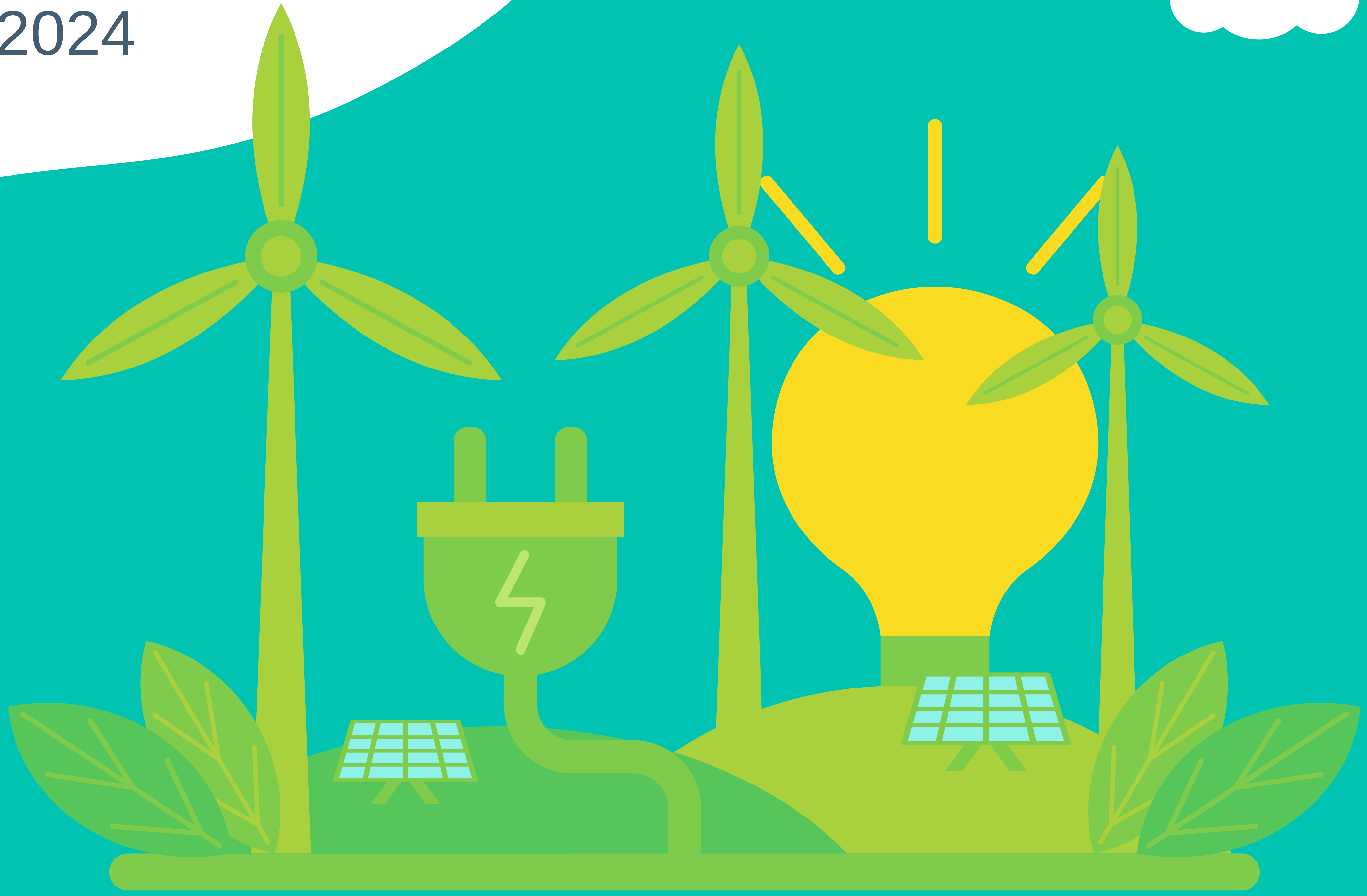
Green Innovation

GrEnFIn SUMMER SCHOOL 2024

