Electricity Prices & Renewable Generation

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2026-02-20

Overview

Motivation: Recall our motivation originally stemming from an interest in the "relative" volatility of fossil fuel versus renewable prices. After repeated discussion regarding the comparability of the two types of energy sources and scoping of the data available we pivoted to questions more directly related to "explaining"/investigating the recent spike in electricity prices (both in level and volatility) following a surge in natural gas prices and the Russian invasion of Ukraine and how it might have been mediated (or not) by increased renewable energy generation.

RQs: Though still to be workshopped, potential guiding questions along these lines (most follow from our past conversations):
1. To what extent, if any, does increased reliance on renewable sources of electricity insulate consumers or industry from the effects of spikes in electricity price inputs (ie. natural gas spike post-Ukraine)?
2. What are the costs (to electricity consumers - industrial and/or household) of recent increased price volatility and to what extent is greater renewable energy as a share of generating capacity a mediating or aggravating force?
3. Setting the price is an economic question - how efficiently does the market translate the true cost into price signals (ie. shifting share to lower cost renewables not yet filtering into price signals due to marginal price-setting in the market)?
4. What is the potential efficiency gain of switching to renewables even if it is not yet translated into prices?
5. Exogenous: use the connection of large wind or solar connections to the grid as plausible exogenous variation. See if there have been changes in capacity and whether they had any detectable effect on prices, all else equal.

Data: The below documents the data currently pulled to attempt a preliminary mean model of hourly wholesale electricity prices in Germany:
* *Wholesale Electricity Prices* (Hourly - EMBER)
* *Electricity Demand/Load* (Hourly - ENTSOE)
* *Electricity Generated by Energy Source* (Hourly - ENTSOE)
* *Various Commodity Price Indices* (Monthly - IMF)
* *Total and Country-Specific Net imports* (Hourly - ENTSOE)
* *Day-ahead Solar and Wind Forecasts* (Hourly - ENTSOE)
* *Redispatching Costs* ("Hourly" - netztransparenz.de - they are reported at a particular hour but are contracted for "implementation" over a certain multi-hour period, I think…as mentioned, to be investigate more)

Data that remains to be integrated:
* *Auction Bid Data* (Data on electricity auction bids - this would likely 1. help us determine if renewables set the market price (if ever) and 2. the variability in generation costs of fossil fuel providers)
* *Economic Activity* (GDP or VAT)

Data Issues: Several data issues cropped up in the process. I note the most glaring issues in **bold** throughout this notebook. Notably, the main issues are:
* the lower-frequency of certain candidate explanatory variables (ie. fuel and non-fuel commodity prices and

redispatching costs)
* missing data on net imports from France and Denmark in specific years (data exists but is not complete)
* how to aggregate the data on redispatching costs which are reported with hourly specificity but with different summarising metrics and "implementation horizons" (ie a load-balancing request made with a 4-hour implementation horizon). Fortunately, it does nto seem to be an issue of data availabilty but rather deeper thinking about what measure (and harmonisation across energy types) is most relevant for our ultimtate research question.

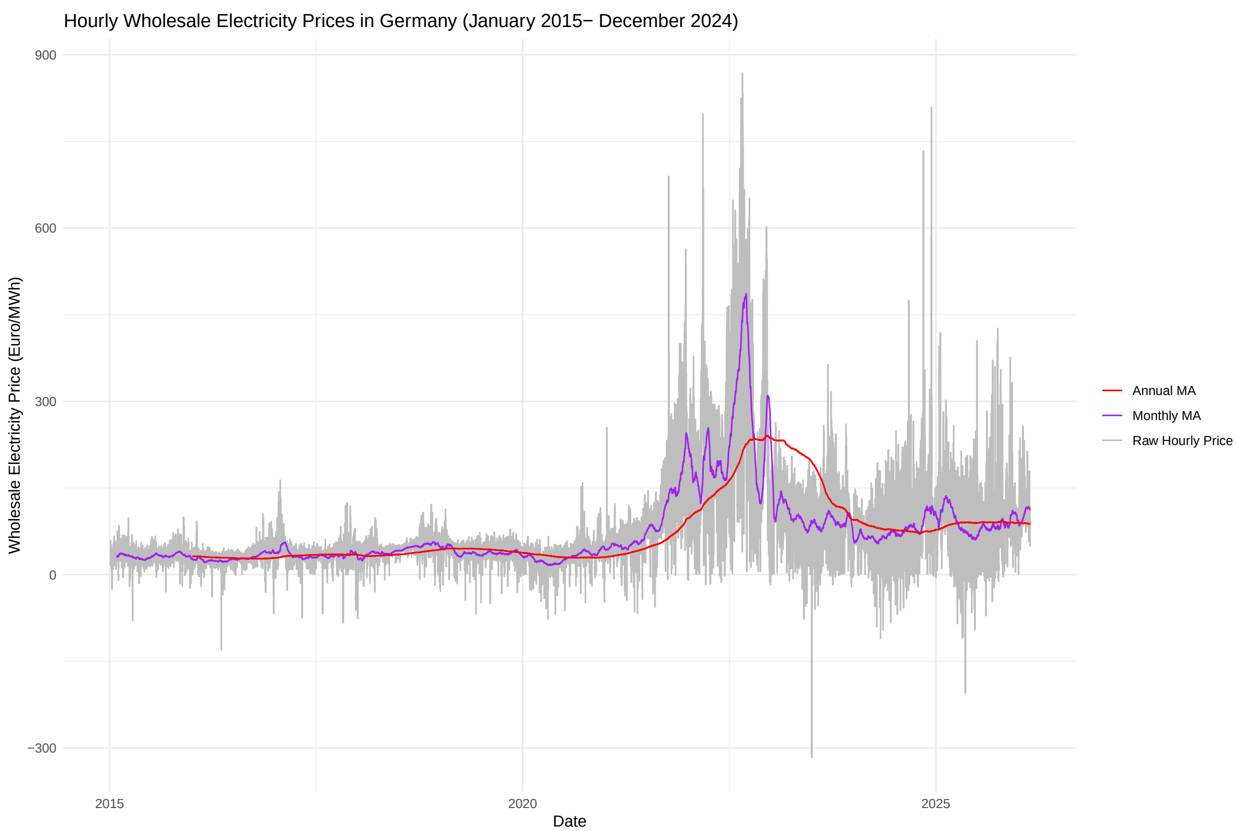
Model Attempt: Preliminary model attempt bringing this data together using gets under the "approaching a model. . . " tab.

Additional thoughts: Though, ultimately, it would be very ineresting to broaden to a multi-country scope (especially if this might allow for some comparative analysis on variable country-specific shares of renewable electricity generation), we decided to focus on Germany as a first case to see how we go. If/when we take the step to further countries, any data that I pull from ENTSO-E has an accompanying scraping script that could (reasonably) easily be repurposed to pull the identical data on other countries.

Start simple: Germany Only

Data

Using data from EMBER on European wholesale electricity prices (hourly - daily and monthly also exist). The hourly prices are the day-ahead wholesale prices in Germany.



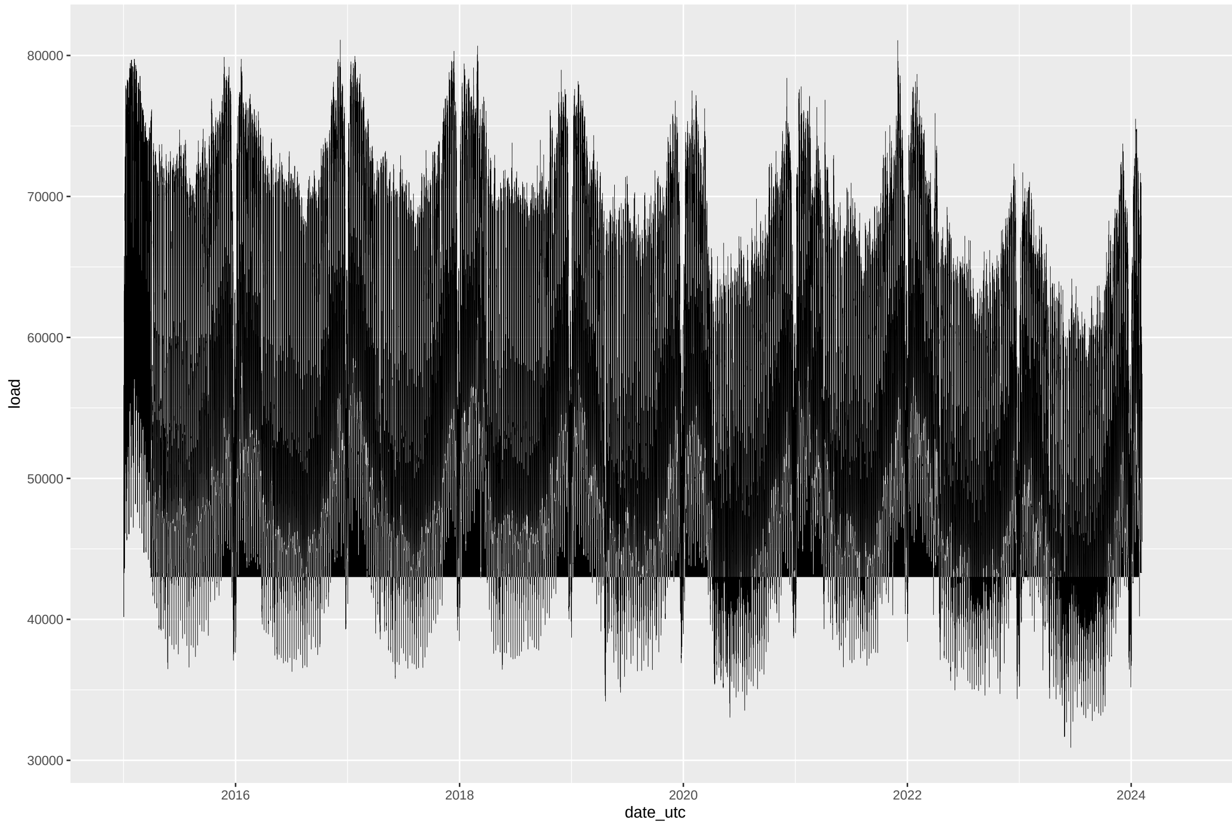
Electricity Demand/Load Total load per bidding zone per market time unit - in our case, total load, per country, per hour in MW.

Source

The following is data from ENTSO-E on hourly electricity loads.

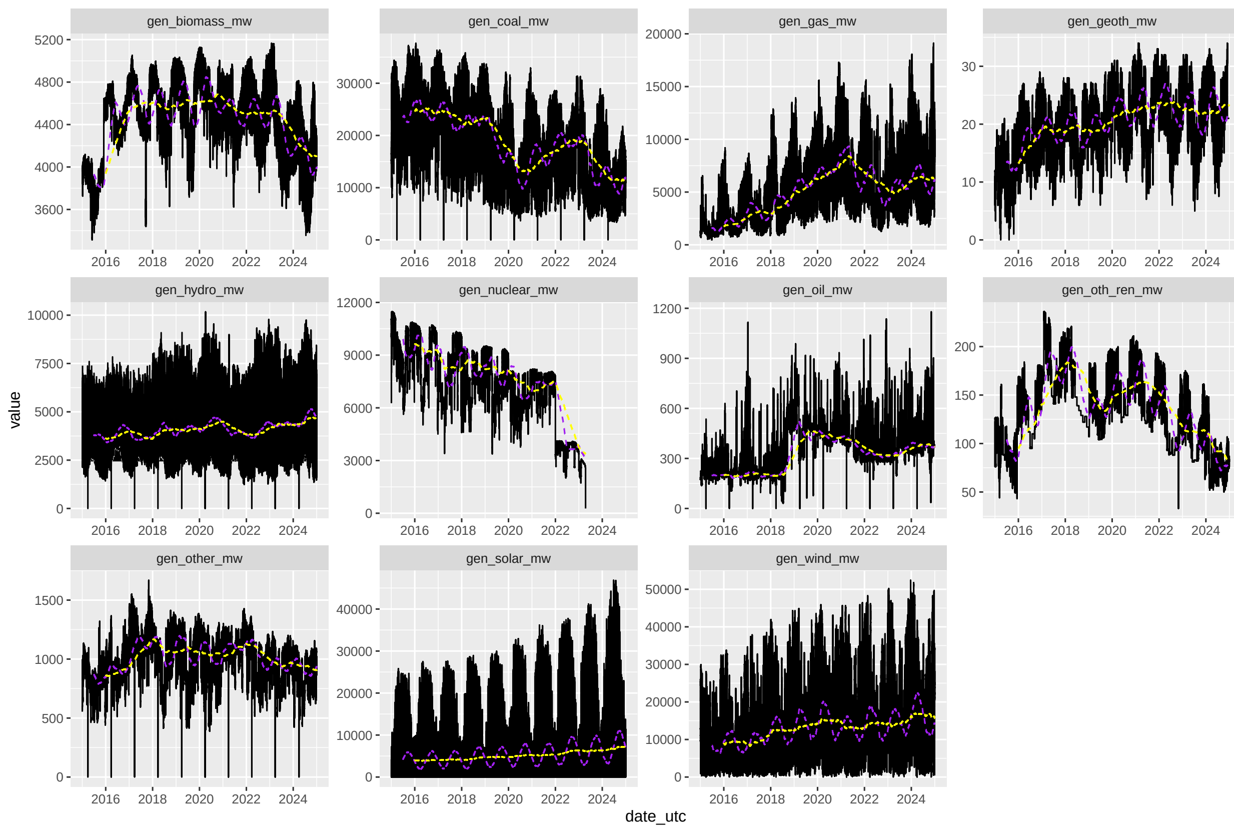
Components: Actual total load (including losses without stored energy) = net generation − exports + imports − absorbed energy

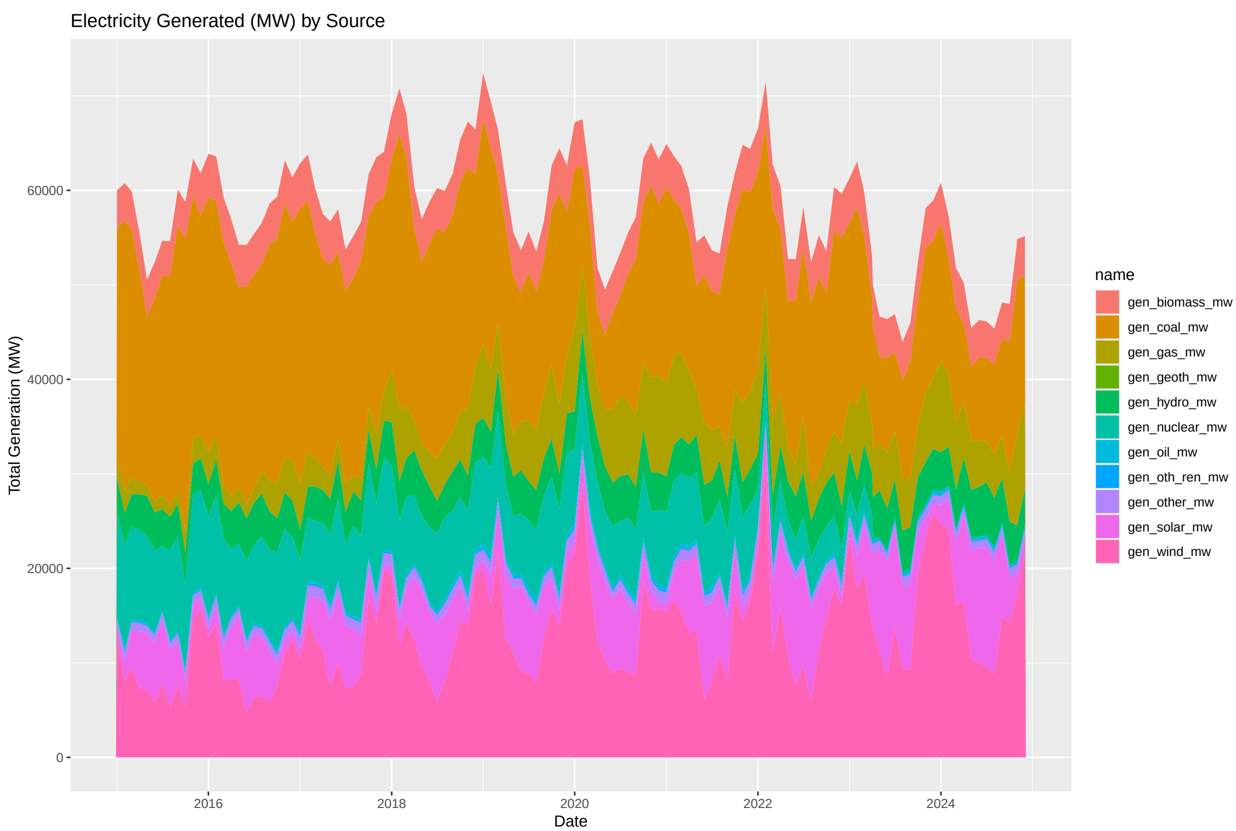
Something interesting happens in December of every year, holiday closures or a data issue?



