will tend to lead to more variation in generation. This may lead to increased incidence of periods of over-supply and negative prices. This is a research question that deserves further research.

6. Conclusion and policy implications

In this article I show that electricity consumption in aggregate did not fall during the period of peak Covid-19 related societal restrictions in the southern section of the Nordic region consisting of Denmark and southern Sweden. In fact, there is some evidence of a slight rise in consumption in the southern Swedish price area.

Though I do not formally study other parts of the Nordic region in the main text, preliminary data analysis suggests that the findings likely also extend to the Nordic region as a whole (see appendix). These findings are in sharp contrast to studies of other regions of the world, which show sharp drops in electricity consumption, with initial magnitudes as high as 30%.

With the available data, it is difficult to come to any definitive conclusions about why results in this part of the Nordic region are in such sharp contrast with other parts of the world. One potential mitigating factor was that none of the Nordic countries imposed strict stay-at-home orders as were imposed in parts of continental Europe as well as other hard-hit regions. But Denmark did nonetheless impose strong restrictions, including the closing of offices, restaurants, schools, day-care centers, and otherwise restricted public gatherings.

But while aggregated electricity consumption did not fall in the region, I show that the distribution of consumption over the day did change, with a relative fall in the middle of the day and especially the afternoon hours of between 14 and 17.

Despite the absence of any fall in consumption, prices in the region fell significantly, even before the imposition of restrictions in Denmark. Mirroring the shift in the distribution of consumption, prices in the middle of the day and late afternoon tended to see a proportionally higher fall.

Perhaps the results that are of the most interest in the long-term is how the shock of the Epidemic interacted with the high share of intermittent generation in this area. I present descriptive evidence showing how under the Epidemic prices appear to collapse towards zero when wind power covers all or most of the load. Relatively simple time series regressions indicate that there was a over-proportional drop in prices under the Epidemic (relative to net consumption), but only when wind power covered all of local load.

A plausible explanation of this result is that it comes from an interaction of the shift in the distribution of consumption over the day and the zero-marginal-cost nature of wind power technology. Even though consumption on the whole remained steady in the area, the shift of consumption away from peak hours increased the number of hours where wind power was able to cover most or all of the local load. In turn, this pressed down both average prices and the variance in prices. In addition, the fall in prices across the Nordic region and especially during peak times lead to a fall in the implicit alternative cost of production in the region's large hydro power plants. This lead to a general reduction in prices and overall variance in the Danish and southern Swedish areas.

These results have implications well beyond the Epidemic. Many leading studies of high renewable penetration scenarios foresee an overbuilding of capacity as a necessary way of dealing with the technologies' inherent intermittency (Clack et al., 2017). This in practice will mean that many if not most hours of load will be covered completely by intermittent energy.