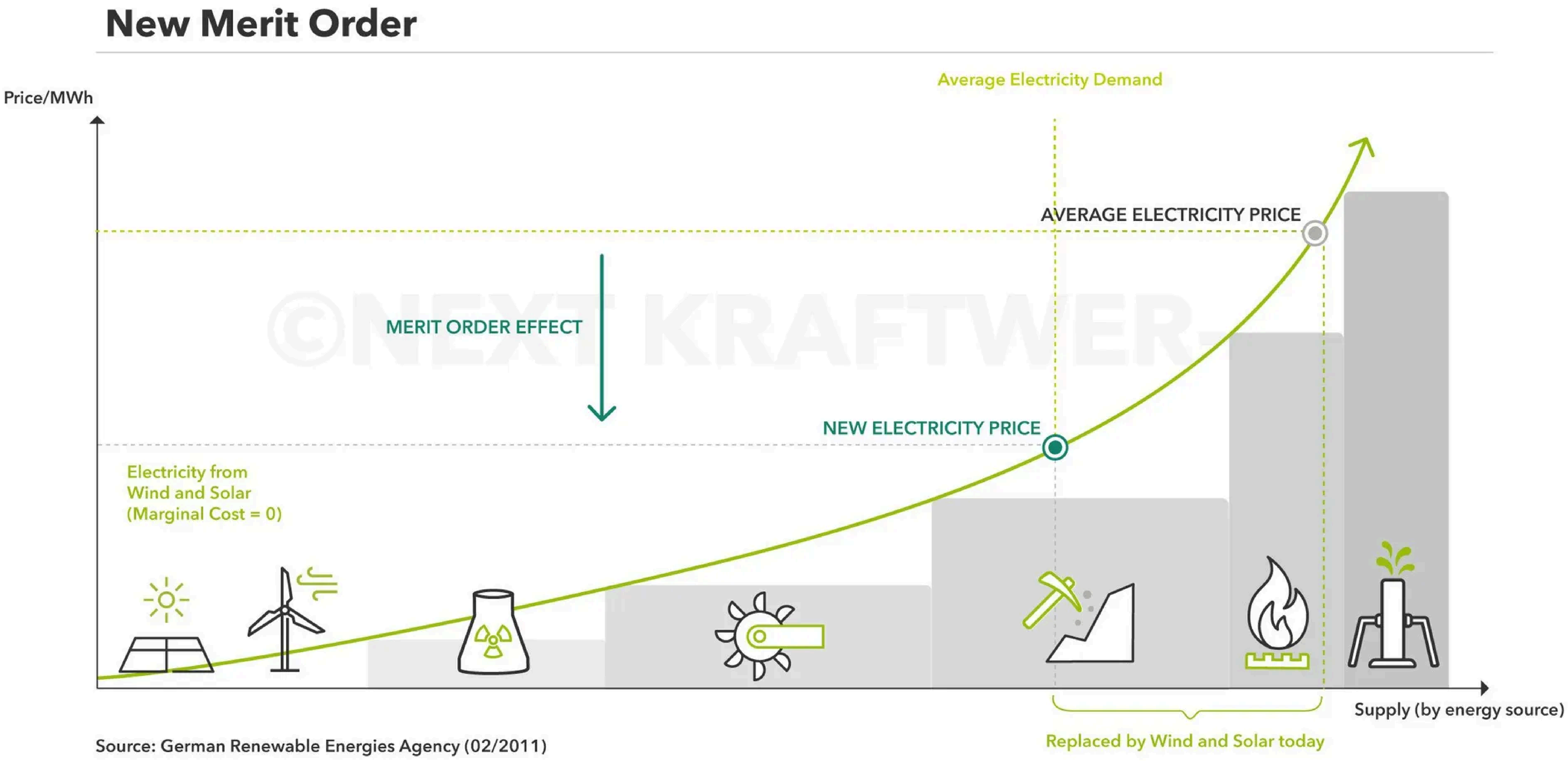
Hourly energy demand generation and weather