Generation by Resource Actual Generation per Production Type from ENTSOE This value represents the actual aggregated net generation output in MW per market time unit (hour) and per production type.

Note: There is 1 observation missing per year (either 0 or NA) on a late day in march at 2 am. . . .a cleaning issue? Something silly?


gen_biomass_mw
gen_coal_mw
gen_gas_mw
gen_geoth_mw
gen_hydro_mw
gen_nuclear_mw
gen_oil_mw
gen_oth_ren_mw
gen_other_mw
gen_solar_mw
gen_wind_mw
value
date_utc


Electricity Generated (MW) by Source
Total Generation (MW)
Date
name
gen_biomass_mw
gen_coal_mw
gen_gas_mw
gen_geoth_mw
gen_hydro_mw
gen_nuclear_mw
gen_oil_mw
gen_oth_ren_mw
gen_other_mw
gen_solar_mw
gen_wind_mw

Fuel and Commodity Prices IMF provides *monthly* commodity prices and price indices.
Source: https://www.imf.org/en/Research/commodity-prices

The commodity prices listed below are:

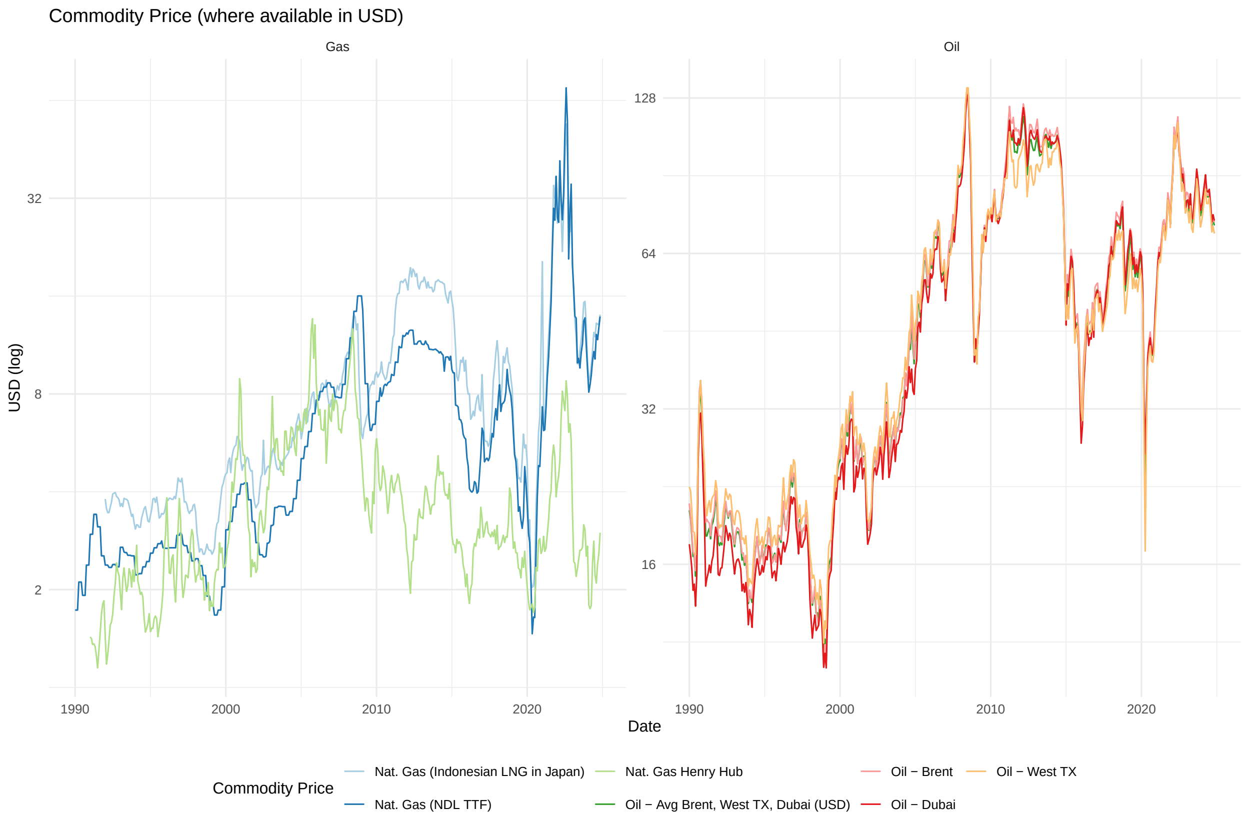
Note: These are MONTHLY values. I fill these values to hourly when merging the data later on.

I include the following three commodity prices in the model selection for now (final plot in this section):
* Natural Gas, Netherlands TTF Natural Gas Forward Day Ahead, US$ per Million Metric British Thermal Unit
* Fuel & Non-Fuel Commodities: All Commodity Price Index, 2016 = 100, includes both Fuel and Non-Fuel Price Indices
* Indust. Input Price: Industrial Inputs Price Index, 2016 = 100, includes Agricultural Raw Materials and Base Metals Price Indices

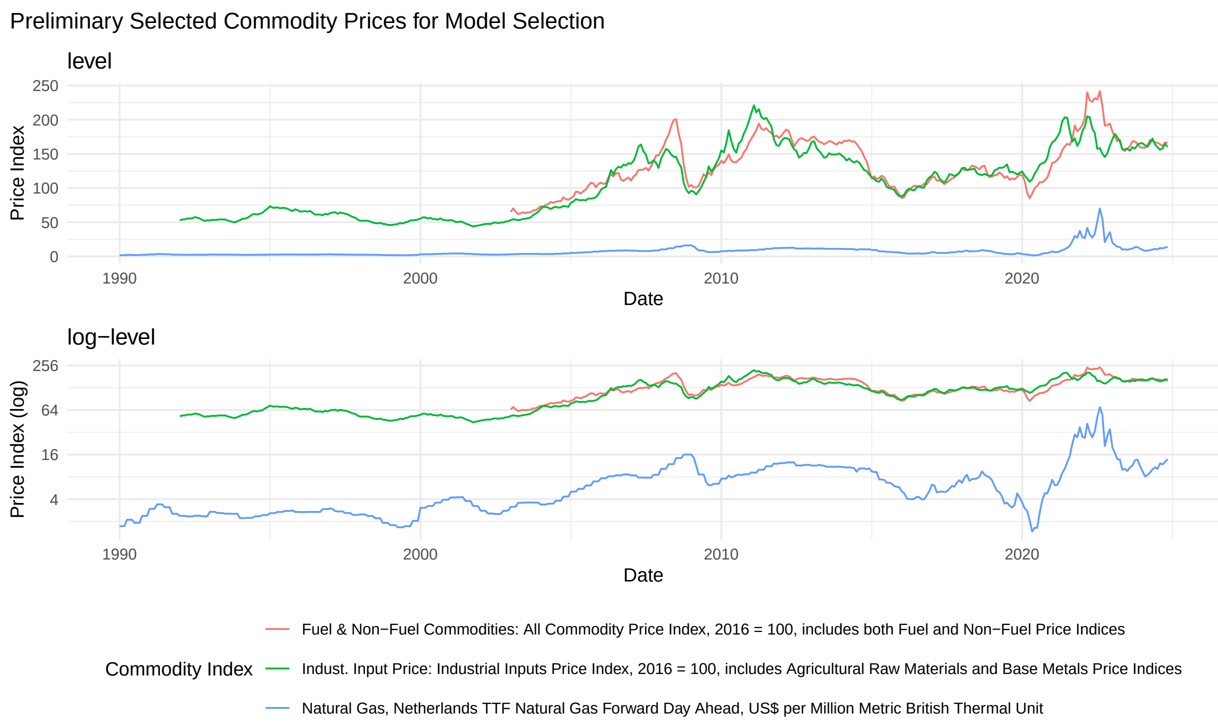
Note: We should probably rethink the non-natural gas prices (the latter two indices). The two latter indices are global indices and given the industrial structure of Germany we might want to consider a Producer Price Index for Germany specifically, assuming that exists? Additionally, as you can see in the graph, the latter two essentially trace each other/collinearity issues.

Commodity Type	Index Label (in plots)	Index Definition	Index Unit (USD or Index)
Coal	Coal	Coal Price Index, 2016 = 100, includes Australian and South African Coal	Index
Gas	Nat. Gas (NDL TTF)	Natural Gas, Netherlands TTF Natural Gas Forward Day Ahead, US$ per Million Metric British Thermal Unit	USD
Oil	Oil - Avg Brent, West TX, Dubai (USD)	Crude Oil (petroleum), Price index, 2016 = 100, simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh	USD
Oil	Oil - Brent	Crude Oil (petroleum), Dated Brent, light blend 38 API, fob U.K., US$ per barrel	USD
Oil	Oil - Dubai	Crude Oil (petroleum), Dubai Fateh Fateh 32 API, US$ per barrel	USD
Oil	Oil - West TX	Crude Oil (petroleum), West Texas Intermediate 40 API, Midland Texas, US$ per barrel	USD
Oil	Oil - Avg Brent, West TX, Dubai	Crude Oil (petroleum), Price index, 2016 = 100, simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh	Index
Gas	Nat. Gas Henry Hub	Natural Gas, Natural Gas spot price at the Henry Hub terminal in Louisiana, US$ per Million Metric British Thermal Unit	USD
Composite Commodity Indices	Indust. Input Price	Industrial Inputs Price Index, 2016 = 100, includes Agricultural Raw Materials and Base Metals Price Indices	Index
Composite Commodity Indices	Fuel (Energy - oil, ng, coal, propane)	Fuel (Energy) Index, 2016 = 100, includes Crude oil (petroleum), Natural Gas, Coal Price and Propane Indices	Index
Gas	Nat. Gas (Euro, Jap, American)	Natural Gas Price Index, 2016 = 100, includes European, Japanese, and American Natural Gas Price Indices	Index
Gas	Nat. Gas (Indonesian LNG in Japan)	Natural Gas, Indonesian Liquefied Natural Gas in Japan, US$ per Million Metric British Thermal Unit	USD

Commodity Type	Index Label (in plots)	Index Definition	Index Unit (USD or Index)
Composite Commodity Indices	Fuel & Non-Fuel Commodities	All Commodity Price Index, 2016 = 100, includes both Fuel and Non-Fuel Price Indices	Index
Nrg. Transition Input Material Prices	Nrg. Transition Metals Composite	Energy Transition Metal Index	Index
Nrg. Transition Input Material Prices	Battery-Grade Lithium	Lithium Metal =99%, Battery Grade	USD
Nrg. Transition Input Material Prices	Manganese	Manganese Electro CIF NWE (US$ perMT)	USD
Nrg. Transition Input Material Prices	Rare Earth Carbonate	Rare Earth Carbonate REO 42-45 Dom.	USD
Nrg. Transition Input Material Prices	Silicon Lumps	Silicon Lumps CIF NWE (US$ perMT)	USD
Nrg. Transition Input Material Prices	Vanad. Pentox.	Vanadium Pentoxide CIF NWE	USD


Commodity Price (where available in USD)
Gas
Oil
USD (log)
Date
Commodity Price
Nat. Gas (Indonesian LNG in Japan)
Nat. Gas (NDL TTF)
Nat. Gas Henry Hub
Oil − Avg Brent, West TX, Dubai (USD)
Oil − Brent
Oil − Dubai
Oil − West TX

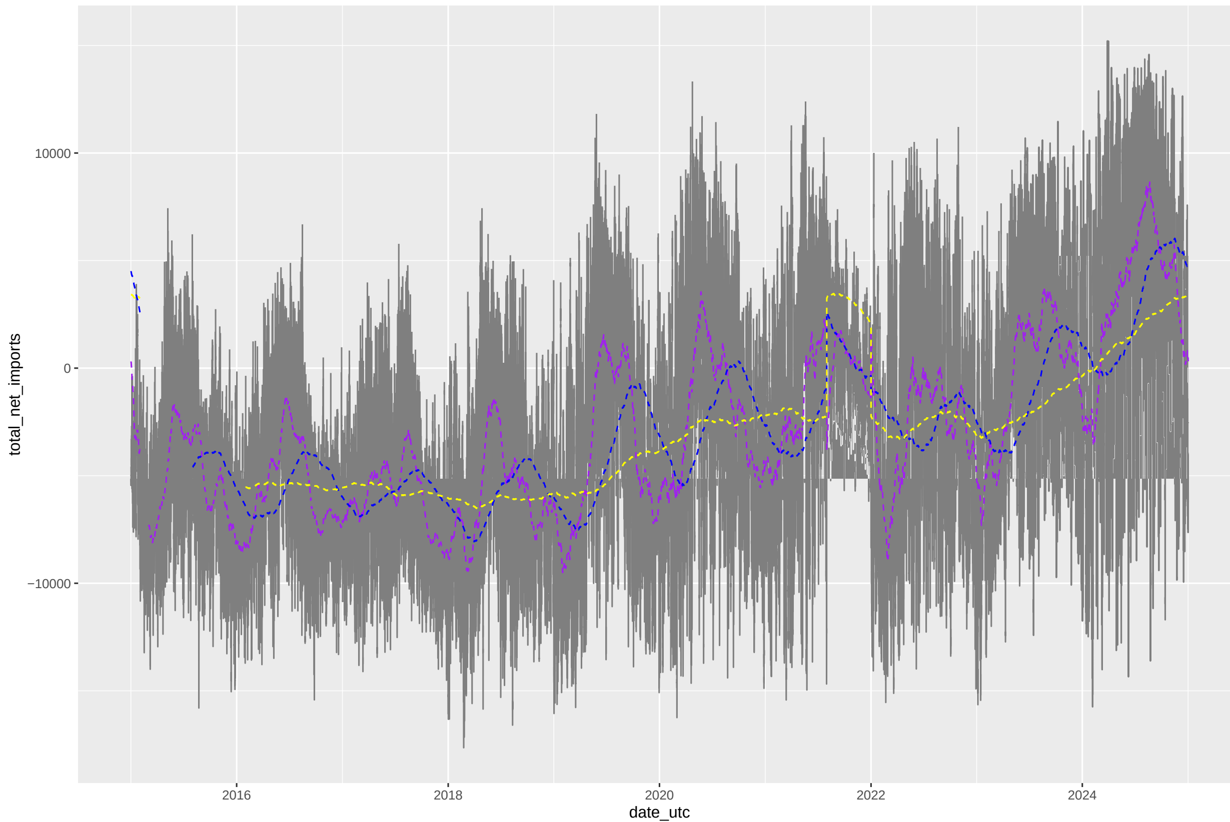

Commodity Price Indices
Index Value (log)
Date
Commodity Price Index
Coal
Fuel (Energy − oil, ng, coal, propane)
Fuel & Non−Fuel Commodities
Indust. Input Price
Nat. Gas (Euro, Jap, American)
Oil − Avg Brent, West TX, Dubai