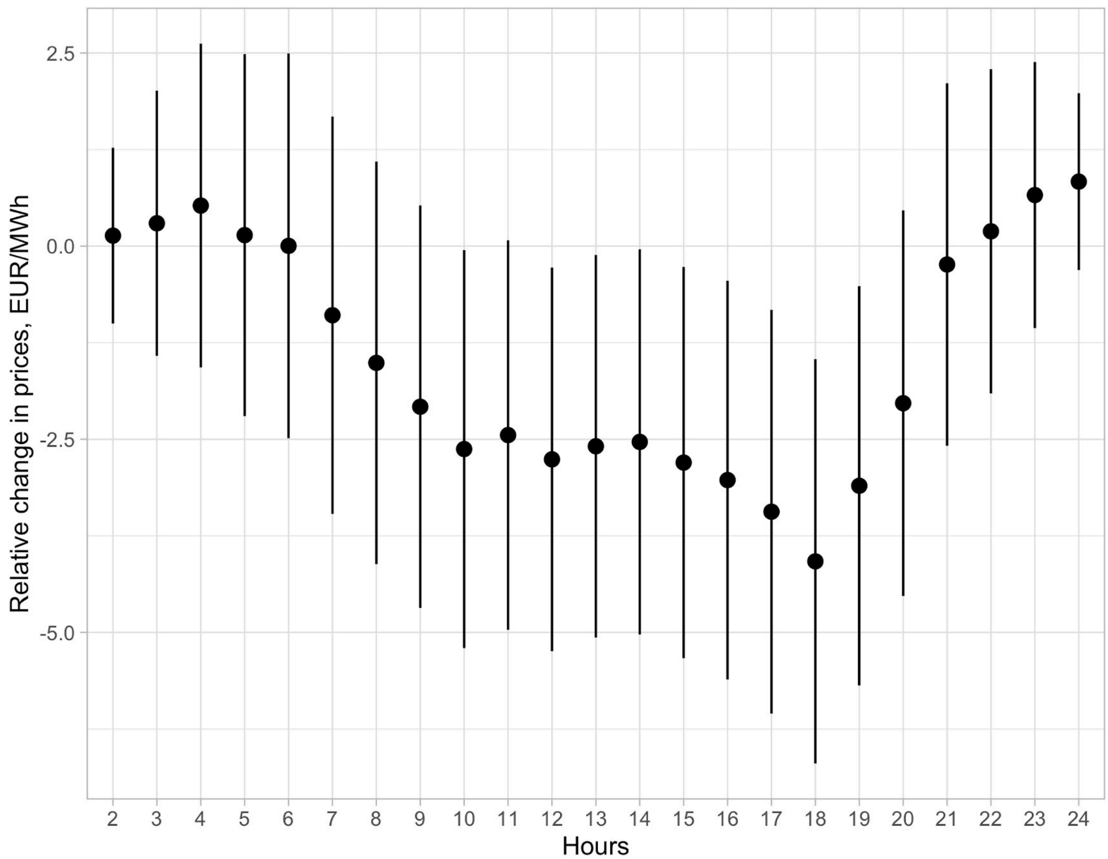

Fig. 12. The points represent the estimated coefficients on the interaction term between $corona_t$ and the hourly indicator variables. The vertical lines represent 95% confidence intervals.

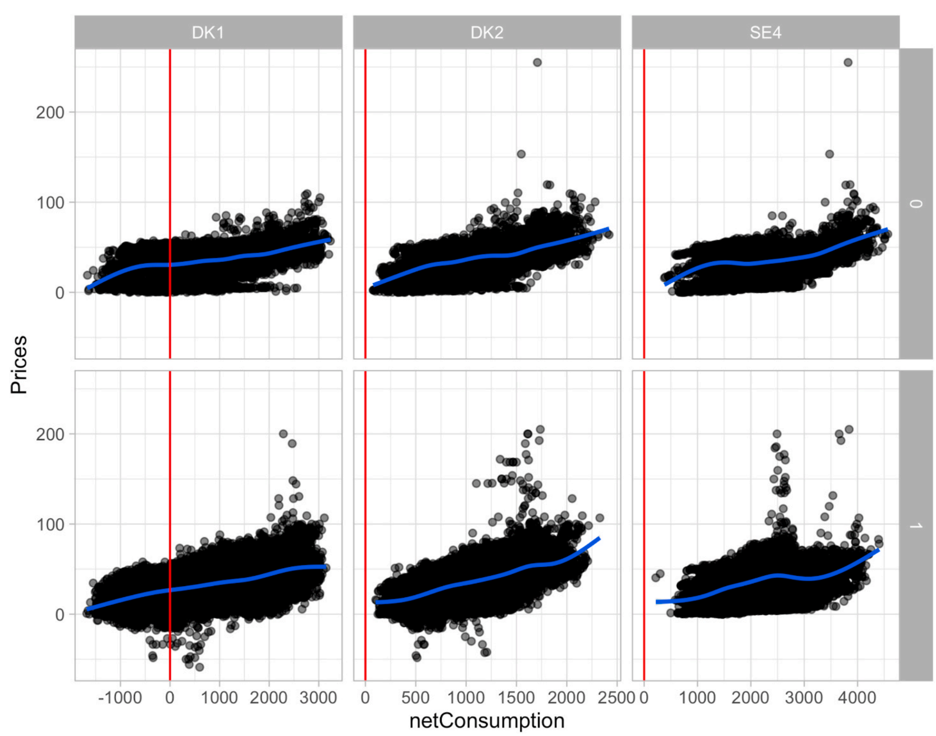

Fig. 13. Prices in the DK1, DK2 and SE4 areas plotted against net consumption (consumption less wind power), and conditional on the existence of congestion (1) or not (0) between the DK1 area and the southern-most Norwegian area, NO2.