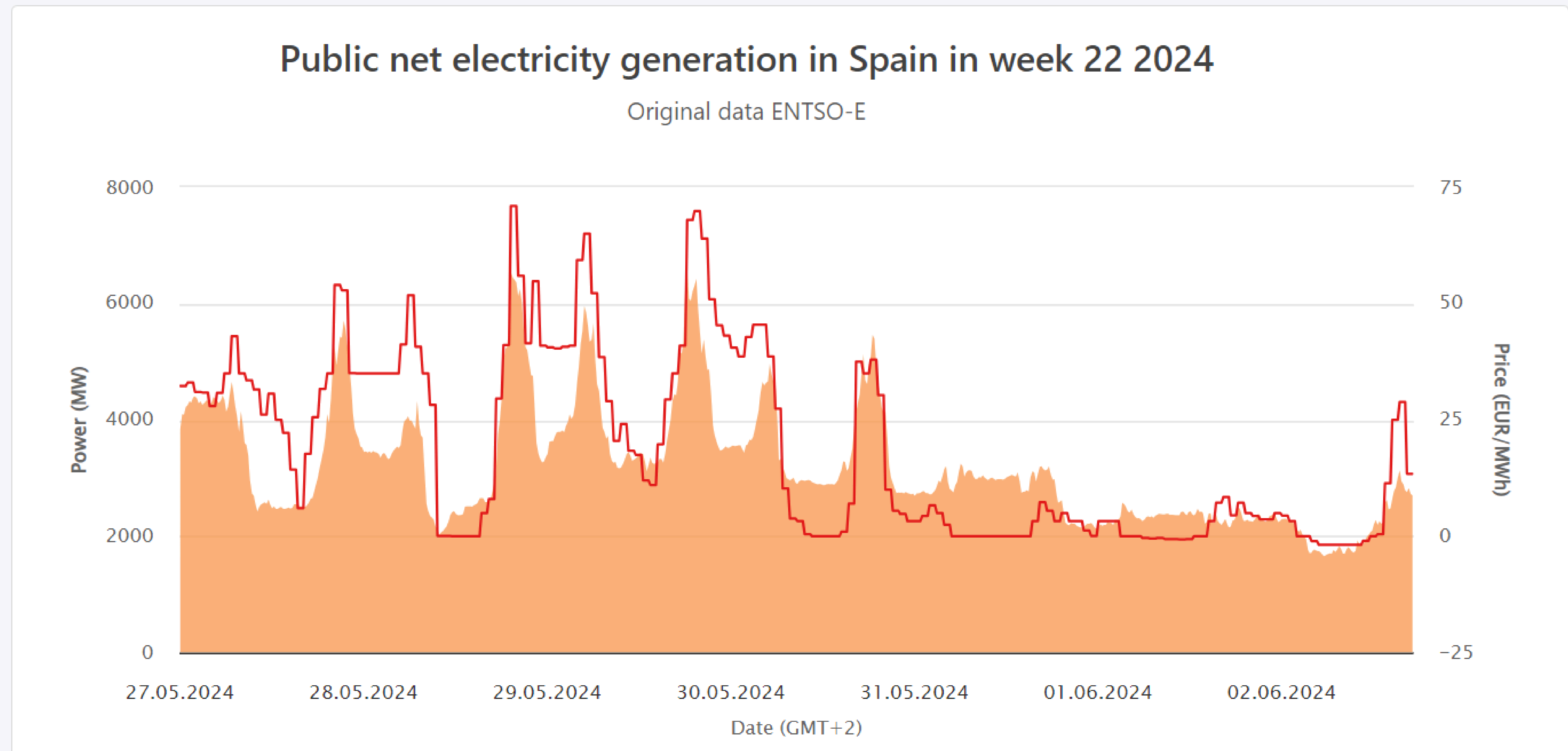
Context and Data

The dataset contains 4 years of electrical consumption, generation, pricing, and weather data for Spain.