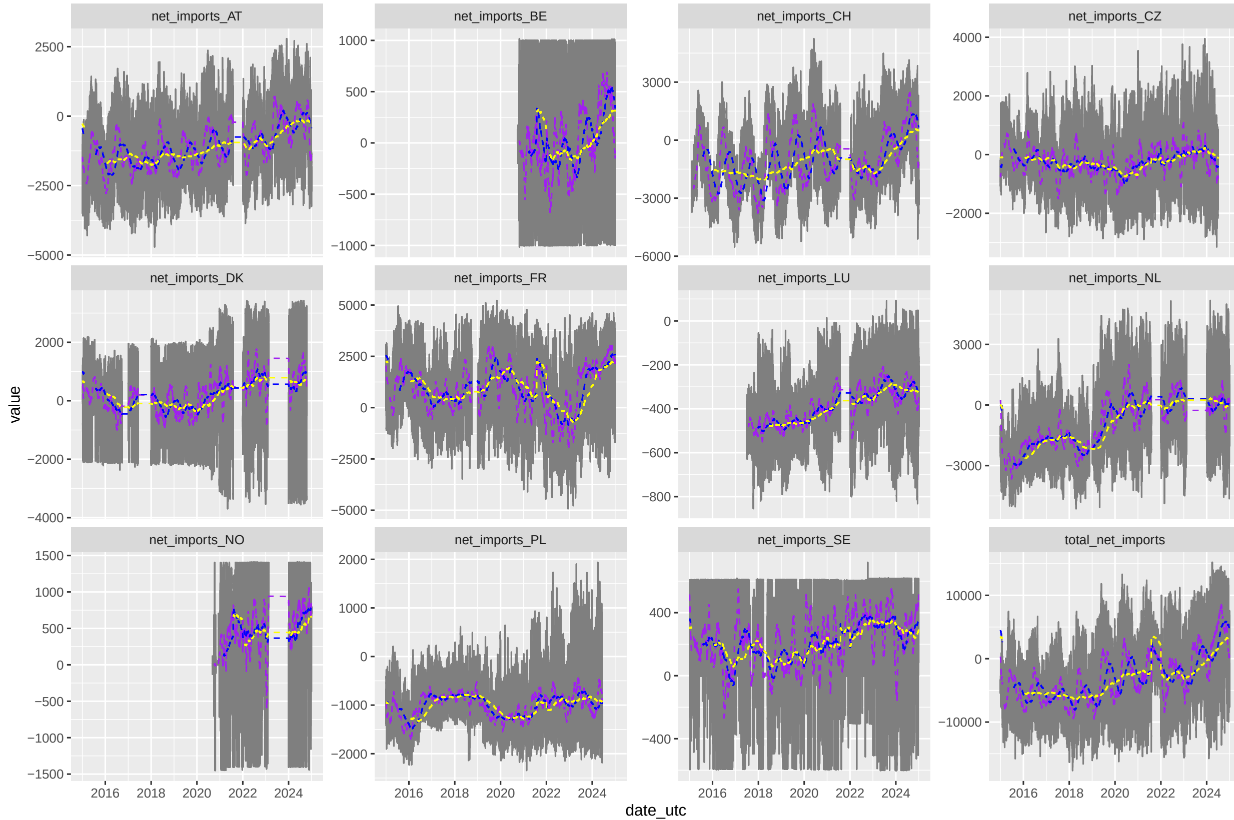


Net Imports Imports and export flows of electricity from ENTSOE Transparency Platform. Physical flows between bidding zones per market time unit.

Physical flow is defined as the measured real flow of energy between neighbouring bidding zones on the cross borders.

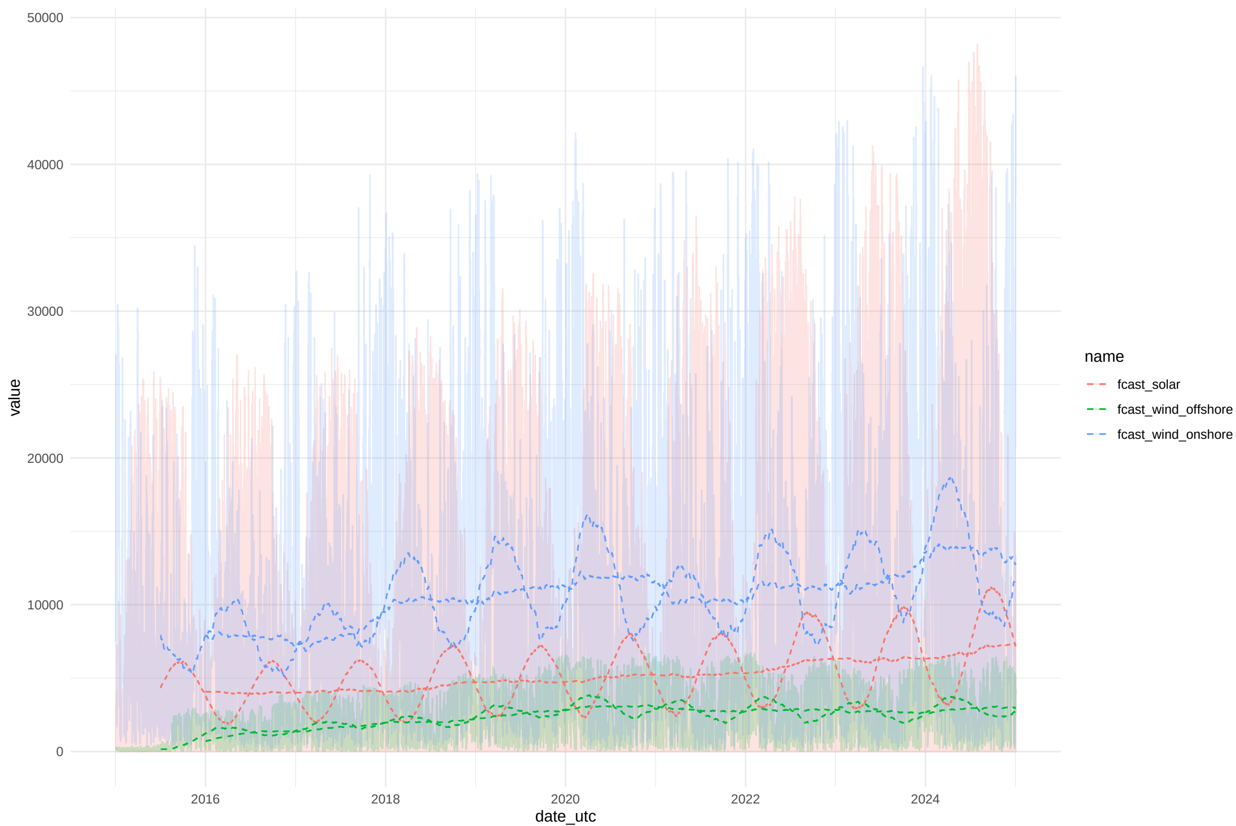
Note 1: Net imports still has some missing data and I'm not quite sure where it comes from (see Austria, Denmark, France, Switzerland).
Note 2: Also, the seeming upper and lower limits must have to do with capacity constraints on imports and exports (see Belgium, Norway, Sweden).





Day-ahead Solar and Wind Forecasts A forecast of wind and solar power generation (MW) per country per hour of the following day data from ENTSOE Transparency Platform.

Note: we need to consider the logical link between these forecasts and price-setting/auction behaviour.



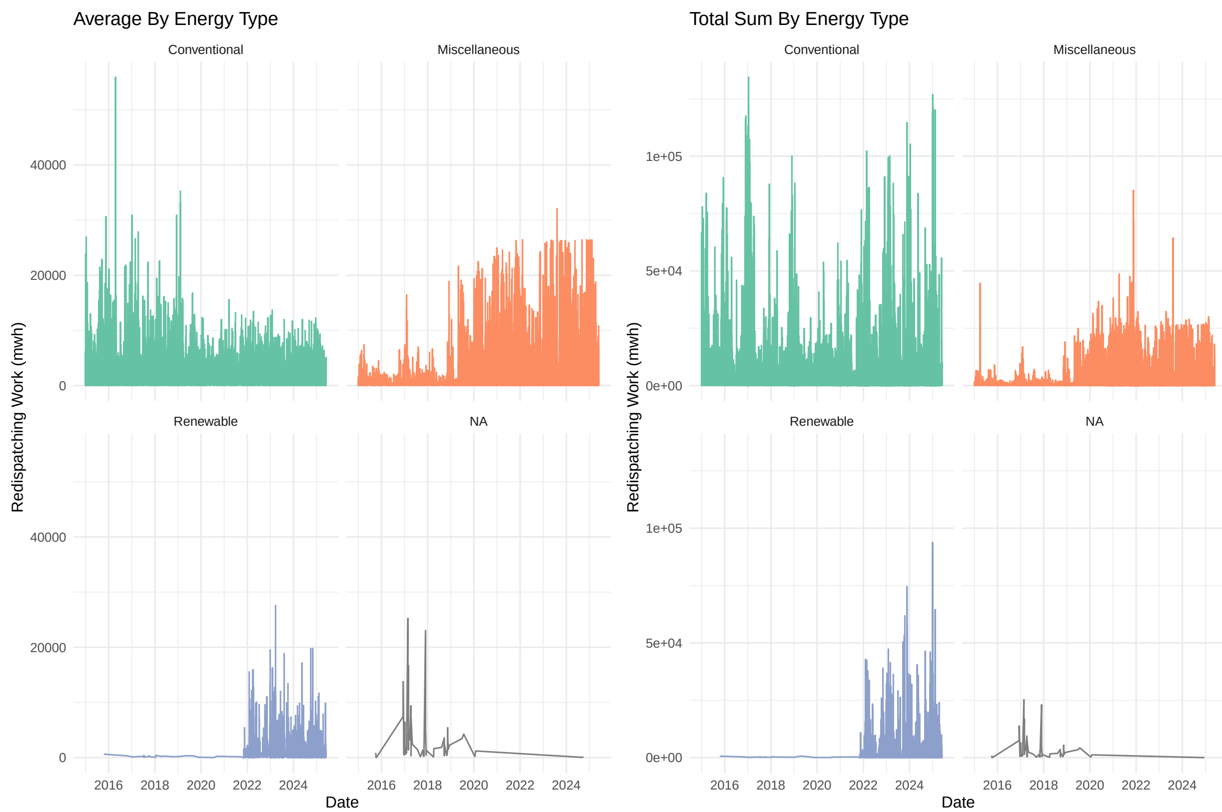
Redispatching Costs Four transmission system operators (TSOs) in Germany actively monitor the contracted transmission of electricity in the grid to ensure load-balancing "in the event of imminent overloads in the electricity grid."

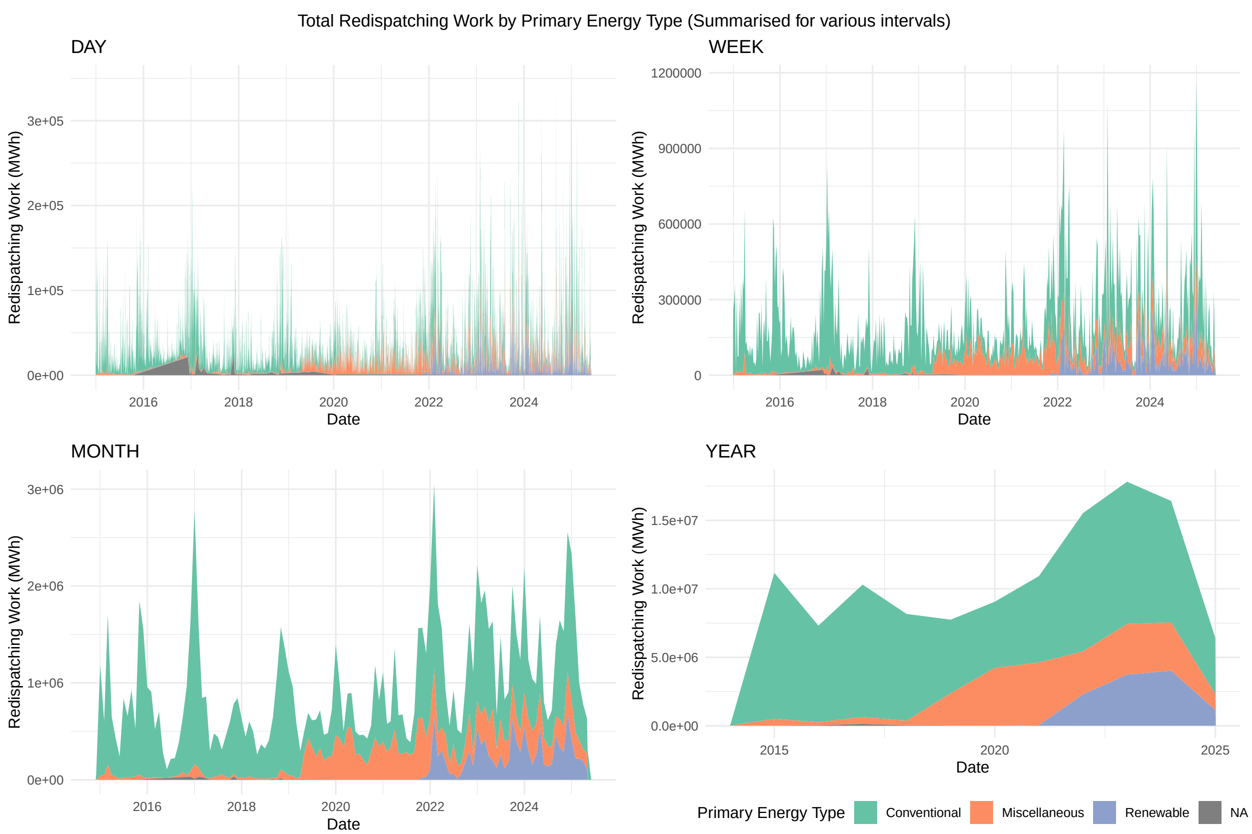
"Redispatch is a request to adjust the active power feed-in of plants (conventional power plants, CHP plants, renewable energy plants, storage facilities) by the grid operator with the aim of avoiding or eliminating any bottlenecks that occur. This measure can be applied within and across control areas. By reducing the active power feed-in of one or more systems while simultaneously increasing the active power feed-in of one or more other systems, the total active power feed-in remains almost unchanged while at the same time relieving a bottleneck" (NETZTRANSPARENZ.DE).

