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Prof. Dr. Yvan Lengwiler

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Universität Basel
Peter Merian-Weg 6
4052 Basel, Switzerland
wwz.unibas.ch

Corresponding Author:
Prof. Dr. Yvan Lengwiler
yvan.lengwiler@unibas.ch
Tel. +41 61 207 33 69

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Yvan Lengwiler[1]

University of Basel, Faculty of Business and Economics (WWZ) and Center for Innovative Finance (CIF), CH-4002 Basel, Switzerland.
email: `yvan.lengwiler@unibas.ch`

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Abstract

The partial shutdown of the economy following the outbreak of the COVID-19 pandemic has highlighted the lack of measurements of economic activity that are available with a short lag and at high frequency. The consumption of electricity is a candidate for such a proxy.

Keyword: COVID-19, electricity, seasonal adjustment, weather data.
JEL classification: C50, E01.

1 Introduction

On February 24, 2020 the first infection with SARS-CoV-2 was detected in Switzerland. On March 5, the first patient deceased. On March 16, the government closed down a significant part of the economy and public life.

The first measure was already taken on February 28: the government issued an ordinance forbidding gatherings of more than 1'000 people.[1] On March 13 it issued an ordinance with more drastic measures. It restricted travel and ordered schools to close. Gatherings of more than 100 people were restricted. Restaurants were restricted to host at most 50 guests at the same time. Only three days later, on March 16, the ordinance was changed and a broad shutdown of parts of the economy was initiated: all shops and open markets, restaurants, entertainment and cultural enterprises (including alpine tourism), and services with physical contact (such as hairdressers etc.) were ordered to close. Exceptions were granted to food shops, take-away restaurants, pharmacies, hospitals, postal services and banks, public transportation, gas stations, social emergency institutions, public administration, and a few others.[2] Several further tightenings were ordered in the following weeks. Notably, on March 21, public gatherings of more than five people were forbidden.

During these developments, it was obvious that the measures would have significant economic impact. But hard data on the quantitative effect was not available. GDP data are available at quarterly frequency and only with considerable delay. What the decision makers need is a rough proxy that is available with short delay and at high frequency, a proxy that can give guidance to the question: "How is the economy doing? Right now?"

One candidate for this is electricity consumption. Electricity is essentially not stored at the site of consumption. Instead, electricity is largely created just in time, and to the extent it is stored, this happens in facilities of the producers. Moreover, almost all economic activity requires electricity. As a result, the consumption of electricity should be a proxy for economic activity. A testament to that is the clearly visible seven-day seasonality of electricity consumption: there is significantly less consumption on weekends than during weekdays.

The role of electricity as a means or as a measure of economic activity has long been recognized. In 1956, the Federal Reserve Board added Electricity Production as a component to the indicator for industrial production (Federal Reserve Board, 2019). Kraft and Kraft (1978) explore the direction of causality between energy consumption and GDP, which initiated a substantial literature. In 2010, the Economist created a proxy for China's GDP that is based on three indices, one of them being electricity (Economist, 2010). Related to this is also Henderson, Storeygard, and Weil (2012), who use light emissions visible from outer space as a proxy.

[1]Verordnung über Massnahmen zur Bekämpfung des Coronavirus (COVID-19), `https://www.admin.ch/opc/de/official-compilation/2020/573.pdf`.

[2]Verordnung 2 über Massnahmen zur Bekämpfung des Coronavirus (COVID-19), `https://www.admin.ch/opc/de/official-compilation/2020/773.pdf` and the much stronger update of March 16 here, `https://www.admin.ch/opc/de/official-compilation/2020/783.pdf`.

Electricity consumption cannot be used as a proxy without treatment, however, because it is influenced by non-economic, exogenous factors. The most important, it turns out, is weather. In the following, I control for fluctuations that are due to weather, day of the week, Easter (and its sister holydays), and the beginning and end of daylight savings time periods. Moreover, a time fixed effect captures seasonality throughout the year that is not weather-related. The result is a series that is adjusted for calendar and weather effects. Remaining fluctuations of this series should be due to fluctuations of economic activity.

2 Data

Electricity consumption data are available from Swissgrid,[3] the national grid company of Switzerland. I use the "final energy consumption" data which is available from Jan 1, 2009 at 15 minutes frequency to Mar 31, 2020 (at time of writing), see Figure 1. The data of the last month are released around 20 days into the next month. There are also monthly data of electricity consumption covering Jan 1990 to Dec 2019.[4] I will explore those data as well.

insert Figure 1 around here

Weather data are available from Meteoswiss.[5] I have experimented with average temperature of the whole day (variable `tre200d0`), average during daytime (variable `tre200j0`), heating degrees (variables `xhd000d0` and `xno000d0`), and precipitation (variable `rka150d0`). Heating degrees is a rough measure of the need for buildings to be heated. There is a Swiss and a US definition, and I try both. These data are collected from weather stations in the major cities (Basel, Bern, Geneva, Lausanne, Lugano, Lucerne, St.Gallen, and Zürich). Weather data are updated daily.