Pricing of Electricity



Pricing of Electricity



Explorative Analysis

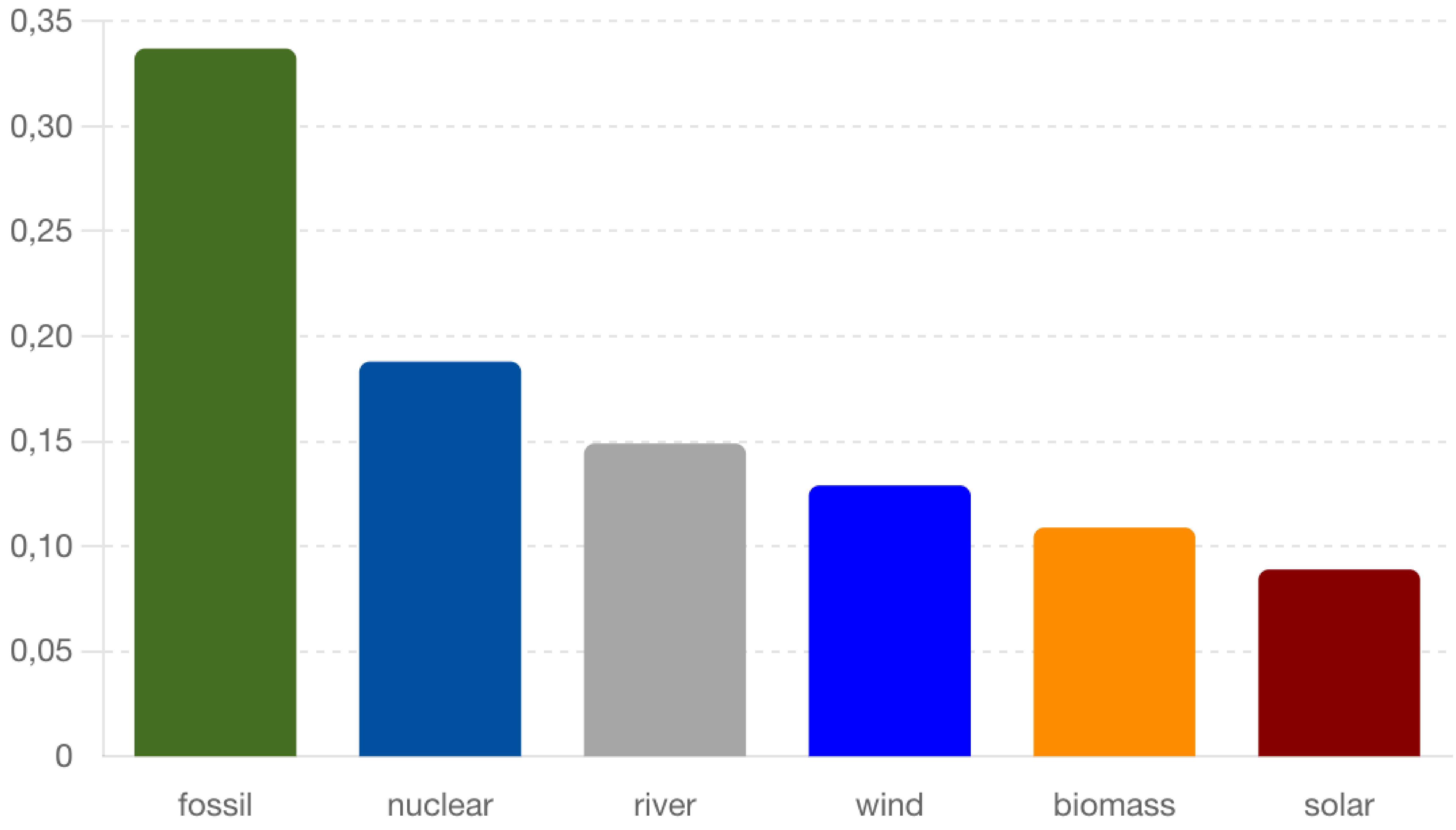
01 Analysis of sources demand