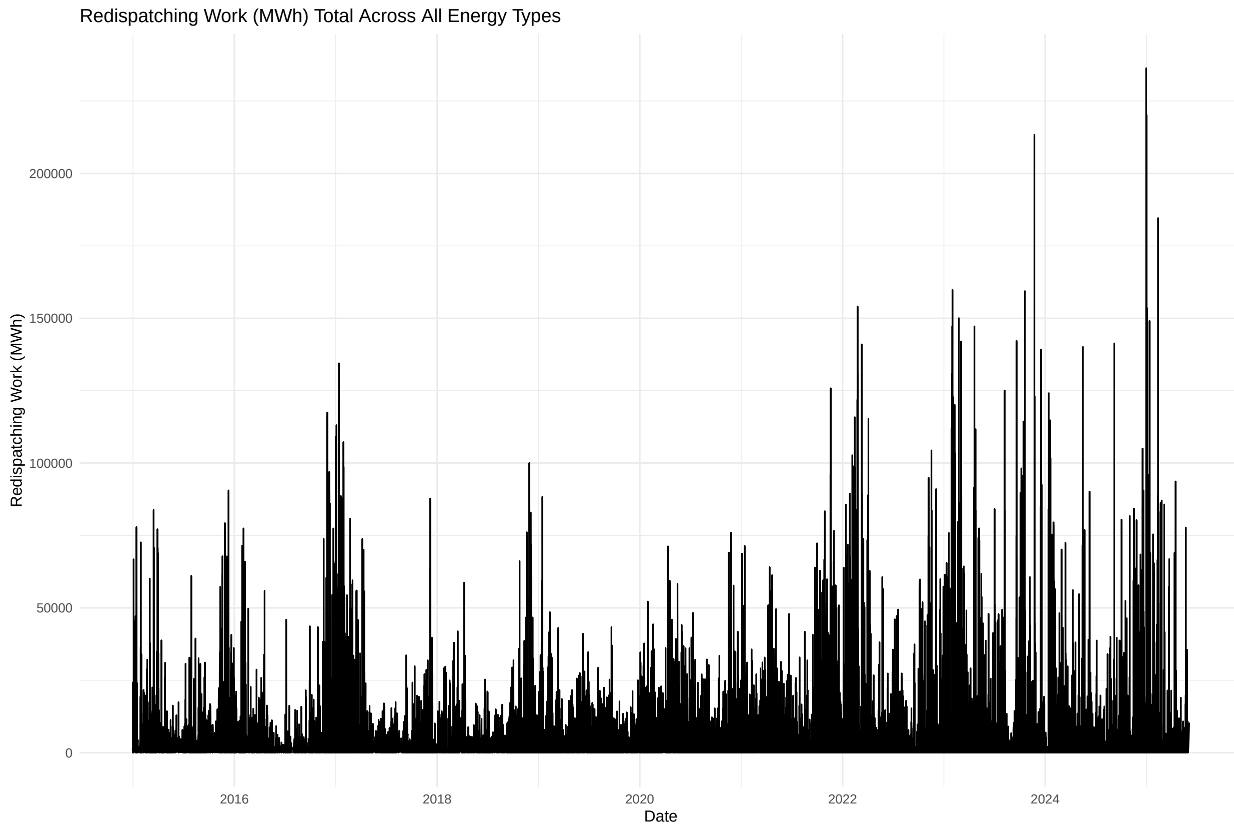
(NETZTRANSPARENZ.DE) provide data on redispatch measures for the average, maximum, and per-quarter-hour(??) MW reduction. I think the latter is most relevant. See example at the link above.

The plots below show the associated "redispatching work" by primary energy type (conventional, renewable, miscellaneous, and unspecified).

Note: This information is also available from ENTSO-E. We might consider using this data source instead for consistency.
Note: to summarise by time period, I use either the mean or sum total of the measure of "redispatching work in mwh." I am still not 100% sure what this means and whether this measure is most appropriate (or best summarised per hour as a sum or mean). We MUST revisit this data before implementation - NON-NEGOTIABLE.


Average By Energy Type
Total Sum By Energy Type
Conventional
Miscellaneous
Renewable
NA
Redispatching Work (mwh)
Date
40000
20000
0
1e+05
5e+04
0e+00
2016
2018
2020
2022
2024


Total Redispatching Work by Primary Energy Type (Summarised for various intervals)
DAY
WEEK
MONTH
YEAR
Redispatching Work (MWh)
Date
3e+05
2e+05
1e+05
0e+00
1200000
900000
600000
300000
0
3e+06
2e+06
1e+06
1.5e+07
1.0e+07
5.0e+06
0.0e+00
2015
2016
2018
2020
2022
2024
2025
Primary Energy Type
Conventional
Miscellaneous
Renewable
NA



Combining Data For transparency's sake, the code is below:
1. merge price, generation data by date-time and country-code
2. upper limit of TS to end of 2024
3. log transform with x + 1 to avoid zero value issues
4. create "share" values by dividing any generation variable by total load
5. for monthly commodity price values I fill these variables *forward*
6. Create hour and month dummies

Note: Potential transformation issues to discuss:
1. Forward-fill of monthly commodity price values
2. To deal with 0 values for certain variables I need to log_transform the value + 1. I don't think this is a major issue given the magnitude of these variables but worth reconsidering.
3. **(!!)** For net imports there are several observations for country-specific flows that are NA. Most result from NA values reported for both imports and exports at those hours. However, for Denmark (1,860 obs) and France (2,234 obs) this issue results from non-NA imports and NA exports. **THIS WILL ABSOLUTELY NEED TO BE REINVESTIGATED - WE CANNOT FORMALISE ANY RESULTS WITHOUT FINDING A WAY TO DEAL WITH THIS.**

```
de_all <- de_hourly_prices %>%
  rename(date_utc = datetime_utc) %>%
  left_join(., entsoe_de, by = c("date_utc", "country")) %>%
  left_join(., de_generation, by = c("date_utc", "country", "country_code")) %>%
  arrange(date_utc) %>%
  select(-starts_with("sum_")) %>%
  filter(date_utc < "2024-03-31 02:00:00" & !is.na(gen_biomass_mw)) %>%
  mutate(across(contains("gen"), ~log(. + 1), .names = "log_{.col}"),
         across(starts_with("gen"), ~./load, .names = "shr_{.col}"),
```

```
        log_load = log(load+1)) %>%
  left_join(., imp_exp, by = "date_utc") %>%
  mutate(across(contains("net_imports"), ~ifelse(is.na(.), 0, .)),
         shr_net_imports = total_net_imports/load) %>%
  left_join(., fcast_sw, by = "date_utc") %>%
  left_join(., redisp_df, by = "date_utc")

de_full <- de_all %>%
  left_join(., ng_price, by = "date_utc") %>%
  # We fill the monthly values down!
  fill(PNGASEU, .direction = "down") %>%
  fill(PALLFNF, .direction = "down") %>%
  fill(PINDU, .direction = "down") %>%
  # Given our redispatching data covers the 2015-2024 time period, it is safe to assume that NA values
  mutate(redisp_work_mwh = ifelse(is.na(redisp_work_mwh), 0, redisp_work_mwh),
         # Create hourly and monthly dummies
        hour = as.factor(hour(datetime_local)),
         month = as.factor(month(datetime_local)),
        log_redisp_mwh = log(redisp_work_mwh + 1),
        log_PNGASEU = log(PNGASEU + 1),
        log_PALLFNF = log(PALLFNF + 1),
        log_PINDU = log(PINDU + 1)) %>%
  dummy_cols(select_columns = c("hour", "month"), remove_first_dummy = TRUE, remove_selected_columns =
```

(TBA) Auction Bid Data

(TBA) Economic Activity

Approaching a model…

Below, I incorporate most explanatory variables (except solar and wind forecasts) above into models of the mean (not yet variance). The first model tab incorporates the variables simply as (log) levels whereas the second incorporates them as shares of total "load." In each tab, I run the model with the same set of regressors to be selected over but with or without a log.ewma argument. In line with Rintamaki et al, we incorporate moving average terms for half-day, daily, and weekly price volatility (levels?) via log.ewma argument (correct?). I need to think more closely about how that functions together with the hourly and monthly dummies.

Note: log.ewma() for half-day, daily, and weekly price volatilities? Correct idea?
Note: Hourly and daily dummies the best way to incorporate "seasonality"? How might this interfere with the ewma terms?
Note: I do not currently incorporate any ARCH terms.
Note: day-ahead versus current prices in all variables? - are we not interested in deviations from forecasts for price-setting?
Note: Finally, a basic question, but I do not currently have the output variable (hourly wholesale electricity prices) in logs as it frequently takes negative values)

```
# Check to make sure data is ordered
de_full %>% arrange(date_utc) %>% all.equal(de_full)
```

```
## [1] TRUE
```

```
reg_mat <- as.matrix(select(de_full,
```

```r
                                          'log_load',
                                          #'log_gen_biomass_mw',
                                          'log_gen_gas_mw',
                                          'log_gen_coal_mw',
                                          'log_gen_hydro_mw',
                                          'log_gen_geoth_mw',
                                          'log_gen_nuclear_mw',
                                          'log_gen_oth_ren_mw',
                                          'log_gen_solar_mw',
                                          'log_gen_wind_mw',
                                          'log_PNGASEU',
                                          'log_PALLFNF',
                                          'log_PINDU',
                                          contains('hour'),
                                          contains('month'),
                                          "net_imports_SE",
                                          "net_imports_PL",
                                          "net_imports_CZ",
                                          "net_imports_BE",
                                          "net_imports_CH",
                                          "net_imports_NO",
                                          "net_imports_NL",
                                          "net_imports_LU",
                                          "net_imports_FR",
                                          "net_imports_DK",
                                          "net_imports_AT",
                                          "log_redisp_mwh"
                                          #"total_net_imports" # Excluded as its sum components are each o
                                          )) # 'gen_wind_mw' 'gen_coal_mw', 'gen_hydro_mw',

de_mod_levs <- arx(de_full$price_eur_m_whe,
              # Question: In theory, the ARCH(24) would proxy the seasonal (daily) AR term?
              #arch = 1:24,
              mxreg = reg_mat)

de_mod_levs_logewma <- arx(de_full$price_eur_m_whe,
              # As in Rintamaki et al. the below line incorporates moving average terms for the half-da
              log.ewma = c(12, 24, 168),
              # Question: In theory, the ARCH(24) would proxy the seasonal (daily) AR term?
              #arch = 1:24,
              mxreg = reg_mat)

# model selection and plotting of residuals
de_levs_sel <- getsm(de_mod_levs, ar.LjungB = NULL, arch.LjungB = NULL)
```

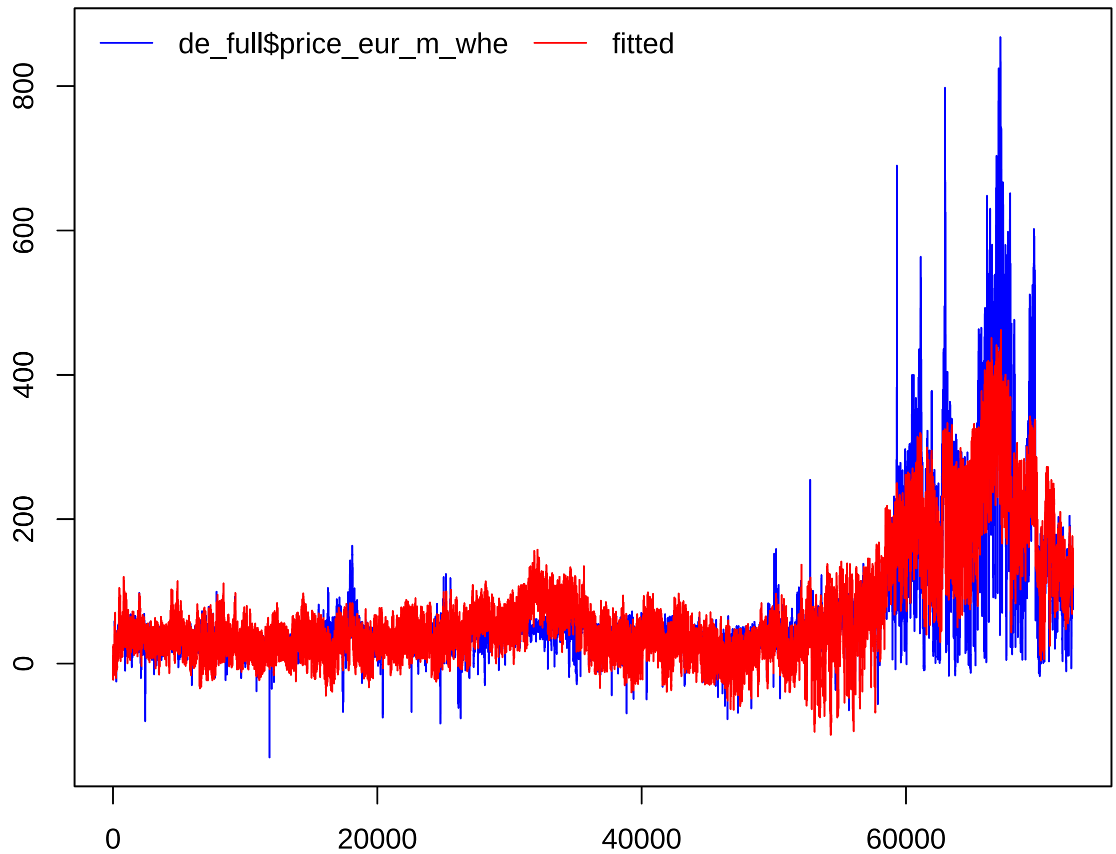
Levels as Exp. Vars.