3 Intraday data

Since the data are available, it may be interesting to quickly look at the intra-day seasonality. Figure 2 depicts the average consumption for each 15-minutes interval over all days from 2009 to 2019 (leaving out 2020), but separately for each month. We see that the seasonality is different in months that are in normal time (NT) from the ones that are in daylight savings time (DST). We also clearly see that there is less activity at night than during the day, and that there are peaks in the late morning and evening. I will not use intraday seasonality at all, so this will not be discussed further here.

insert Figure 2 around here

[3] https://www.swissgrid.ch/en/home/operation/grid-data.html

[4] Schweizerische Elektrizitätsbilanz, see a link on https://www.bfe.admin.ch/bfe/de/home/versorgung/statistik-und-geodaten/energiestatistiken/elektrizitaetsstatistik.html.

[5] https://gate.meteoswiss.ch/idaweb/

4 Daily data

4.1 Specification of the regression

Aggregation. Data are aggregated to daily frequency by adding up the 15-minute data. Care must be taken for days at which DST starts or ends. On the last Sunday of March, an hour is removed at night, and the reverse is done on the last Sunday of October. The data are denoted with Y and the logarithm of the data with y. The analysis will be performed on logarithmic data.

Trend. All the explanatory variables (calendar, weather) are stationary by principle.[6] To remove a trend that may be present in the electricity consumption, I compute a slow moving trend and perform the analysis on the difference from the trend. I use the Hodrick-Prescott (HP) filter because this filter has relatively good edge of sample properties. The HP trend of y is denoted with y^*. The non-logarithmic version is denoted with $Y^* := \exp(y^*)$.[7]

Weather. Various regressions have revealed that the heating day variables have more explanatory power for electricity consumption than raw temperature. Also, the US definition seems to do slightly better in most cases, so I use that in place of the Swiss definition. In addition, precipitation also has some explanatory power, so this is included as well.

Moving calendar effects. I use dummies for Monday to Friday. It turns out that the seasonal effect of Saturdays and Sundays is not constant across calendar months. I therefore use dummies for Saturdays and Sundays interacted with the calendar month.

I also use a dummy for Easter, which does not have a fixed position in the Gregorian calendar. Connected to Easter are several other holidays, which are also moving around in the calendar and for which I also use dummies. One of these is Ascention Day, which is 39 days after Easter and always on a Thursday. It is common for many workers to take the Friday after Ascention off, so I add another dummy for the day after Ascention.

Moreover, I add dummies for the days at which DST starts (those days are an hour shorter), and when DST ends (those days a an hour longer).

Fixed calendar effects (seasonality). To catch the obvious seasonality, I add fixed effects to each calendar day in the year. Think of this as a panel regression where T is the calendar day of a year (i.e. day and month), and N is the year of observation. The calendar-day fixed effects are dummies for each day and month combination in T. The coefficients of

[6] Stationarity of the weather may be debatable, but not over the relatively short horizons that we analyze.

[7] The HP filter minimizes a weighted sum of the deviations of the smoothed series from the original data, and the square of the curvatures of the smoothed series. The weight is controlled by one parameter, traditionally denoted with λ. Ravn and Uhlig (2002) have elaborated on the correct choice of λ. They suggest that $\lambda = 6.25 + p^4$ is roughly appropriate, where p is a periodicity of the fluctuations that should still be contained in the smoothed series. For monthly data ($p = 12$), this implies $\lambda = 129600$; for daily data, $p = 365.25$, this implies $\lambda = 107e9$.

these fixed effects trace the volatility that repeat on a yearly basis, what we normally call seasonal factor.

Holidays on weekends. The seasonal effect of some obvious holidays (such a Christmas etc) is negative. But it turns out that the effect of lower electricity consumption due to holidays and lower consumption due to the day being part of a weekend are not simply added together. I therefore add one more dummy that interacts most important holidays with the day being a Saturday or Sunday.

Estimation. The regression is performed on $y - y^*$. The explanatory variables are as introduced above (weather, moving calendar effects, fixed calendar effects) and are denoted with x. β denotes the coefficients. Residuals are autocorrelated, so I add an AR(1) term. Thus,

$$y_t - y_t^* = \beta x_t + g_t, \qquad \text{with} \qquad g_t = \rho g_{t-1} + \epsilon_t,$$

where ϵ are the innovations. We can rearrange this equation in a meaningful way,

$$y - y^* - \beta x = g.$$

g is the logarithmic *gap*. It measures the relative deviation of electricity consumption from the trend after all the non-economic influences — weather and calendar effects — have been removed. It is therefore a measure of economically induced variations of electricity consumption.

The *adjusted series* is defined as

$$Z := \exp(y^* + g) = \exp(y - \beta x).$$

This series measures consumption (in GWh) again after all the non-economic influences have been removed, but keeping the general multi-year trend (if present).

The adjusted R^2 of the regression is 99.1%.[8] The day of the week dummies explain 35.9% of the variance, the seasonal factors explains 19.1%, the weather data explain 11.6%, Easter and the holidays connected to it explain 2.1%, and cross-terms of weather data and seasonality explain 10.9%.

4.2 Seasonal pattern

Before moving on to studying the adjusted series Z, it may be interesting to take a look at the seasonality of electricity consumption. The seasonal structure is captured by the coefficients of the calendar-day fixed effects. I normalize these coefficients to be zero on

[8]Number of observations: 4108, degrees of freedom: 3685, SSE: 0.7105, RMSE: 0.01389, D.W.: 2.094.

average and call this the *seasonal factor*. This factor captures how electricity consumption is larger or smaller than average on particular days of the year. It is depicted in Figure 3.

insert Figure 3 around here

We see distinct downward spikes at specific dates: labor day (May 01), National Celebration Day (Aug 01), Mary Ascension (Aug 15), All Saints' Day (Nov 01), Immaculate Conception (Dec 08), Christmas (Dec 24–25), and Sylvester-New Year (Dec 31–Jan 01).