02 Renewable vs Non-Renewable

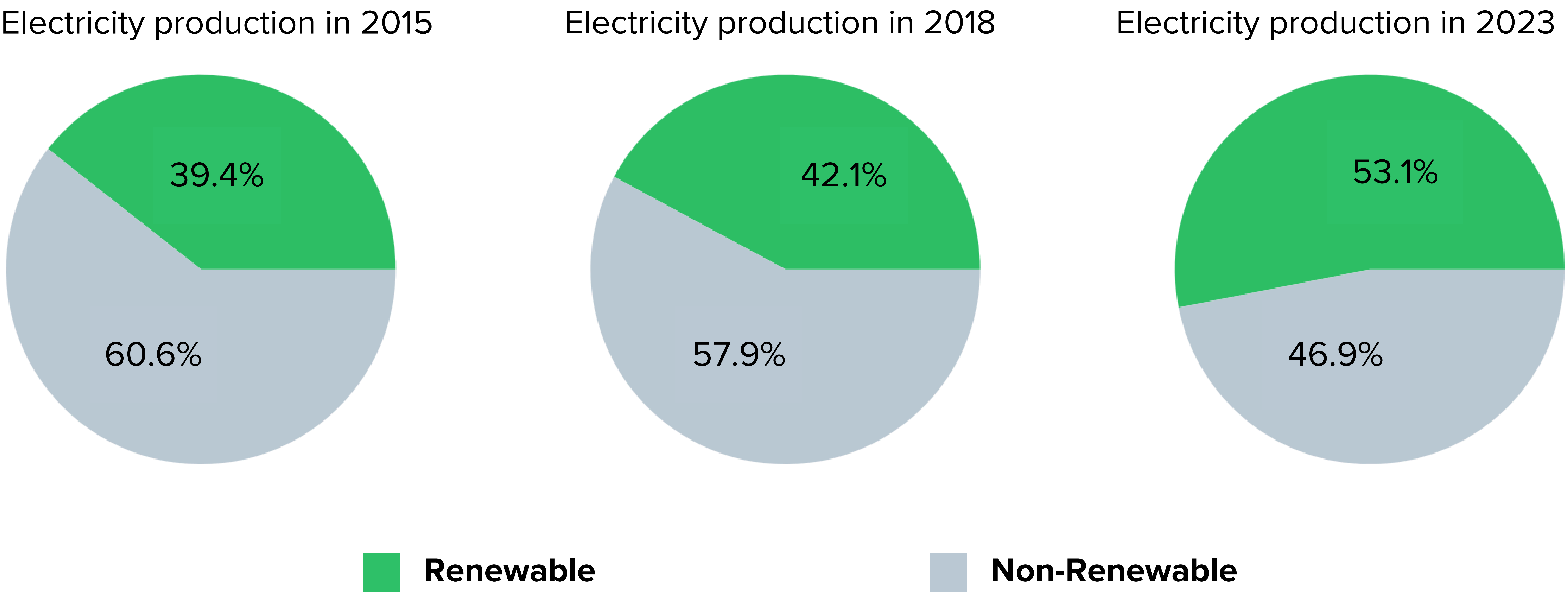
03 Monthly Statistical Analysis

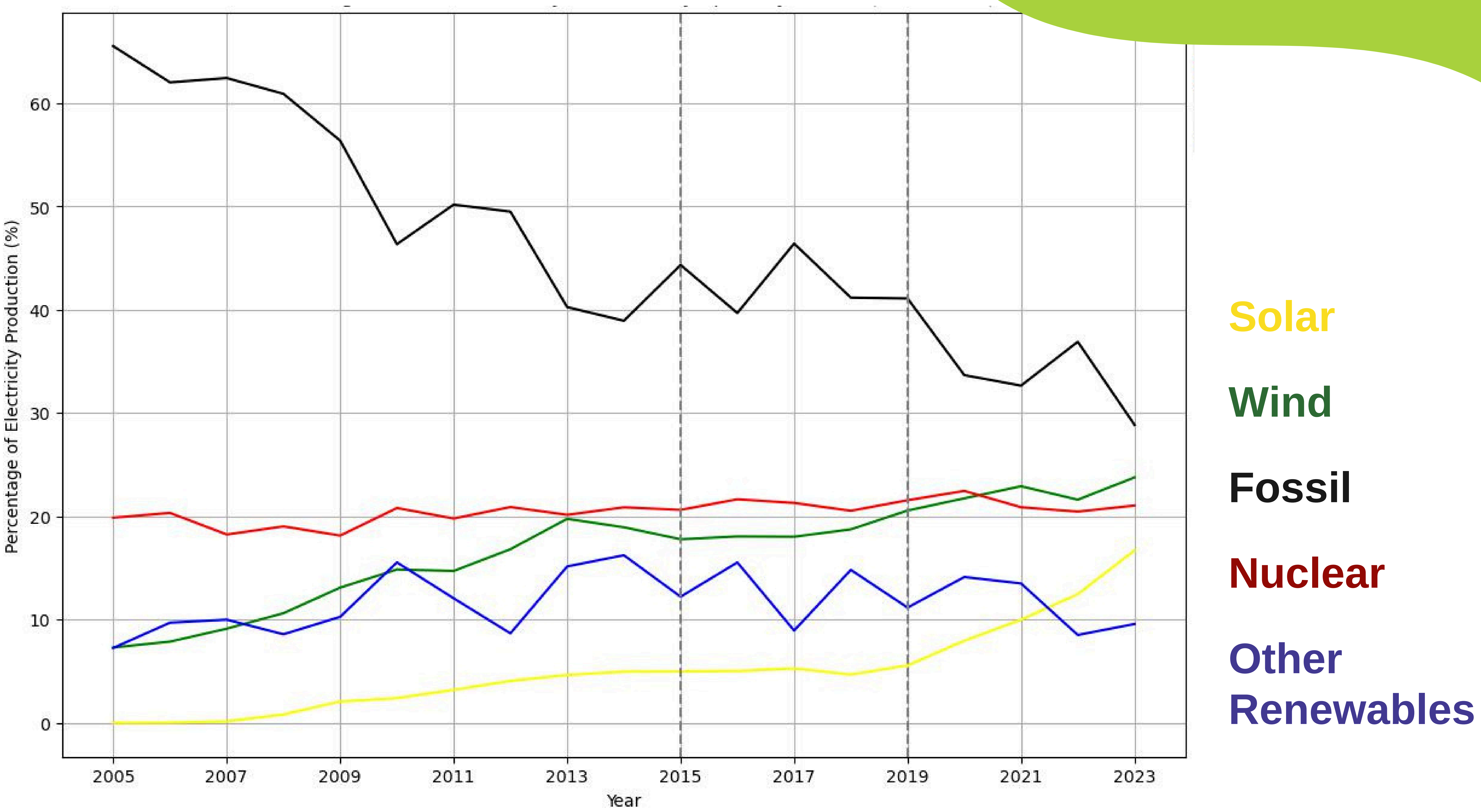