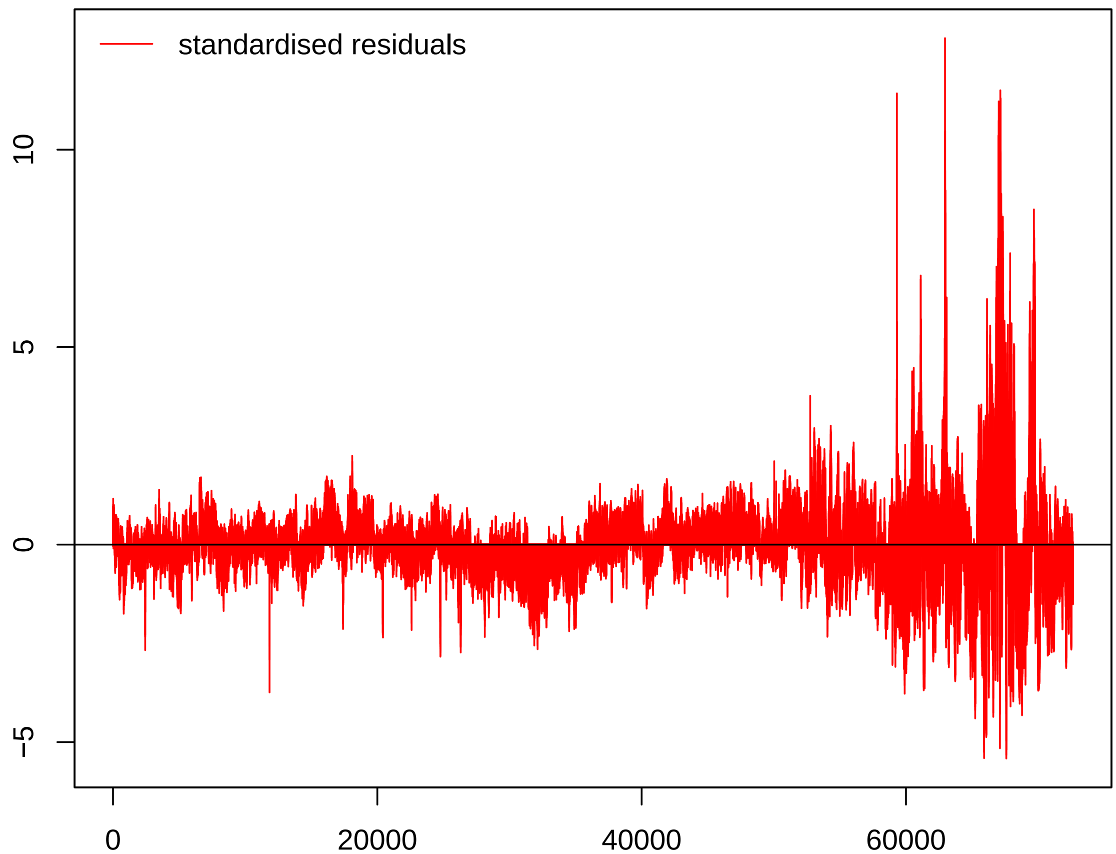
```
##
## GUM mean equation:
##
##                      reg.no. keep        coef   std.error    t-stat   p-value
## mconst                     1    0  3.2813e+02  2.0264e+01   16.1927 < 2.2e-16 ***
## log_load                   2    0  1.4265e+01  1.7982e+00    7.9330 2.170e-15 ***
## log_gen_gas_mw             3    0  2.9921e+01  4.1248e-01   72.5380 < 2.2e-16 ***
```

```
## log_gen_coal_mw          4    0 -1.0527e+01  6.9903e-01  -15.0591 < 2.2e-16 ***
## log_gen_hydro_mw         5    0 -4.2343e+00  4.9264e-01   -8.5952 < 2.2e-16 ***
## log_gen_geoth_mw         6    0  1.4893e+01  7.3486e-01   20.2671 < 2.2e-16 ***
## log_gen_nuclear_mw       7    0 -2.3938e+01  6.8937e-01  -34.7247 < 2.2e-16 ***
## log_gen_oth_ren_mw       8    0  1.4739e+01  7.9204e-01   18.6092 < 2.2e-16 ***
## log_gen_solar_mw         9    0  4.9120e-01  8.9646e-02    5.4793 4.283e-08 ***
## log_gen_wind_mw         10    0  6.2981e-01  2.5612e-01    2.4590 0.0139355 *
## log_PNGASEU             11    0  8.5731e+01  9.4949e-01   90.2917 < 2.2e-16 ***
## log_PALLFNF             12    0  9.4049e+01  3.5942e+00   26.1669 < 2.2e-16 ***
## log_PINDU               13    0 -2.2499e+02  2.1116e+00 -106.5502 < 2.2e-16 ***
## hour_1                  14    0 -1.7632e+00  1.0281e+00   -1.7150 0.0863563 .
## hour_2                  15    0 -5.8966e-01  1.0359e+00   -0.5692 0.5691916
## hour_3                  16    0 -9.6674e-01  1.0444e+00   -0.9256 0.3546547
## hour_4                  17    0  3.1430e-01  1.0517e+00    0.2988 0.7650584
## hour_5                  18    0  3.1167e+00  1.0512e+00    2.9649 0.0030284 **
## hour_6                  19    0  9.6352e+00  1.0577e+00    9.1098 < 2.2e-16 ***
## hour_7                  20    0  1.4310e+01  1.0842e+00   13.1982 < 2.2e-16 ***
## hour_8                  21    0  1.1163e+01  1.1569e+00    9.6493 < 2.2e-16 ***
## hour_9                  22    0  4.8684e+00  1.2666e+00    3.8435 0.0001214 ***
## hour_10                 23    0  9.3337e-02  1.3436e+00    0.0695 0.9446163
## hour_11                 24    0 -2.4434e+00  1.3952e+00   -1.7513 0.0799066 .
## hour_12                 25    0 -6.0279e+00  1.4129e+00   -4.2664 1.989e-05 ***
## hour_13                 26    0 -8.7513e+00  1.4188e+00   -6.1679 6.955e-10 ***
## hour_14                 27    0 -6.4457e+00  1.4069e+00   -4.5814 4.625e-06 ***
## hour_15                 28    0 -1.9415e+00  1.3882e+00   -1.3986 0.1619483
## hour_16                 29    0  3.6884e+00  1.3592e+00    2.7136 0.0066570 **
## hour_17                 30    0  1.3920e+01  1.3180e+00   10.5614 < 2.2e-16 ***
## hour_18                 31    0  1.8904e+01  1.2515e+00   15.1049 < 2.2e-16 ***
## hour_19                 32    0  1.5360e+01  1.2098e+00   12.6967 < 2.2e-16 ***
## hour_20                 33    0  8.0380e+00  1.1584e+00    6.9391 3.978e-12 ***
## hour_21                 34    0  3.5557e+00  1.1126e+00    3.1957 0.0013953 **
## hour_22                 35    0  3.4225e+00  1.0698e+00    3.1993 0.0013783 **
## hour_23                 36    0 -2.3987e+00  1.0416e+00   -2.3029 0.0212857 *
## month_2                 37    0  5.2213e+00  6.9419e-01    7.5213 5.484e-14 ***
## month_3                 38    0  1.2213e+01  6.9551e-01   17.5605 < 2.2e-16 ***
## month_4                 39    0  1.4991e+01  7.9217e-01   18.9242 < 2.2e-16 ***
## month_5                 40    0  1.6876e+01  8.9936e-01   18.7648 < 2.2e-16 ***
## month_6                 41    0  2.8414e+01  9.4585e-01   30.0407 < 2.2e-16 ***
## month_7                 42    0  2.8659e+01  9.1942e-01   31.1704 < 2.2e-16 ***
## month_8                 43    0  4.6855e+01  9.0613e-01   51.7089 < 2.2e-16 ***
## month_9                 44    0  3.0545e+01  8.2174e-01   37.1714 < 2.2e-16 ***
## month_10                45    0  6.8511e+00  7.6636e-01    8.9398 < 2.2e-16 ***
## month_11                46    0  1.2200e-01  7.2122e-01    0.1692 0.8656766
## month_12                47    0  1.3598e+01  7.1351e-01   19.0574 < 2.2e-16 ***
## net_imports_SE          48    0  3.6401e-03  5.7645e-04    6.3146 2.724e-10 ***
## net_imports_PL          49    0 -8.7696e-03  4.1434e-04  -21.1650 < 2.2e-16 ***
## net_imports_CZ          50    0  7.6347e-03  2.4742e-04   30.8569 < 2.2e-16 ***
## net_imports_BE          51    0  2.0309e-02  4.7000e-04   43.2104 < 2.2e-16 ***
## net_imports_CH          52    0  4.8365e-03  1.6588e-04   29.1570 < 2.2e-16 ***
## net_imports_NO          53    0  4.3056e-02  4.1139e-04  104.6607 < 2.2e-16 ***
## net_imports_NL          54    0  6.7014e-03  1.3600e-04   49.2758 < 2.2e-16 ***
## net_imports_LU          55    0 -8.9557e-03  8.8479e-04  -10.1218 < 2.2e-16 ***
## net_imports_FR          56    0 -6.0007e-03  1.2437e-04  -48.2490 < 2.2e-16 ***
## net_imports_DK          57    0  1.9053e-03  1.7998e-04   10.5858 < 2.2e-16 ***
```

```
## net_imports_AT          58    0 -5.1728e-05  2.7211e-04   -0.1901 0.8492326
## log_redisp_mwh          59    0 -4.7653e-01  5.1345e-02   -9.2809 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Diagnostics:
##
##                   Chi-sq df p-value
## Ljung-Box AR(1)    66776  1       0
## Ljung-Box ARCH(1)  63312  1       0

## 9 path(s) to search

## Searching: 1 2 3 4 5 6 7 8 9

##
##   Path 1: 14 16 58 46 15 23 17 28 24
##   Path 2: 15 46 58 23 17 16 14 28 24
##   Path 3: 16 15 58 46 23 17 14 28 24
##   Path 4: 17 23 46 58 15 16 14 28 24
##   Path 5: 23 46 58 17 15 16 14 28 24
##   Path 6: 24 15 58 46 28 16 14 36 17
##   Path 7: 28 15 58 46 16 24 14 36 17
##   Path 8: 46 23 58 17 15 16 14 28 24
##   Path 9: 58 23 46 17 15 16 14 28 24
##
## Terminal models:
##
##                 info(sc)      logl     n  k
## spec 1 (1-cut): 10.14578 -368210.0 72639 50
## spec 2:         10.14576 -368209.1 72639 50
##
## Retained regressors (final model):
##
##   mconst   log_load   log_gen_gas_mw   log_gen_coal_mw   log_gen_hydro_mw   log_gen_geoth_mw   log_g
```

```
de_levs_sel %>% plot
```