4.3 The adjusted series

The adjusted series Z tracks electricity consumption fluctuations that happen for reasons other than weather or calendar. Figure 4 depicts the adjusted Z and the trend Y^*.

insert Figure 4 around here

Let us first meditate a little bit on what we see here. The trend Y^* is roughly constant over the sample period. The adjusted series Z has high frequency volatility but is also essentially flat. The consumption of electric energy in Switzerland, after controlling for various non-economic influences, is essentially flat. We consume today the same amount of electricity as we did eleven years ago. Real GDP has increased by 21% in that time-frame. Population has increased by almost 10%. Yet, electricity consumption remained unchanged. This is remarkable.

4.4 The relative gap — How large is the impact of the shutdown?

So electricity consumption is essentially flat over the sample. But this is true only until March 16, 2020, the day the shutdown came into effect. We see a sharp decline of consumption at and after that date. Figure 5 depicts the gap g for the last six months of the sample. We see that in the days after the shutdown became effective, there was drop of 12%. This is huge in historical perspective.

insert Figure 5 around here

The seasonal effect of Aug 1st is -33%, that of Christmas -18%, and labor day is -11.5%, see Figure 3. The quantitative effect of the shutdown is therefore about a third of an Aug 1st, or two thirds of a Christmas, or about the same as labor day, but for as long as the shutdown lasts.

5 Monthly data and robustness check

Before 2009, only monthly data of electricity consumption are available. They are available from Jan 1990 to Dec 2019. The weather data for one of the stations is available only from

Apr 1991 onward on, however, so the estimation will be done from Apr 1991 to Dec 2019. The procedure that has been used for the daily data is applicable in much the same way on the monthly data. I do this as a robustness check for the method, and to test consistency of the result.

insert Figure 6 around here

The monthly data Y do show an increase from 1990 to 1999 (Figure 6). This low frequency movement is removed by taking the difference of the logarithmic data y from the trend y^* (HP filter for $p = 12$), and the regression is performed on $y - y^*$.

The procedure is the same before, but the regressors are a bit simpler: the average heating temperature (US definition) in each month; the month in which Easter Monday is located;[9] the number of Mondays, Tuesdays, ..., Sundays in a month; and finally a dummy for the calendar month to capture seasonality that is unrelated to temperature. All of these explanatory variables are highly significant and the fit is again very good (adjusted $R^2 = 0.983$).

insert Figure 7 around here

The robustness check amounts to checking whether the relative gap — the main indicator of economic fluctuations — computed with the monthly data provide the same signals as the relative gape derived from daily data does. Figure 7 makes that comparison. The daily gap (fine dotted line) has of course much more volatility, because it is able to capture day-to-day changes. A more comparable version is a 30-day central moving average of the daily gap, represented by the blue line. The red line is the monthly estimate. The match is not perfect, but the more substantial shocks are captured by the monthly and the daily data in much the same way. Even their sizes are very similar, although the monthly indicator appears somewhat more volatile. I conclude therefore that the two measures capture similar disturbances. I also conclude that the daily gap is more useful than the monthly gap, because a smoothed version of the daily gap produces less volatility and provides a cleaner signal for large disturbances.

6 Comparing the shutdown with the GFC

I have compared the effect of the shutdown to the yearly shutdowns that happen at particular holidays. This is informative, but a comparison with the global financial crisis (GFC) would be interesting as well. Alas, daily electricity data are not available before 2009. Of course, the GFC (in the form of the Euro crisis) was very much going on in 2009, but for our daily sample this is close to the beginning of the sample and it may be difficult to judge if the GFC is captured by these data. The whole GFC is safely covered by the time span available at monthly frequency.

[9] Having multiple Easter-related dummies did not enhance the fit, and Easter Monday turned out to be the best choice.

insert Figure 8 around here

In the monthly gap, the GFC shows up only during 2009, not before (when it was still the banking crisis). According to the monthly gap, the GFC is estimated to be a −4% shock. According to the daily gap (30-day moving average), the shock is −5% (see Figure 7 or 8). Using the same daily measure, the COVID-19 shutdown is −9.5% (or −12% using the non-smoothed version, Figures 5 and 9). Thus, using electicity consumption as guideline, this implies that the shutdown is a shock that is about twice as large as the GFC was.

insert Figure 9 around here

7 Conclusion

In an emergency, speediness of information becomes more important compared to accuracy. A piece of information that points in the correct direction without getting the details right is of higher value than a detailed and precise account that is available three months too late. GDP is a slow measure. It is not even very accurate, but it is the most accurate measure of economic activity we have. But because it is available with such a long delay, and then is typically revised with the benefit of new information later, it is of little use in a crisis such as the COVID-19 pandemic.

Several high frequency data sources could be considered to construct a rough but quickly available proxy for economic activity. Travel, cargo, payment activity could all be helpful, as is electricity consumption. A most useful high frequency proxy will combine the information of several such inputs.