The effect that the Epidemic had of shifting consumption away from peak-periods can potentially give us a preview of what happens to price formation when intermittent energy covers large portions of load over the course of the day and load shifting technologies move consumption away from peak periods: Prices and variation tend to collapse towards zero.

This scenario presents some difficult policy implications. Beyond a certain point of intermittent penetration in a given market, deregulated energy-only markets such as the Nordic electricity market, may not be able to provide the incentives for further investment in renewable energy, no matter how cost competitive such technologies are. Instead, policymakers may need to rely on other mechanisms to ensure continued investment in carbon-free generation, like capacity markets and green subsidies, that carry with them their own particular economic inefficiencies and potential for regulatory overreach.

In this article, I have taken a descriptive and exploratory approach, which I argue is well suited to an initial analysis of the effects on electricity markets of the wide-ranging economic and societal shock of the Epidemic. The exploratory approach I take necessarily leads to more questions than answers, many of which could be fruitful avenues of future research. For example, I can only speculate on why electricity consumption as a whole did not decline under the Epidemic in Denmark and southern Sweden. An analysis of the underlying economic and policy reasons for why some regions saw dramatic declines in consumption while others did not would be of great interest. I also briefly touch on the issue of negative prices in the market. This is a topic that has received too little attention in the literature, and deserves more attention, especially as more countries adopt ambitious targets for renewable energy generation.

CRediT authorship contribution statement

Johannes Mauritzen: I am the sole author of this article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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A Appendix. Analysis of Norwegian Consumption

The pattern shown for the Danish and southern Swedish price areas appears to hold in other parts of the Nordic region as well. Norway imposed societal restrictions a day after Denmark, with restrictions that were similar in scope.

Fig. 14 and Fig. 15 show daily consumption data from the five Norwegian price areas. The red vertical line represents the imposition of societal restrictions in Norway. Relative to the normal seasonal consumption patterns, no significant divergence of daily consumption patterns are apparent for any of the five Norwegian price areas.