de_full$price_eur_m_whe
fitted
800
600
400
200
0
0
20000
40000
60000

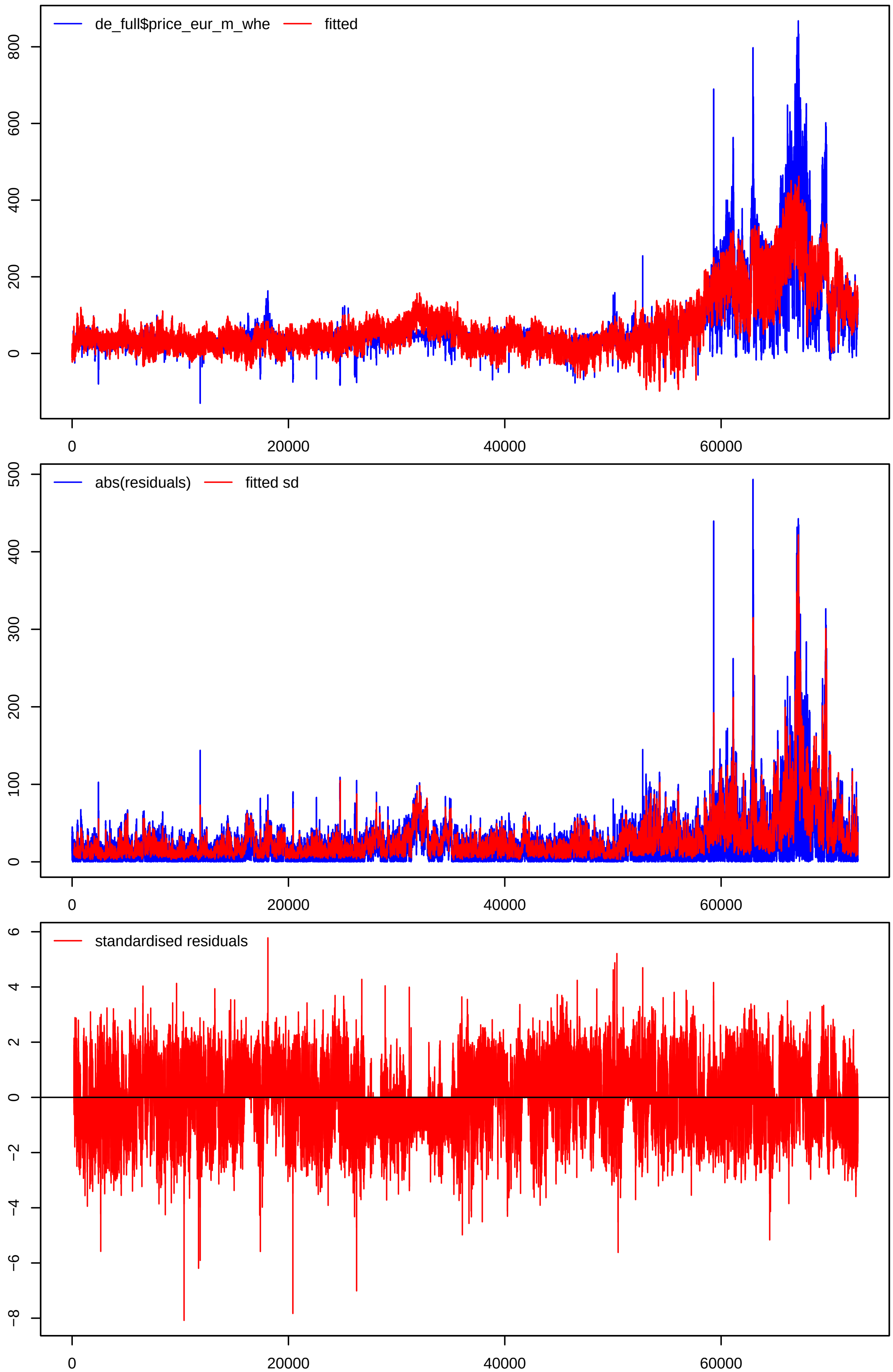

standardised residuals
10
5
0
−5
0
20000
40000
60000

```r
de_levs_sel_logewma <- getsm(de_mod_levs_logewma, ar.LjungB = NULL, arch.LjungB = NULL)
```

```
##
## GUM mean equation:
##
##                    reg.no. keep         coef   std.error    t-stat   p-value
## mconst                   1    0  3.2813e+02  2.0264e+01   16.1927 < 2.2e-16 ***
## log_load                 2    0  1.4265e+01  1.7982e+00    7.9330 2.170e-15 ***
## log_gen_gas_mw           3    0  2.9921e+01  4.1248e-01   72.5380 < 2.2e-16 ***
## log_gen_coal_mw          4    0 -1.0527e+01  6.9903e-01  -15.0591 < 2.2e-16 ***
## log_gen_hydro_mw         5    0 -4.2343e+00  4.9264e-01   -8.5952 < 2.2e-16 ***
## log_gen_geoth_mw         6    0  1.4893e+01  7.3486e-01   20.2671 < 2.2e-16 ***
## log_gen_nuclear_mw       7    0 -2.3938e+01  6.8937e-01  -34.7247 < 2.2e-16 ***
## log_gen_oth_ren_mw       8    0  1.4739e+01  7.9204e-01   18.6092 < 2.2e-16 ***
## log_gen_solar_mw         9    0  4.9120e-01  8.9646e-02    5.4793 4.283e-08 ***
## log_gen_wind_mw         10    0  6.2981e-01  2.5612e-01    2.4590 0.0139355 *
## log_PNGASEU             11    0  8.5731e+01  9.4949e-01   90.2917 < 2.2e-16 ***
## log_PALLFNF             12    0  9.4049e+01  3.5942e+00   26.1669 < 2.2e-16 ***
## log_PINDU               13    0 -2.2499e+02  2.1116e+00 -106.5502 < 2.2e-16 ***
## hour_1                  14    0 -1.7632e+00  1.0281e+00   -1.7150 0.0863563 .
## hour_2                  15    0 -5.8966e-01  1.0359e+00   -0.5692 0.5691916
## hour_3                  16    0 -9.6674e-01  1.0444e+00   -0.9256 0.3546547
## hour_4                  17    0  3.1430e-01  1.0517e+00    0.2988 0.7650584
## hour_5                  18    0  3.1167e+00  1.0512e+00    2.9649 0.0030284 **
## hour_6                  19    0  9.6352e+00  1.0577e+00    9.1098 < 2.2e-16 ***
## hour_7                  20    0  1.4310e+01  1.0842e+00   13.1982 < 2.2e-16 ***
## hour_8                  21    0  1.1163e+01  1.1569e+00    9.6493 < 2.2e-16 ***
## hour_9                  22    0  4.8684e+00  1.2666e+00    3.8435 0.0001214 ***
## hour_10                 23    0  9.3337e-02  1.3436e+00    0.0695 0.9446163
## hour_11                 24    0 -2.4434e+00  1.3952e+00   -1.7513 0.0799066 .
## hour_12                 25    0 -6.0279e+00  1.4129e+00   -4.2664 1.989e-05 ***
## hour_13                 26    0 -8.7513e+00  1.4188e+00   -6.1679 6.955e-10 ***
## hour_14                 27    0 -6.4457e+00  1.4069e+00   -4.5814 4.625e-06 ***
## hour_15                 28    0 -1.9415e+00  1.3882e+00   -1.3986 0.1619483
## hour_16                 29    0  3.6884e+00  1.3592e+00    2.7136 0.0066570 **
## hour_17                 30    0  1.3920e+01  1.3180e+00   10.5614 < 2.2e-16 ***
## hour_18                 31    0  1.8904e+01  1.2515e+00   15.1049 < 2.2e-16 ***
## hour_19                 32    0  1.5360e+01  1.2098e+00   12.6967 < 2.2e-16 ***
## hour_20                 33    0  8.0380e+00  1.1584e+00    6.9391 3.978e-12 ***
## hour_21                 34    0  3.5557e+00  1.1126e+00    3.1957 0.0013953 **
## hour_22                 35    0  3.4225e+00  1.0698e+00    3.1993 0.0013783 **
## hour_23                 36    0 -2.3987e+00  1.0416e+00   -2.3029 0.0212857 *
## month_2                 37    0  5.2213e+00  6.9419e-01    7.5213 5.484e-14 ***
## month_3                 38    0  1.2213e+01  6.9551e-01   17.5605 < 2.2e-16 ***
## month_4                 39    0  1.4991e+01  7.9217e-01   18.9242 < 2.2e-16 ***
## month_5                 40    0  1.6876e+01  8.9936e-01   18.7648 < 2.2e-16 ***
## month_6                 41    0  2.8414e+01  9.4585e-01   30.0407 < 2.2e-16 ***
## month_7                 42    0  2.8659e+01  9.1942e-01   31.1704 < 2.2e-16 ***
## month_8                 43    0  4.6855e+01  9.0613e-01   51.7089 < 2.2e-16 ***
## month_9                 44    0  3.0545e+01  8.2174e-01   37.1714 < 2.2e-16 ***
## month_10                45    0  6.8511e+00  7.6636e-01    8.9398 < 2.2e-16 ***
## month_11                46    0  1.2200e-01  7.2122e-01    0.1692 0.8656766
## month_12                47    0  1.3598e+01  7.1351e-01   19.0574 < 2.2e-16 ***
## net_imports_SE          48    0  3.6401e-03  5.7645e-04    6.3146 2.724e-10 ***
```

```
## net_imports_PL         49    0 -8.7696e-03  4.1434e-04  -21.1650 < 2.2e-16 ***
## net_imports_CZ         50    0  7.6347e-03  2.4742e-04   30.8569 < 2.2e-16 ***
## net_imports_BE         51    0  2.0309e-02  4.7000e-04   43.2104 < 2.2e-16 ***
## net_imports_CH         52    0  4.8365e-03  1.6588e-04   29.1570 < 2.2e-16 ***
## net_imports_NO         53    0  4.3056e-02  4.1139e-04  104.6607 < 2.2e-16 ***
## net_imports_NL         54    0  6.7014e-03  1.3600e-04   49.2758 < 2.2e-16 ***
## net_imports_LU         55    0 -8.9557e-03  8.8479e-04  -10.1218 < 2.2e-16 ***
## net_imports_FR         56    0 -6.0007e-03  1.2437e-04  -48.2490 < 2.2e-16 ***
## net_imports_DK         57    0  1.9053e-03  1.7998e-04   10.5858 < 2.2e-16 ***
## net_imports_AT         58    0 -5.1728e-05  2.7211e-04   -0.1901 0.8492326
## log_redisp_mwh         59    0 -4.7653e-01  5.1345e-02   -9.2809 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## GUM log-variance equation:
##
##                     coef std.error  t-stat   p-value
## vconst        -0.076336  0.038363  3.9595   0.04661 *
## logEqWMA(12)   0.799096  0.013012 61.4139 < 2.2e-16 ***
## logEqWMA(24)   0.184435  0.015957 11.5586 < 2.2e-16 ***
## logEqWMA(168)  0.061473  0.010402  5.9095 3.447e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Diagnostics:
##
##                   Chi-sq df p-value
## Ljung-Box AR(1)    57846  1       0
## Ljung-Box ARCH(1)  25153  1       0

## 9 path(s) to search
## Searching: 1 2 3 4 5 6 7 8 9

##
##   Path 1: 14 16 58 46 15 23 17 28 24
##   Path 2: 15 46 58 23 17 16 14 28 24
##   Path 3: 16 15 58 46 23 17 14 28 24
##   Path 4: 17 23 46 58 15 16 14 28 24
##   Path 5: 23 46 58 17 15 16 14 28 24
##   Path 6: 24 15 58 46 28 16 14 36 17
##   Path 7: 28 15 58 46 16 24 14 36 17
##   Path 8: 46 23 58 17 15 16 14 28 24
##   Path 9: 58 23 46 17 15 16 14 28 24
##
## Terminal models:
##
##                 info(sc)      logl     n  k
## spec 1 (1-cut): 9.010489 -326976.6 72639 50
## spec 2:         9.010629 -326981.7 72639 50
##
## Retained regressors (final model):
##
##   mconst   log_load   log_gen_gas_mw   log_gen_coal_mw   log_gen_hydro_mw   log_gen_geoth_mw   log_g
```

```
de_levs_sel_logewma %>% plot
```



de_full$price_eur_m_whe
fitted
abs(residuals)
fitted sd
standardised residuals

```
reg_mat_shares <- as.matrix(select(de_full,
                                       #'shr_gen_biomass_mw',
                                       'shr_gen_gas_mw',
                                       'shr_gen_coal_mw',
                                       'shr_gen_hydro_mw',
                                       'shr_gen_geoth_mw',
                                       'shr_gen_nuclear_mw',
                                       'shr_gen_oth_ren_mw',
                                       'shr_gen_solar_mw',
                                       'shr_gen_wind_mw',
                                       'log_PNGASEU',
                                       'log_PALLFNF',
                                       'log_PINDU',
                                       contains('hour'),
                                       contains('month'),
                                       "log_redisp_mwh",
                                       shr_net_imports)) # 'gen_wind_mw' 'gen_coal_mw', 'gen_hydro_mw',

de_mod_shares <- arx(de_full$price_eur_m_whe,
              mxreg = reg_mat_shares)

de_mod_shares_logewma <- arx(de_full$price_eur_m_whe,
                     log.ewma = c(12, 24, 168),
                     mxreg = reg_mat_shares)

de_shares_sel <- getsm(de_mod_shares, ar.LjungB = NULL, arch.LjungB = NULL)
```

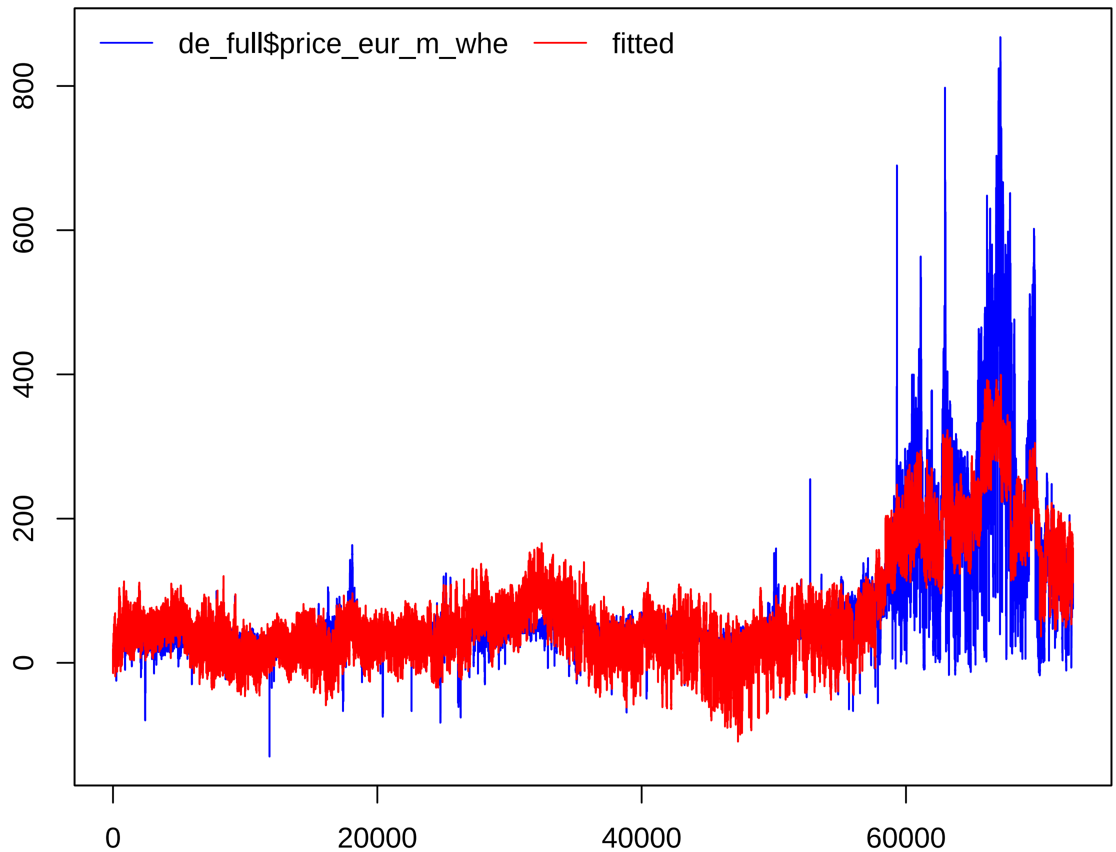
Shares as Exp. Vars.

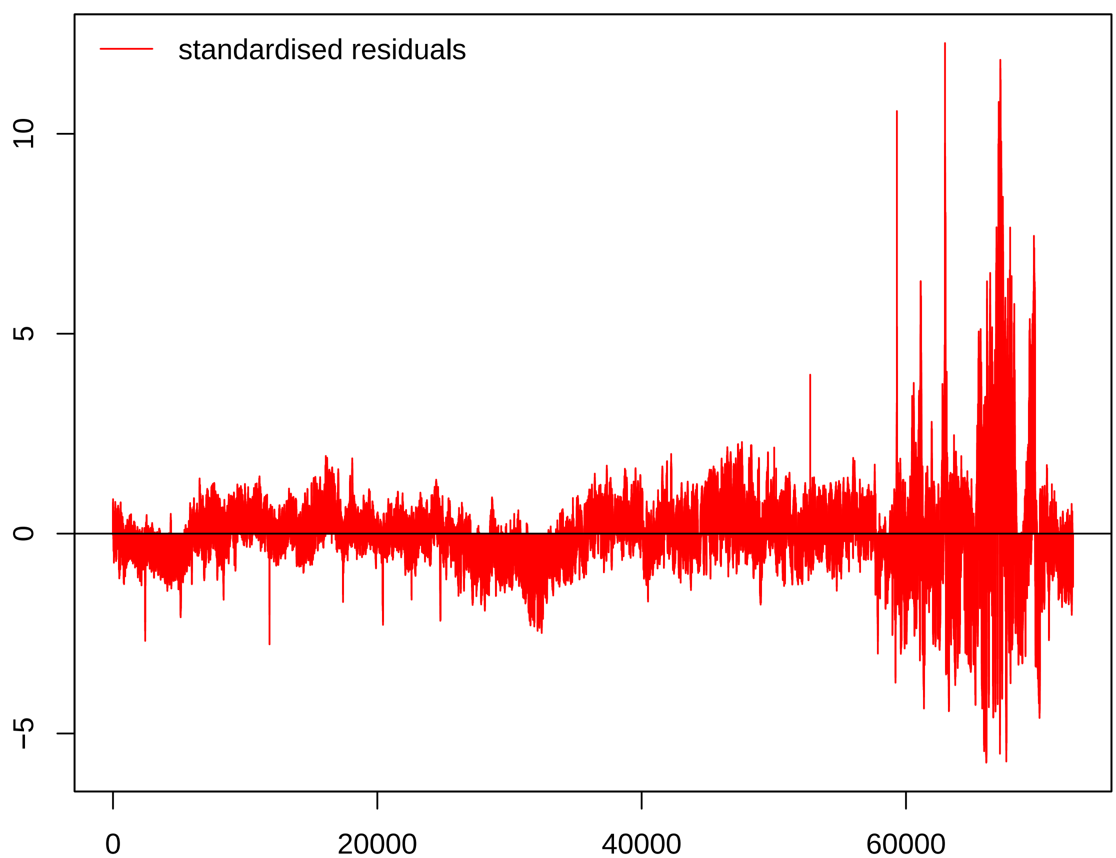
```
##
## GUM mean equation:
##
##                      reg.no. keep        coef   std.error    t-stat   p-value
## mconst                     1    0  342.164337   11.477018   29.8130 < 2.2e-16 ***
## shr_gen_gas_mw             2    0  506.016002    5.163198   98.0044 < 2.2e-16 ***
## shr_gen_coal_mw            3    0 -159.294054    4.174795  -38.1561 < 2.2e-16 ***
## shr_gen_hydro_mw           4    0  -69.768179    6.881032  -10.1392 < 2.2e-16 ***
## shr_gen_geoth_mw           5    0 4241.149578 2139.534334    1.9823 0.0474520 *
## shr_gen_nuclear_mw         6    0 -363.787770    6.868367  -52.9657 < 2.2e-16 ***
## shr_gen_oth_ren_mw         7    0 9602.297723  338.542874   28.3636 < 2.2e-16 ***
## shr_gen_solar_mw           8    0  -71.196965    3.026697  -23.5230 < 2.2e-16 ***
## shr_gen_wind_mw            9    0 -130.493896    3.078204  -42.3929 < 2.2e-16 ***
## log_PNGASEU               10    0   87.008405    0.969777   89.7200 < 2.2e-16 ***
## log_PALLFNF               11    0  154.363934    3.650784   42.2824 < 2.2e-16 ***
## log_PINDU                 12    0 -236.041593    2.278155 -103.6109 < 2.2e-16 ***
## hour_1                    13    0   -1.755044    1.138291   -1.5418 0.1231207
## hour_2                    14    0   -1.496980    1.145233   -1.3071 0.1911693
## hour_3                    15    0   -3.236111    1.153009   -2.8067 0.0050071 **
## hour_4                    16    0   -4.542194    1.158570   -3.9205 8.844e-05 ***
## hour_5                    17    0   -4.810758    1.160488   -4.1455 3.395e-05 ***
## hour_6                    18    0   -1.360918    1.195200   -1.1387 0.2548515
## hour_7                    19    0    3.181228    1.231975    2.5822 0.0098187 **
## hour_8                    20    0    1.532142    1.254422    1.2214 0.2219412
```

```
## hour_9                21    0   -3.963190    1.264281   -3.1347 0.0017208 **
## hour_10               22    0   -8.565509    1.290769   -6.6360 3.246e-11 ***
## hour_11               23    0  -10.046360    1.328997   -7.5594 4.098e-14 ***
## hour_12               24    0  -10.775520    1.346589   -8.0021 1.241e-15 ***
## hour_13               25    0  -10.671360    1.360775   -7.8421 4.490e-15 ***
## hour_14               26    0   -8.771171    1.356598   -6.4656 1.016e-10 ***
## hour_15               27    0   -4.962141    1.338845   -3.7063 0.0002105 ***
## hour_16               28    0   -0.813099    1.311925   -0.6198 0.5354076
## hour_17               29    0    7.161256    1.294861    5.5305 3.204e-08 ***
## hour_18               30    0   11.832921    1.269719    9.3193 < 2.2e-16 ***
## hour_19               31    0   12.164161    1.244803    9.7720 < 2.2e-16 ***
## hour_20               32    0    6.631639    1.202594    5.5144 3.511e-08 ***
## hour_21               33    0    0.017766    1.180562    0.0150 0.9879935
## hour_22               34    0   -1.739371    1.165329   -1.4926 0.1355460
## hour_23               35    0   -5.182842    1.150157   -4.5062 6.610e-06 ***
## month_2               36    0    4.873917    0.762043    6.3959 1.606e-10 ***
## month_3               37    0   13.940156    0.762769   18.2757 < 2.2e-16 ***
## month_4               38    0   14.159450    0.836584   16.9253 < 2.2e-16 ***
## month_5               39    0   14.477383    0.928680   15.5892 < 2.2e-16 ***
## month_6               40    0   22.608241    0.946743   23.8800 < 2.2e-16 ***
## month_7               41    0   24.020259    0.900793   26.6657 < 2.2e-16 ***
## month_8               42    0   44.952315    0.892768   50.3516 < 2.2e-16 ***
## month_9               43    0   31.260618    0.838985   37.2601 < 2.2e-16 ***
## month_10              44    0   13.069371    0.811587   16.1035 < 2.2e-16 ***
## month_11              45    0    7.290560    0.782806    9.3134 < 2.2e-16 ***
## month_12              46    0   15.754496    0.775940   20.3038 < 2.2e-16 ***
## log_redisp_mwh        47    0   -0.496054    0.056503   -8.7792 < 2.2e-16 ***
## shr_net_imports       48    0   14.309031    3.970856    3.6035 0.0003142 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Diagnostics:
##
##                    Chi-sq df p-value
## Ljung-Box AR(1)     67854  1       0
## Ljung-Box ARCH(1)   63977  1       0

## 7 path(s) to search

## Searching: 1 2 3 4 5 6 7

##
##   Path 1: 13 28 18 14 34 33 5
##   Path 2: 14 28 18 34 13 33 5
##   Path 3: 18 28 33 14 13 34 5
##   Path 4: 20 33 28 14 18 13 34 -5
##   Path 5: 28 33 18 14 13 34 5
##   Path 6: 33 28 18 14 13 34 5
##   Path 7: 34 28 18 14 13 33 5
##
## Terminal models:
##
##                  info(sc)      logl     n  k
## spec 1 (1-cut): 10.35056 -375697.8 72639 41
```

```
## spec 2:         10.35050 -375695.6 72639 41
##
## Retained regressors (final model):
##
##   mconst   shr_gen_gas_mw   shr_gen_coal_mw   shr_gen_hydro_mw   shr_gen_nuclear_mw   shr_gen_oth_re
```

```
de_shares_sel %>% plot
```