This paper explores the use of electricity consumption for this purpose. It was born out of the need to have some indicator now. So it is not perfect. It could be improved, possibly, by evaluating in a more granular fashion the local amount of electricity that is being used, and correlating this with industries that are locally present.

The analysis has also shown that it is advisable to work with high frequency data (daily in this case), and then generate a smoothed signal from this. The resulting measure appears more informative and less volatile than if monthly data are used to begin with.

The conclusion of this paper is that the shutdown is about twice as strong as the GFC was. Comparing to major holidays, it is as strong as one thirds of the "natural shutdown" that occurs each year at August 1st, two thirds of Christmas, or similar to a labor day. But it lasts as long as the shutdown is in effect. This should give us an understanding of the economic impact of the shutdown.

The government has decided that on April 27 some of the shutdown will be eased, and on May 11 most of it will be lifted. This means that the shutdown will have lasted eight weeks. It is possible that further shutdowns may become necessary should there be flare ups of the disease. But even if this is not the case, the shutdown amounts to eight weeks of of a third of the effect of August 1st, akin to 19 days of National celebration day in a row.

Of course, this takes only electricity into account. It is entirely possible that the GFC recession had an impact on other parts of the economy than the shutdown has, so that this comparison is not fully meaningful. Still, gauging the size of the electricity shock, there is little doubt that the current shutdown is a shock of historical proportions, and greater than anything we have seen so far in this still young century, and we should brace for the impact.

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Figures

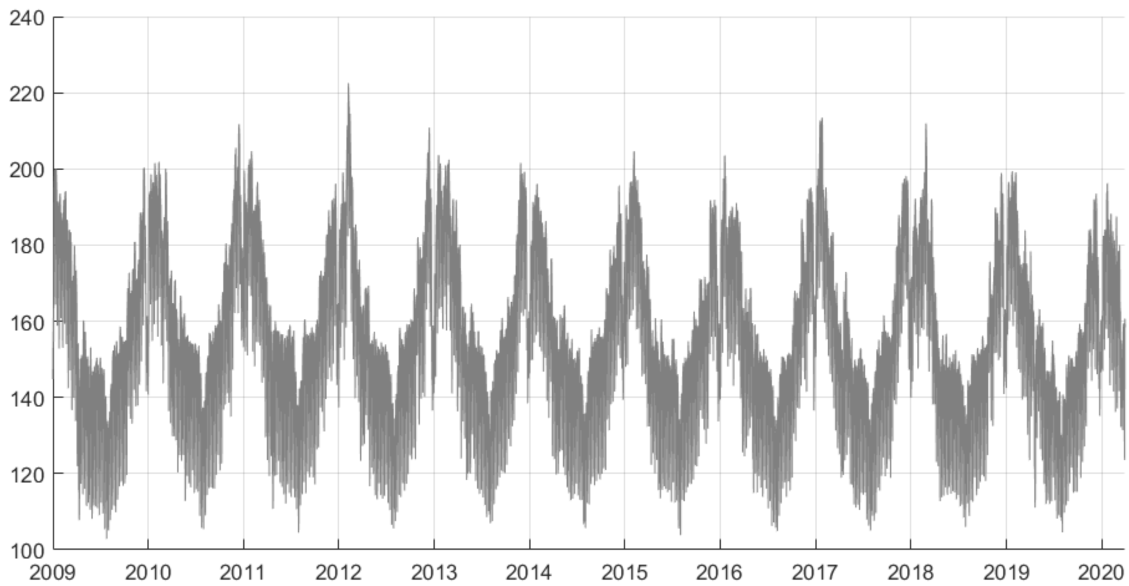

Figure 1: Raw data: final consumption of electrical energy in Switzerland, aggregated to daily frequency [GWh], Jan 01, 2009 to March 31, 2020.