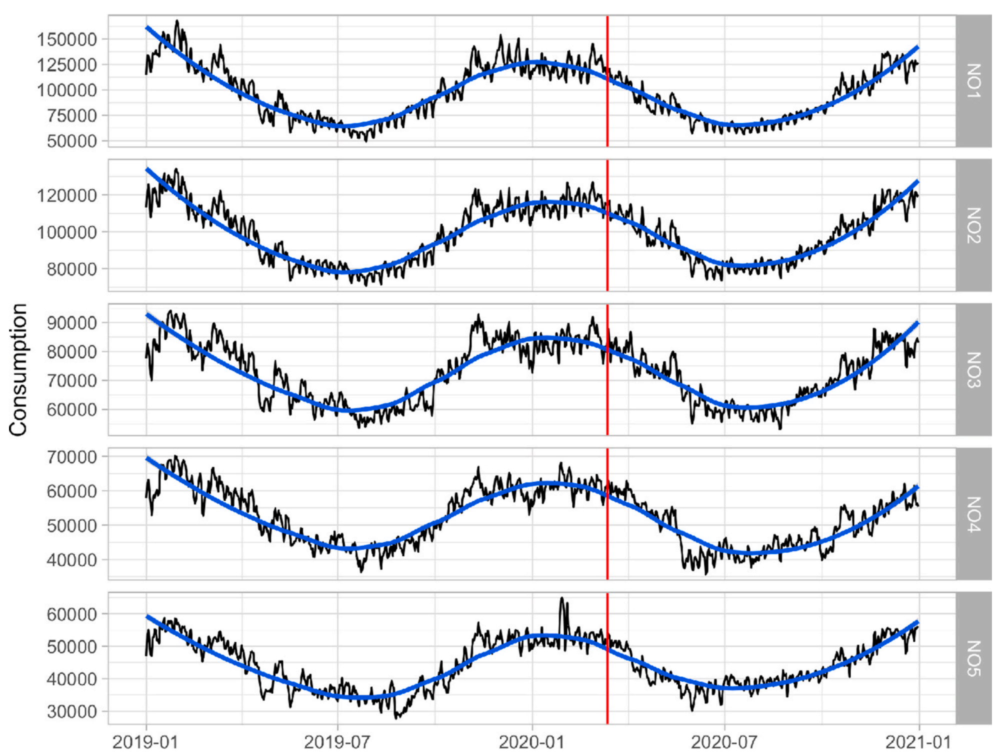

Fig. 14. Daily consumption in MWH in the years 2019 through 2020. The blue line is a Loess smoothed curve. The vertical red line represents the beginning of societal restrictions on March 13th, 2020 in Norway.

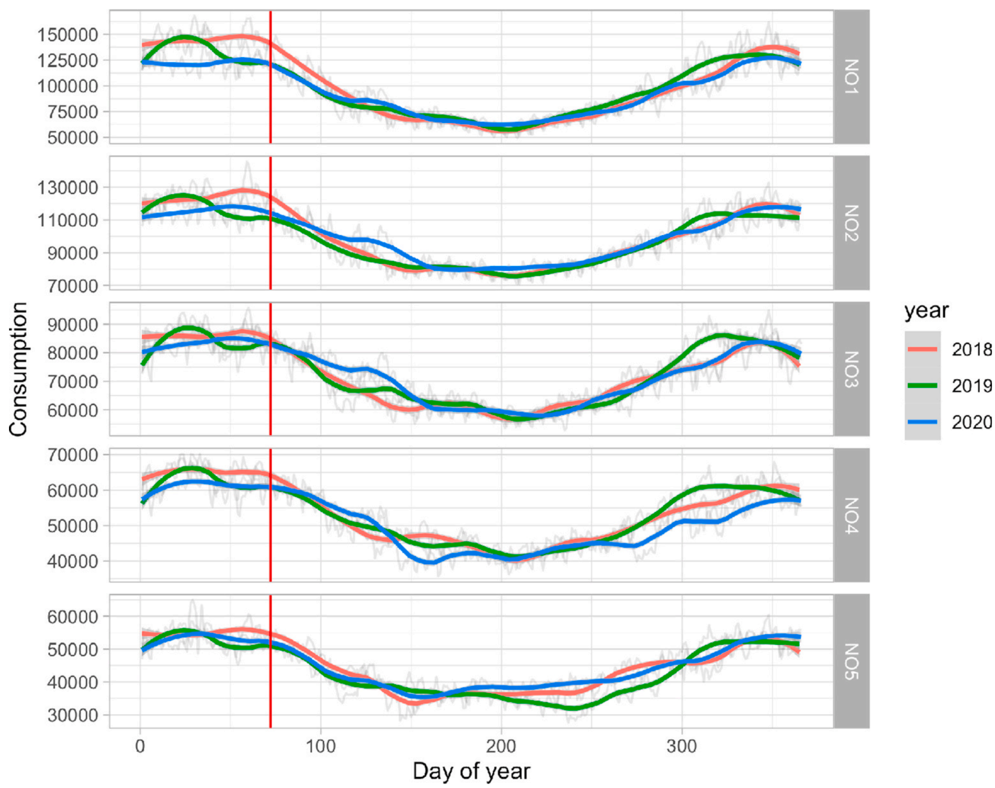

Fig. 15. Daily consumption in MWh for the years 2018–2020. The red, green and blue lines represent Loess smoothed curves for the three years respectively. The red vertical line represents the imposition of societal restrictions on March 13th.

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