de_full$price_eur_m_whe
fitted
800
600
400
200
0
0
20000
40000
60000

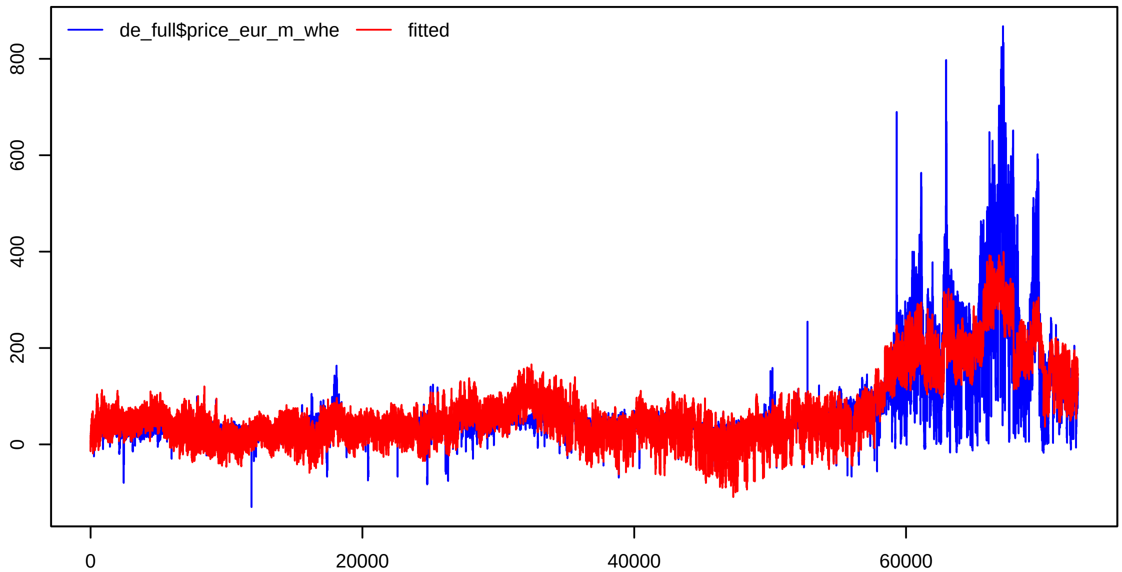

standardised residuals
10
5
0
−5
0
20000
40000
60000

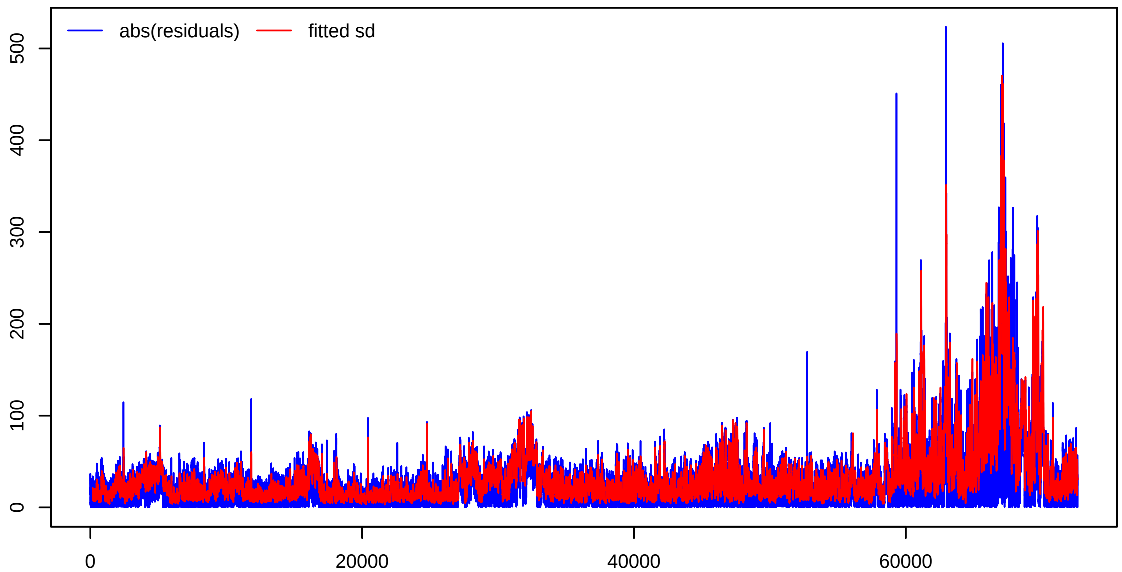
```r
de_shares_sel_logewma <- getsm(de_mod_shares_logewma, ar.LjungB = NULL, arch.LjungB = NULL)
```

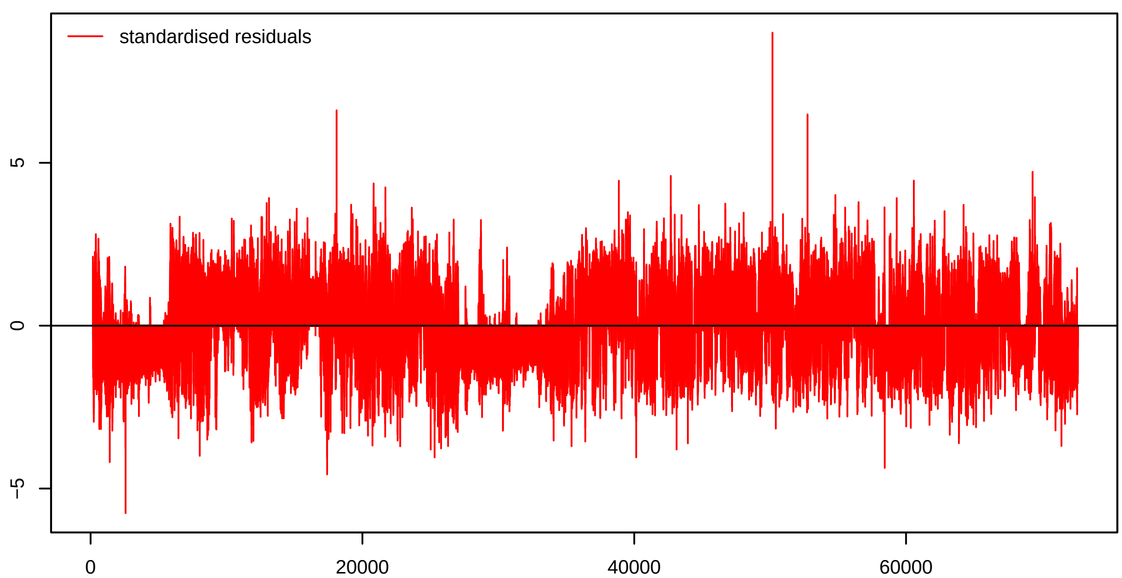
```
##
## GUM mean equation:
##
##                      reg.no. keep        coef   std.error    t-stat   p-value
## mconst                     1    0  342.164337   11.477018   29.8130 < 2.2e-16 ***
## shr_gen_gas_mw             2    0  506.016002    5.163198   98.0044 < 2.2e-16 ***
## shr_gen_coal_mw            3    0 -159.294054    4.174795  -38.1561 < 2.2e-16 ***
## shr_gen_hydro_mw           4    0  -69.768179    6.881032  -10.1392 < 2.2e-16 ***
## shr_gen_geoth_mw           5    0 4241.149578 2139.534334    1.9823 0.0474520 *
## shr_gen_nuclear_mw         6    0 -363.787770    6.868367  -52.9657 < 2.2e-16 ***
## shr_gen_oth_ren_mw         7    0 9602.297723  338.542874   28.3636 < 2.2e-16 ***
## shr_gen_solar_mw           8    0  -71.196965    3.026697  -23.5230 < 2.2e-16 ***
## shr_gen_wind_mw            9    0 -130.493896    3.078204  -42.3929 < 2.2e-16 ***
## log_PNGASEU               10    0   87.008405    0.969777   89.7200 < 2.2e-16 ***
## log_PALLFNF               11    0  154.363934    3.650784   42.2824 < 2.2e-16 ***
## log_PINDU                 12    0 -236.041593    2.278155 -103.6109 < 2.2e-16 ***
## hour_1                    13    0   -1.755044    1.138291   -1.5418 0.1231207
## hour_2                    14    0   -1.496980    1.145233   -1.3071 0.1911693
## hour_3                    15    0   -3.236111    1.153009   -2.8067 0.0050071 **
## hour_4                    16    0   -4.542194    1.158570   -3.9205 8.844e-05 ***
## hour_5                    17    0   -4.810758    1.160488   -4.1455 3.395e-05 ***
## hour_6                    18    0   -1.360918    1.195200   -1.1387 0.2548515
## hour_7                    19    0    3.181228    1.231975    2.5822 0.0098187 **
## hour_8                    20    0    1.532142    1.254422    1.2214 0.2219412
## hour_9                    21    0   -3.963190    1.264281   -3.1347 0.0017208 **
## hour_10                   22    0   -8.565509    1.290769   -6.6360 3.246e-11 ***
## hour_11                   23    0  -10.046360    1.328997   -7.5594 4.098e-14 ***
## hour_12                   24    0  -10.775520    1.346589   -8.0021 1.241e-15 ***
## hour_13                   25    0  -10.671360    1.360775   -7.8421 4.490e-15 ***
## hour_14                   26    0   -8.771171    1.356598   -6.4656 1.016e-10 ***
## hour_15                   27    0   -4.962141    1.338845   -3.7063 0.0002105 ***
## hour_16                   28    0   -0.813099    1.311925   -0.6198 0.5354076
## hour_17                   29    0    7.161256    1.294861    5.5305 3.204e-08 ***
## hour_18                   30    0   11.832921    1.269719    9.3193 < 2.2e-16 ***
## hour_19                   31    0   12.164161    1.244803    9.7720 < 2.2e-16 ***
## hour_20                   32    0    6.631639    1.202594    5.5144 3.511e-08 ***
## hour_21                   33    0    0.017766    1.180562    0.0150 0.9879935
## hour_22                   34    0   -1.739371    1.165329   -1.4926 0.1355460
## hour_23                   35    0   -5.182842    1.150157   -4.5062 6.610e-06 ***
## month_2                   36    0    4.873917    0.762043    6.3959 1.606e-10 ***
## month_3                   37    0   13.940156    0.762769   18.2757 < 2.2e-16 ***
## month_4                   38    0   14.159450    0.836584   16.9253 < 2.2e-16 ***
## month_5                   39    0   14.477383    0.928680   15.5892 < 2.2e-16 ***
## month_6                   40    0   22.608241    0.946743   23.8800 < 2.2e-16 ***
## month_7                   41    0   24.020259    0.900793   26.6657 < 2.2e-16 ***
## month_8                   42    0   44.952315    0.892768   50.3516 < 2.2e-16 ***
## month_9                   43    0   31.260618    0.838985   37.2601 < 2.2e-16 ***
## month_10                  44    0   13.069371    0.811587   16.1035 < 2.2e-16 ***
## month_11                  45    0    7.290560    0.782806    9.3134 < 2.2e-16 ***
## month_12                  46    0   15.754496    0.775940   20.3038 < 2.2e-16 ***
## log_redisp_mwh            47    0   -0.496054    0.056503   -8.7792 < 2.2e-16 ***
## shr_net_imports           48    0   14.309031    3.970856    3.6035 0.0003142 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## GUM log-variance equation:
##
##                    coef std.error  t-stat   p-value
## vconst        -0.154385  0.040584 14.4710 0.0001423 ***
## logEqWMA(12)   0.719482  0.012433 57.8679 < 2.2e-16 ***
## logEqWMA(24)   0.293823  0.015572 18.8690 < 2.2e-16 ***
## logEqWMA(168)  0.041525  0.010375  4.0025 6.273e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Diagnostics:
##
##                   Chi-sq df p-value
## Ljung-Box AR(1)    61586  1       0
## Ljung-Box ARCH(1)  31777  1       0

## 7 path(s) to search
## Searching: 1 2 3 4 5 6 7

##
##   Path 1: 13 28 18 14 34 33 5
##   Path 2: 14 28 18 34 13 33 5
##   Path 3: 18 28 33 14 13 34 5
##   Path 4: 20 33 28 14 18 13 34 -5
##   Path 5: 28 33 18 14 13 34 5
##   Path 6: 33 28 18 14 13 34 5
##   Path 7: 34 28 18 14 13 33 5
##
## Terminal models:
##
##                 info(sc)    logl     n  k
## spec 1 (1-cut): 9.251738 -335789 72639 41
## spec 2:         9.251379 -335776 72639 41
##
## Retained regressors (final model):
##
##   mconst   shr_gen_gas_mw   shr_gen_coal_mw   shr_gen_hydro_mw   shr_gen_nuclear_mw   shr_gen_oth_ren
```

```
de_shares_sel_logewma %>% plot
```