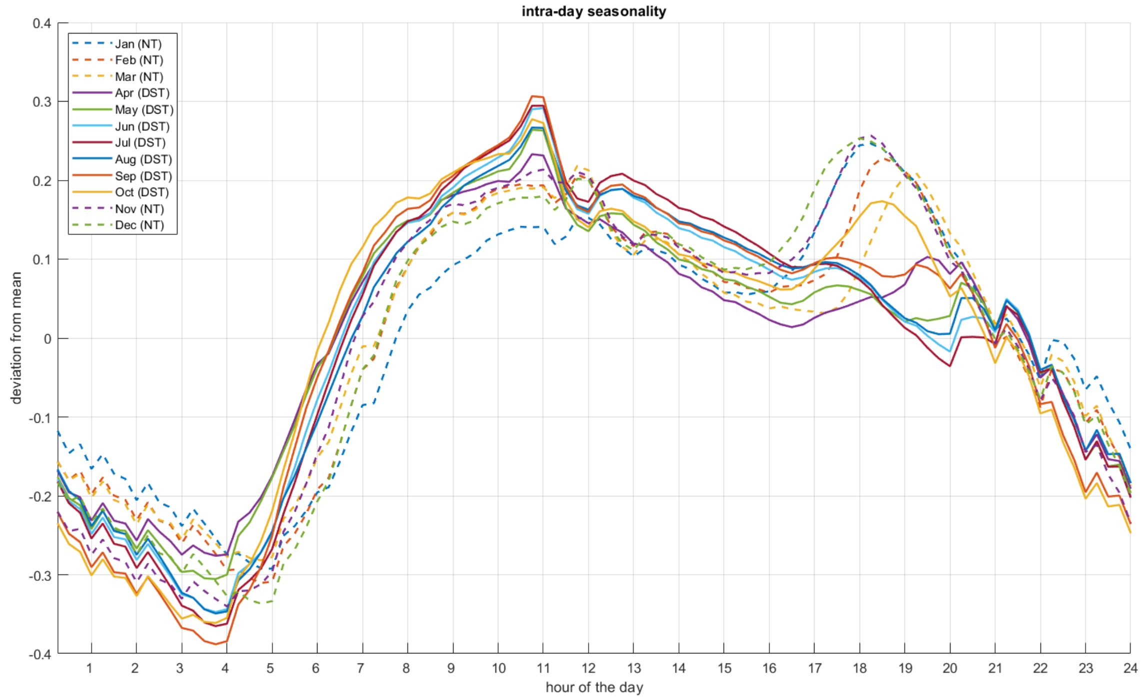

Figure 2: Intraday seasonality, conditional on the month of year.

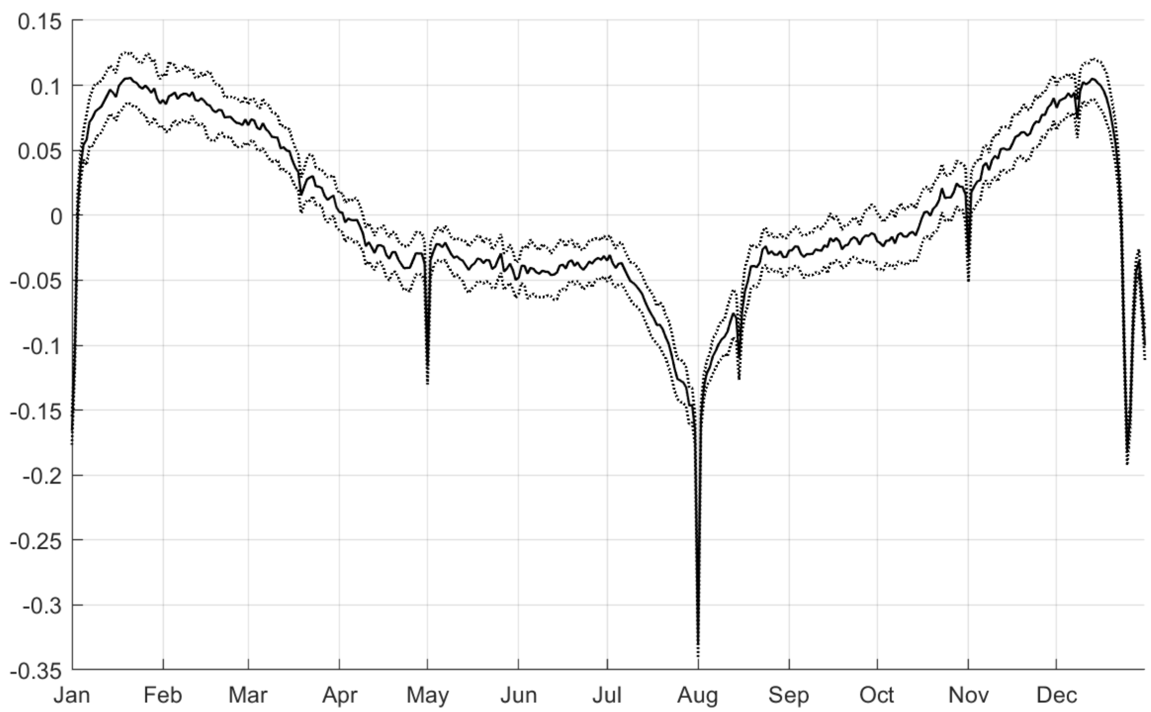

Figure 3: Daily seasonal factors (calendar-day fixed effects), with 95% confidence bands.