04 Electricity Price Analysis

Composition of sources

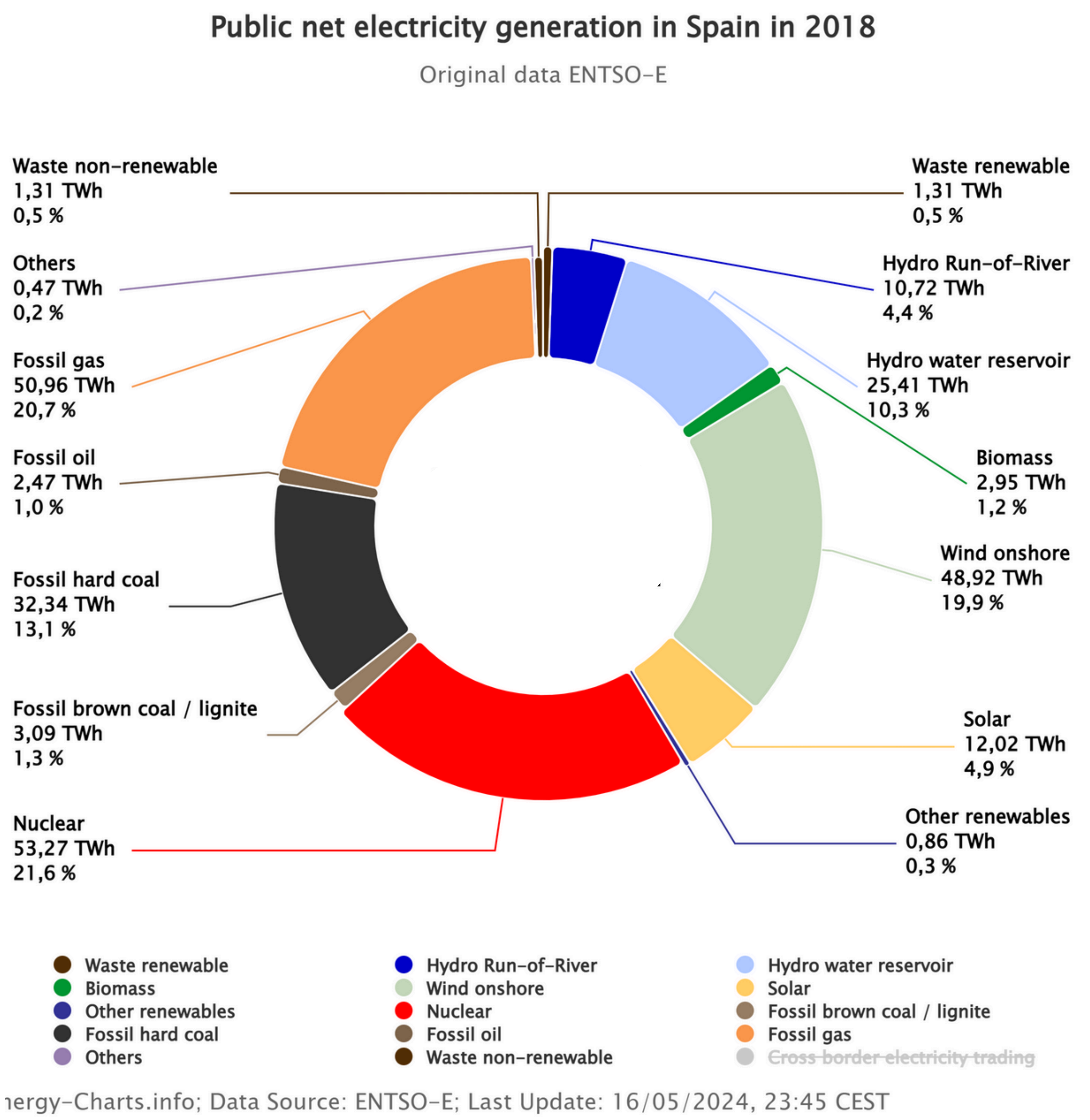


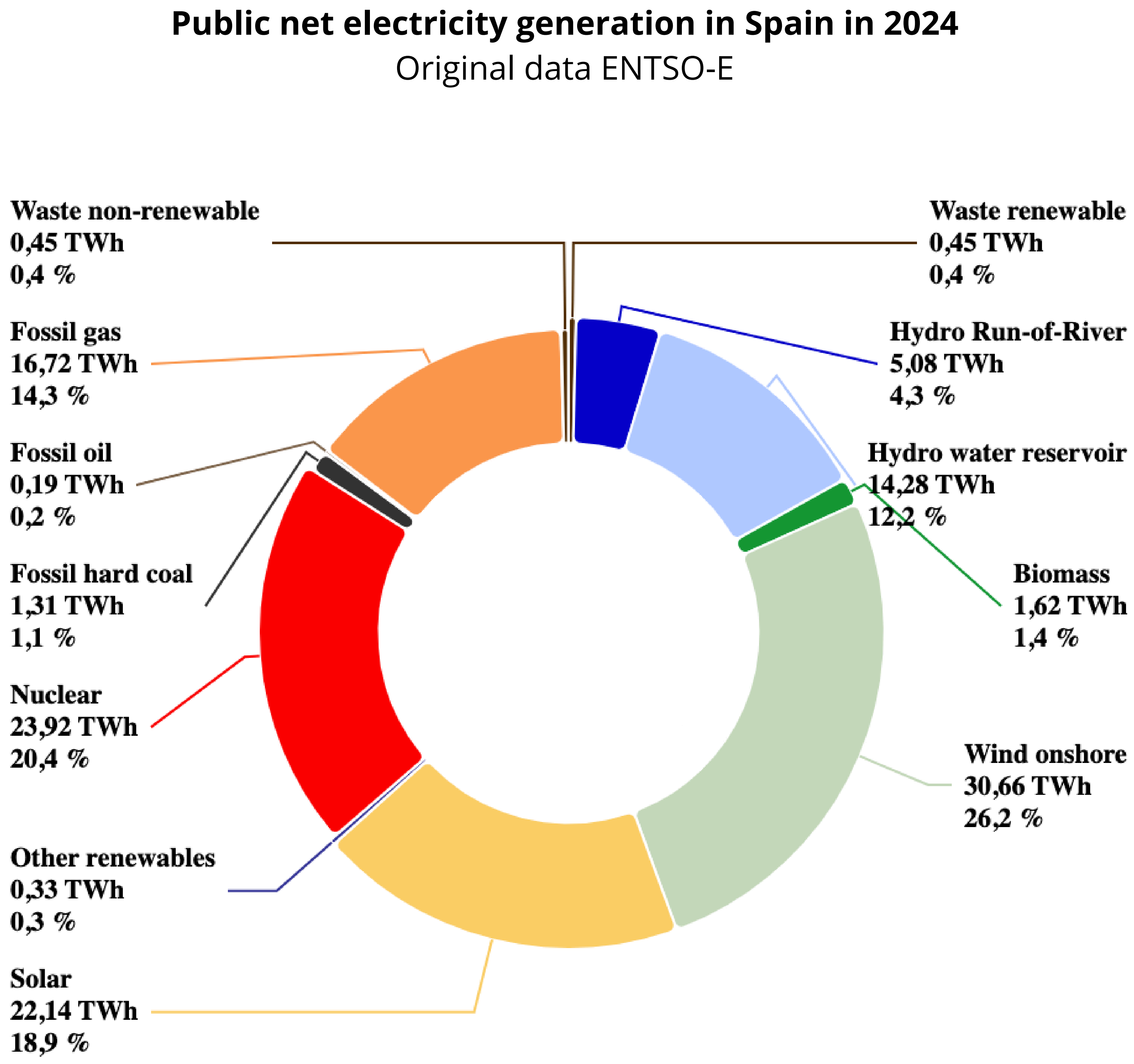