de_full$price_eur_m_whe
fitted
800
600
400
200
0
0
20000
40000
60000

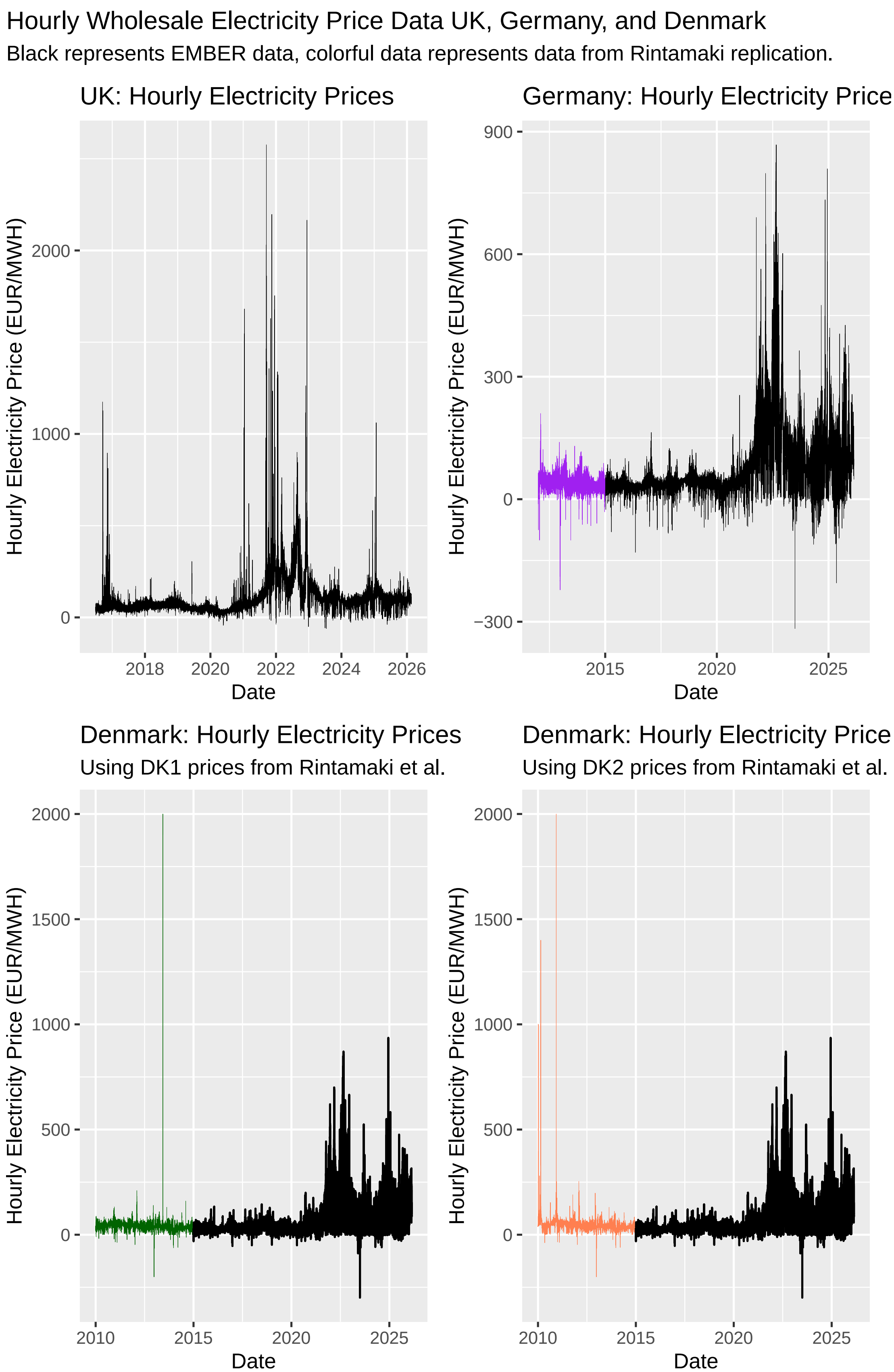

abs(residuals)
fitted sd
500
400
300
200
100
0
0
20000
40000
60000


standardised residuals
5
0
−5
0
20000
40000
60000

```r
# # Perform gets model selection over the log-variance model above
# de_vmod <- getsv(de_mod, t.pval = 0.001, ar.LjungB = NULL)
#
# de_vmod %>% plot
#
# data_de %>% filter(de_price < 0)
```

(TBA) Spotlight on UK, Germany, Denmark

Here, see the time series for Germany and Denmark (to compare to the data avialable in Rintamaki et al. - color portion of the TS plots). UK spotlight to discuss potential interest to David.

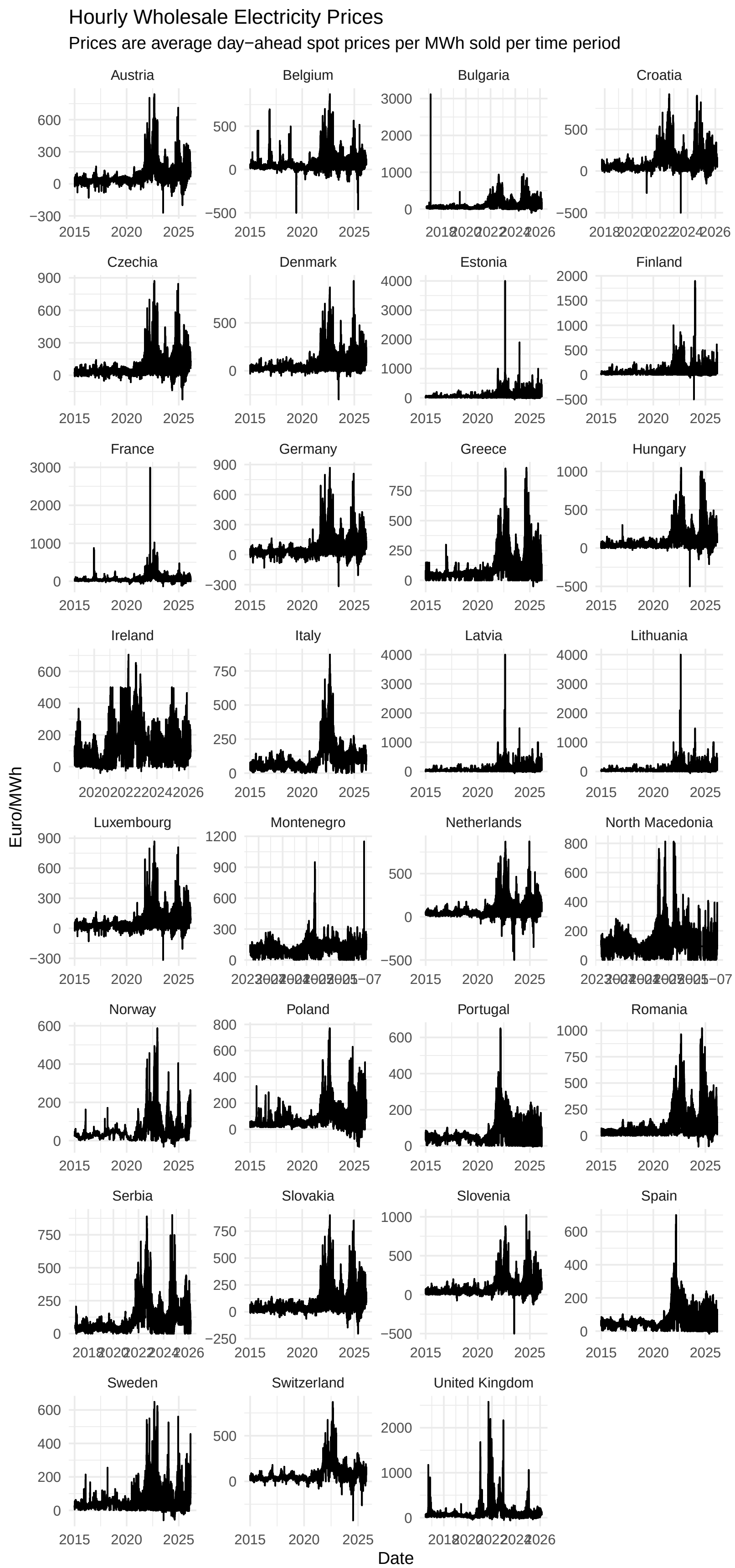

Hourly Wholesale Electricity Price Data UK, Germany, and Denmark
Black represents EMBER data, colorful data represents data from Rintamaki replication.
UK: Hourly Electricity Prices
Hourly Electricity Price (EUR/MWH)
2000
1000
0
2018
2020
2022
2024
2026
Date
Germany: Hourly Electricity Price
Hourly Electricity Price (EUR/MWH)
900
600
300
0
−300
2015
2020
2025
Date
Denmark: Hourly Electricity Prices
Using DK1 prices from Rintamaki et al.
Hourly Electricity Price (EUR/MWH)
2000
1500
1000
500
0
2010
2015
2020
2025
Date
Denmark: Hourly Electricity Price
Using DK2 prices from Rintamaki et al.
Hourly Electricity Price (EUR/MWH)
2000
1500
1000
500
0
2010
2015
2020
2025
Date

(TBA) Full Extension to Europe

Note: Recall also that you can find our replication of Rintamaki et al. here. We have yet to analyse the differences between the hourly volatility specification using getsv() versus the Rintamaki results.

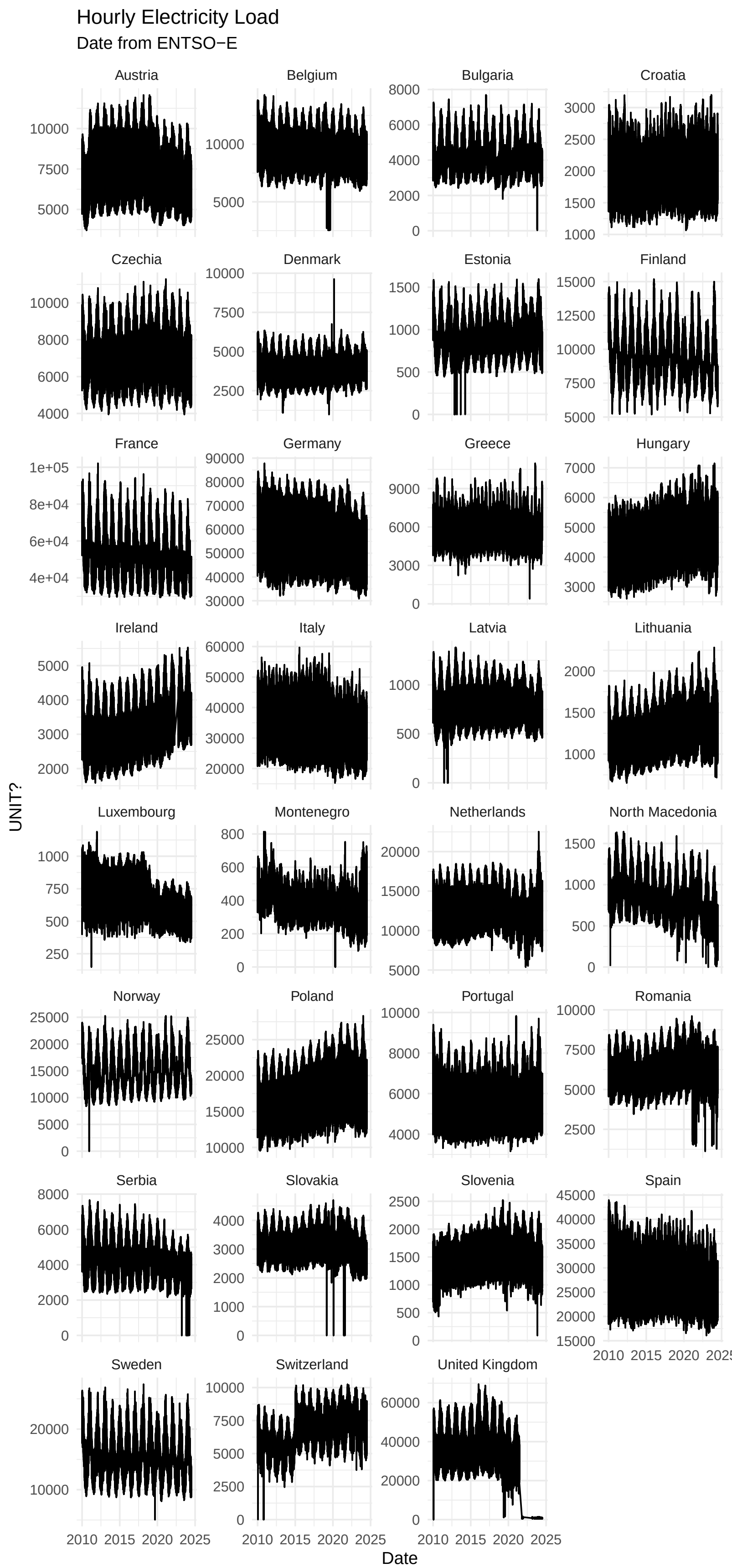
Hourly Prices

Using data from EMBER on European wholesale electricity prices (hourly - daily and monthly also exist), The hourly prices are the day-ahead wholesale prices by country.


Hourly Wholesale Electricity Prices
Prices are average day−ahead spot prices per MWh sold per time period
Austria
Belgium
Bulgaria
Croatia
Czechia
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Montenegro
Netherlands
North Macedonia
Norway
Poland
Portugal
Romania
Serbia
Slovakia
Slovenia
Spain
Sweden
Switzerland
United Kingdom
Euro/MWh
Date

The following is data from ENTSO-E on hourly electricity loads.

```
## [1] TRUE
```



Hourly Electricity Load
Date from ENTSO−E
Austria
Belgium
Bulgaria
Croatia
Czechia
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Montenegro
Netherlands
North Macedonia
Norway
Poland
Portugal
Romania
Serbia
Slovakia
Slovenia
Spain
Sweden
Switzerland
United Kingdom
UNIT?
Date
2010 2015 2020 2025

Daily and Monthly Prices