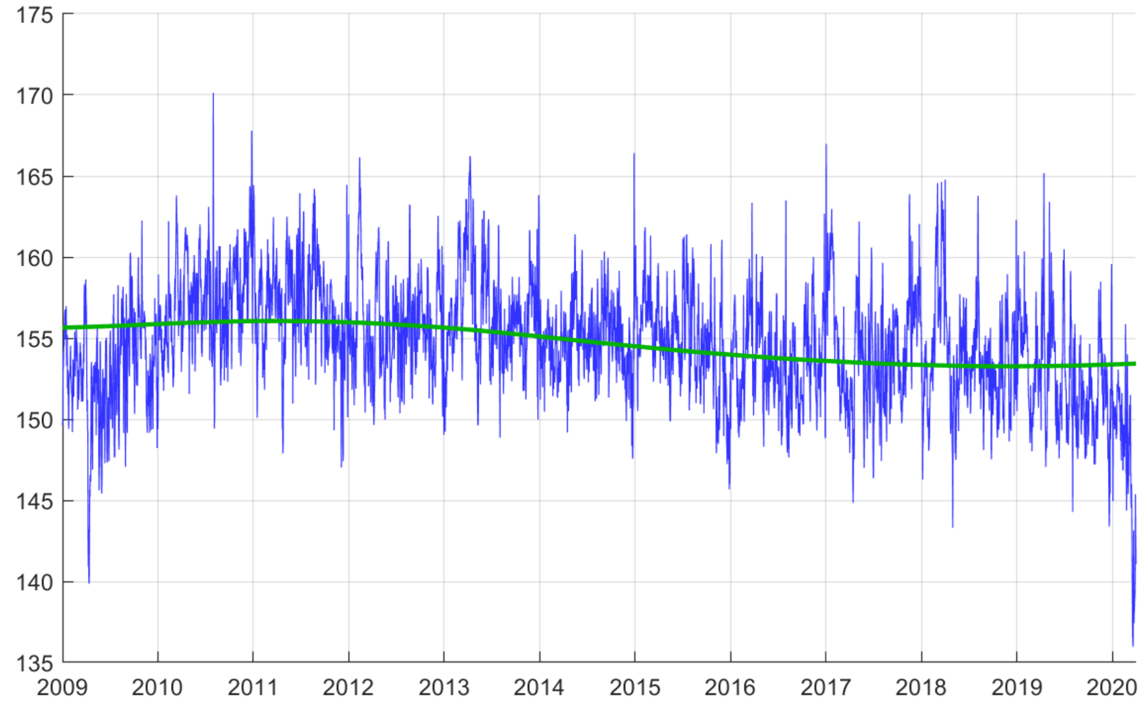

Figure 4: Daily data adjusted for weather, calendar effects, and seasonality (Z), together with the trend (Y^*).

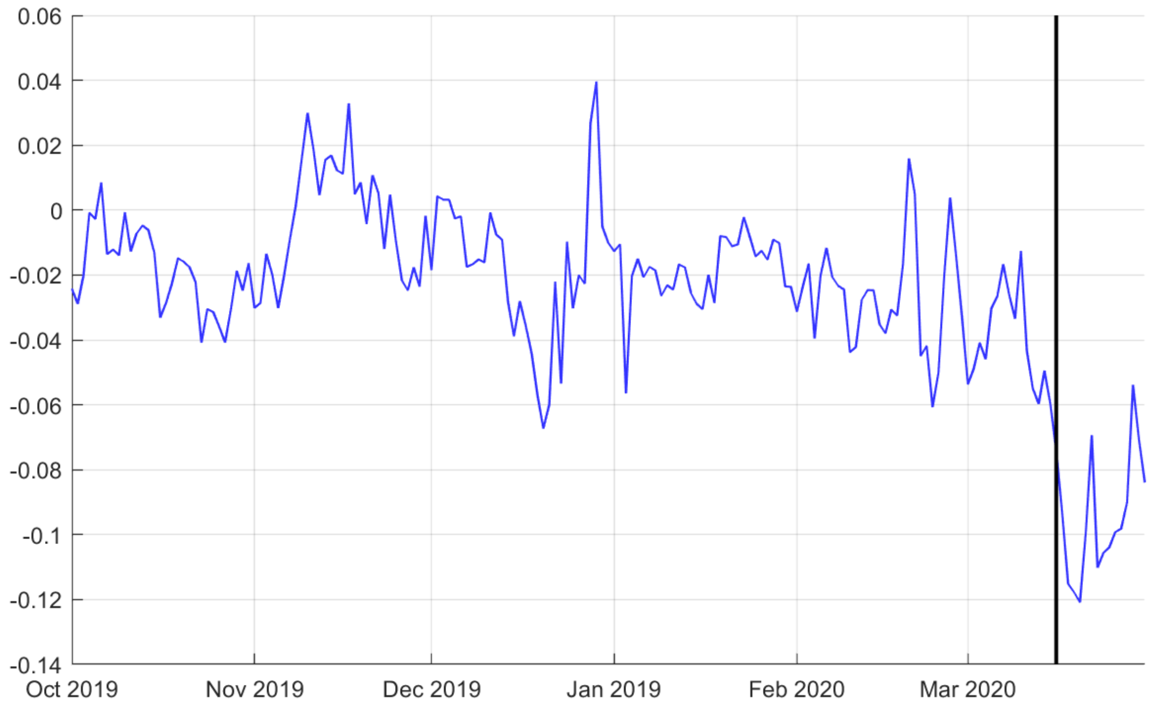

Figure 5: Relative gap (g) in the last six months of the sample. The full force of the shutdown became effective on March 16, 2020, indicated by the vertical line.

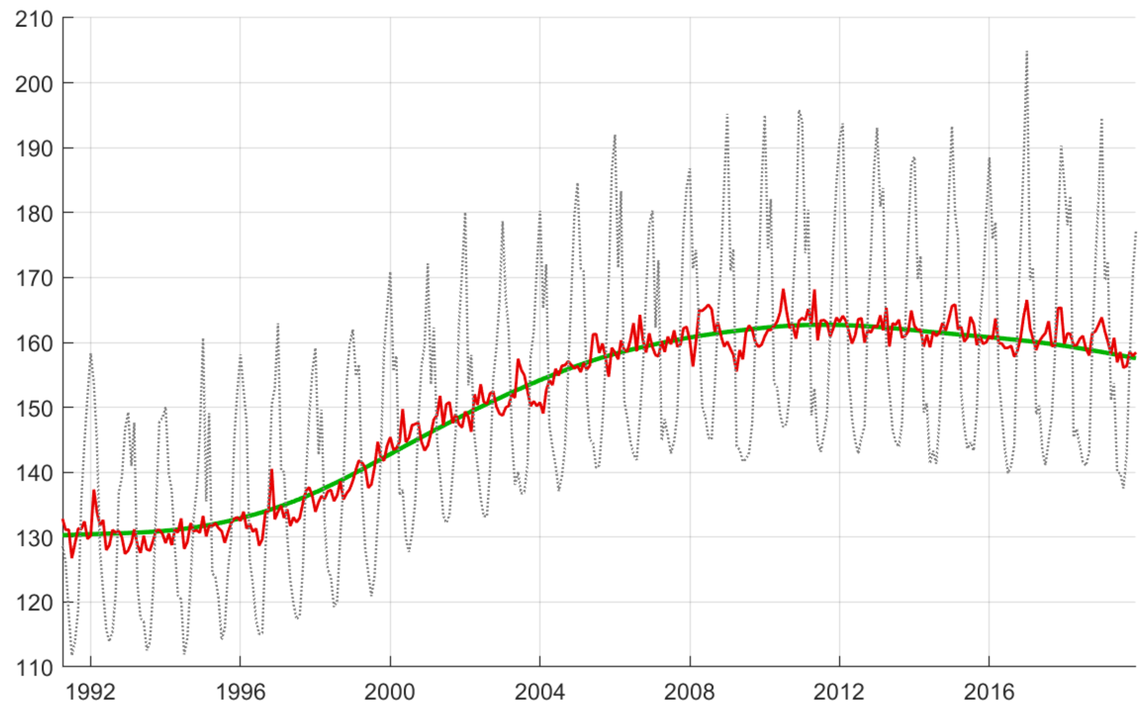

Figure 6: Montly data (Y), adjusted series (Z), and HP trend (Y^*) [measured in GWh]. The original data are divided by 30, to make them roughly comparable to the daily data.

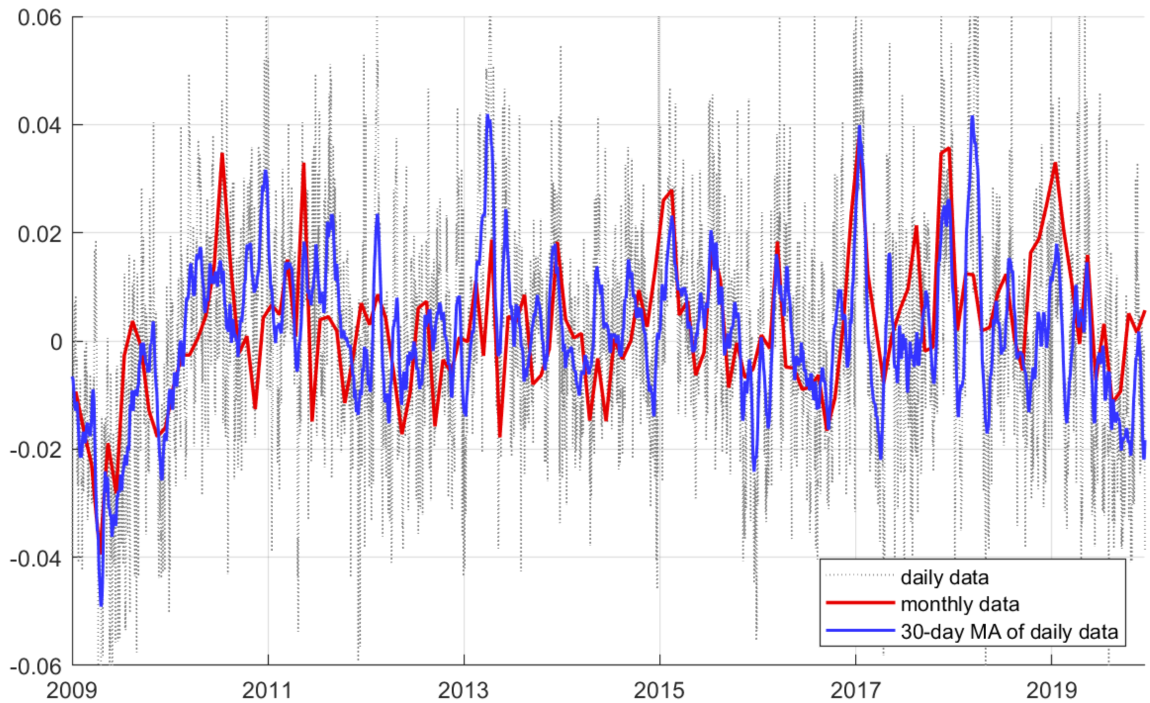

Figure 7: Relative gap (g), using monthly data (red), daily data (light dotted), and the 30-day central moving average of the daily gap.

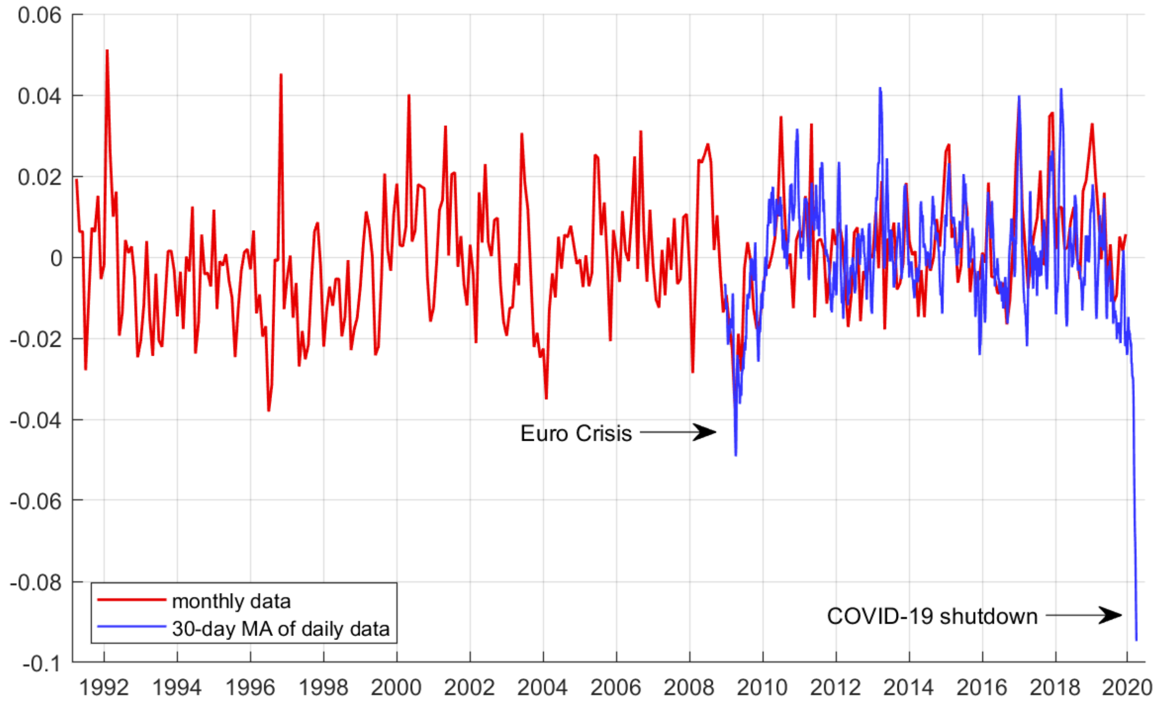

Figure 8: Monthly gap (g) in red, Apr 1991 to Dec 2019, and 30-day moving average of the daily gap in blue, Jan 2009 to March 2020.

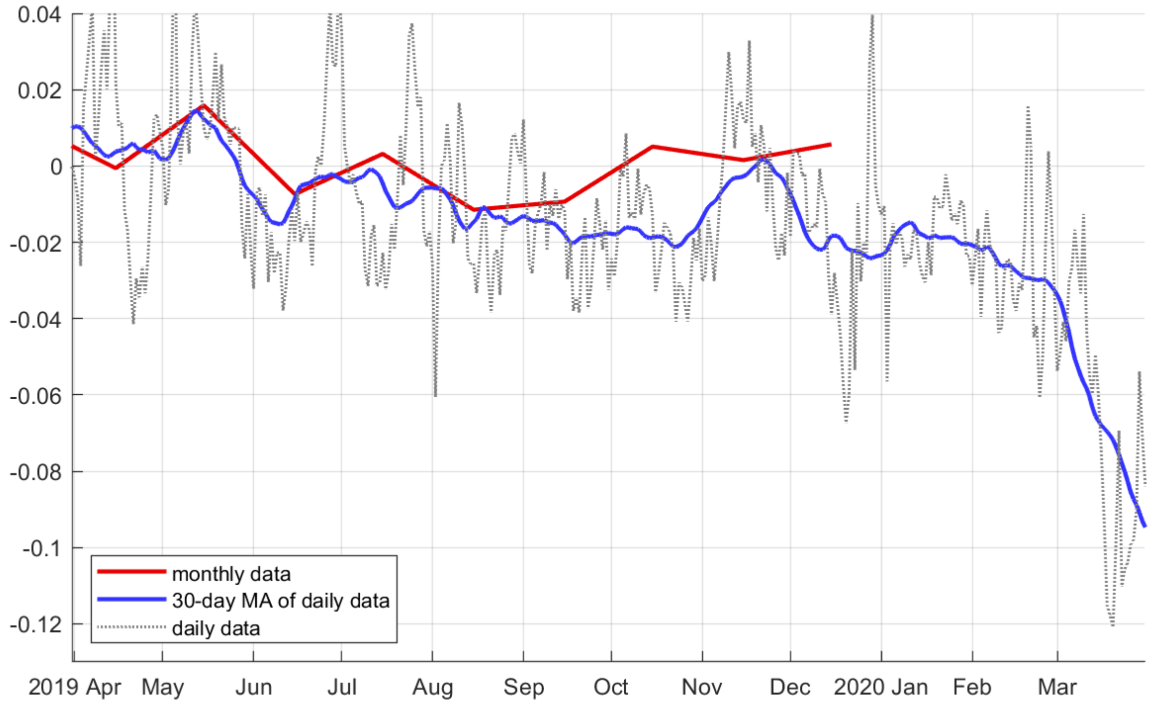

Figure 9: Monthly gap (g) (red), 30-day moving average of daily gap (blue), and daily gap (black dotted line). Last 12 months.