Renewable vs Non-Renewable

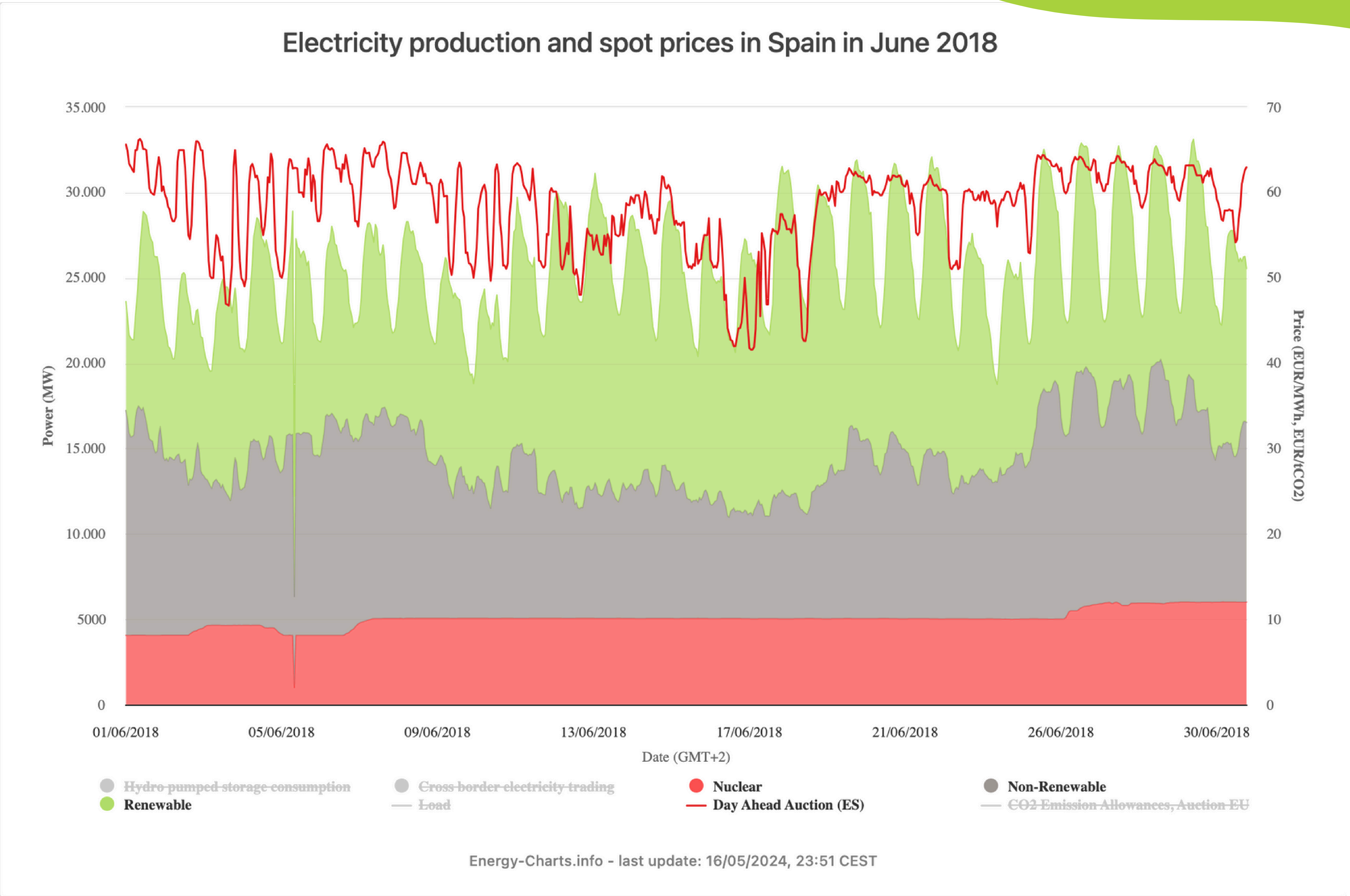


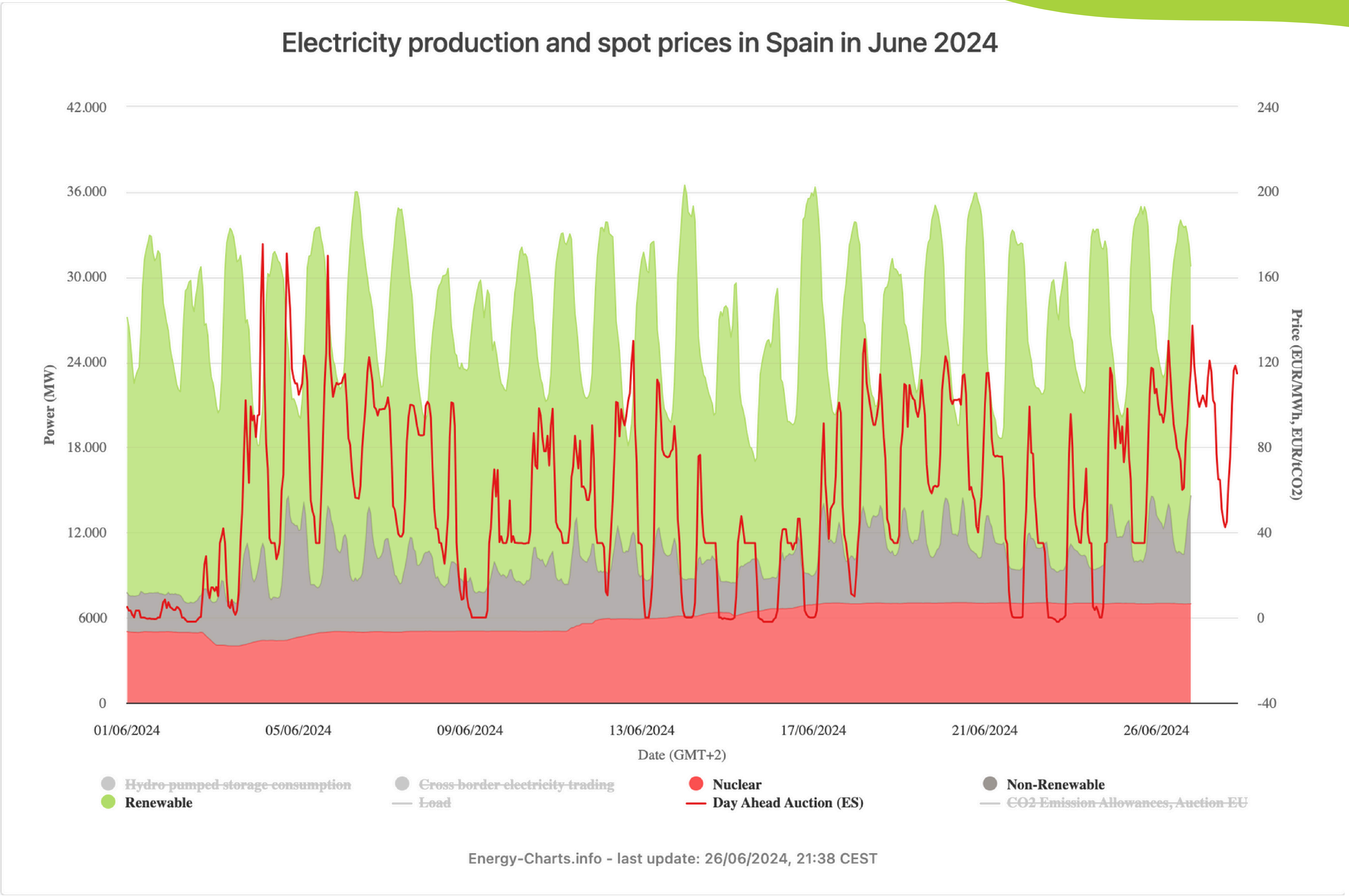

60
50
40
30
20
10
0
Percentage of Electricity Production (%)
2005
2007
2009
2011
2013
2015
2017
2019
2021
2023
Year
Solar
Wind
Fossil
Nuclear
Other Renewables

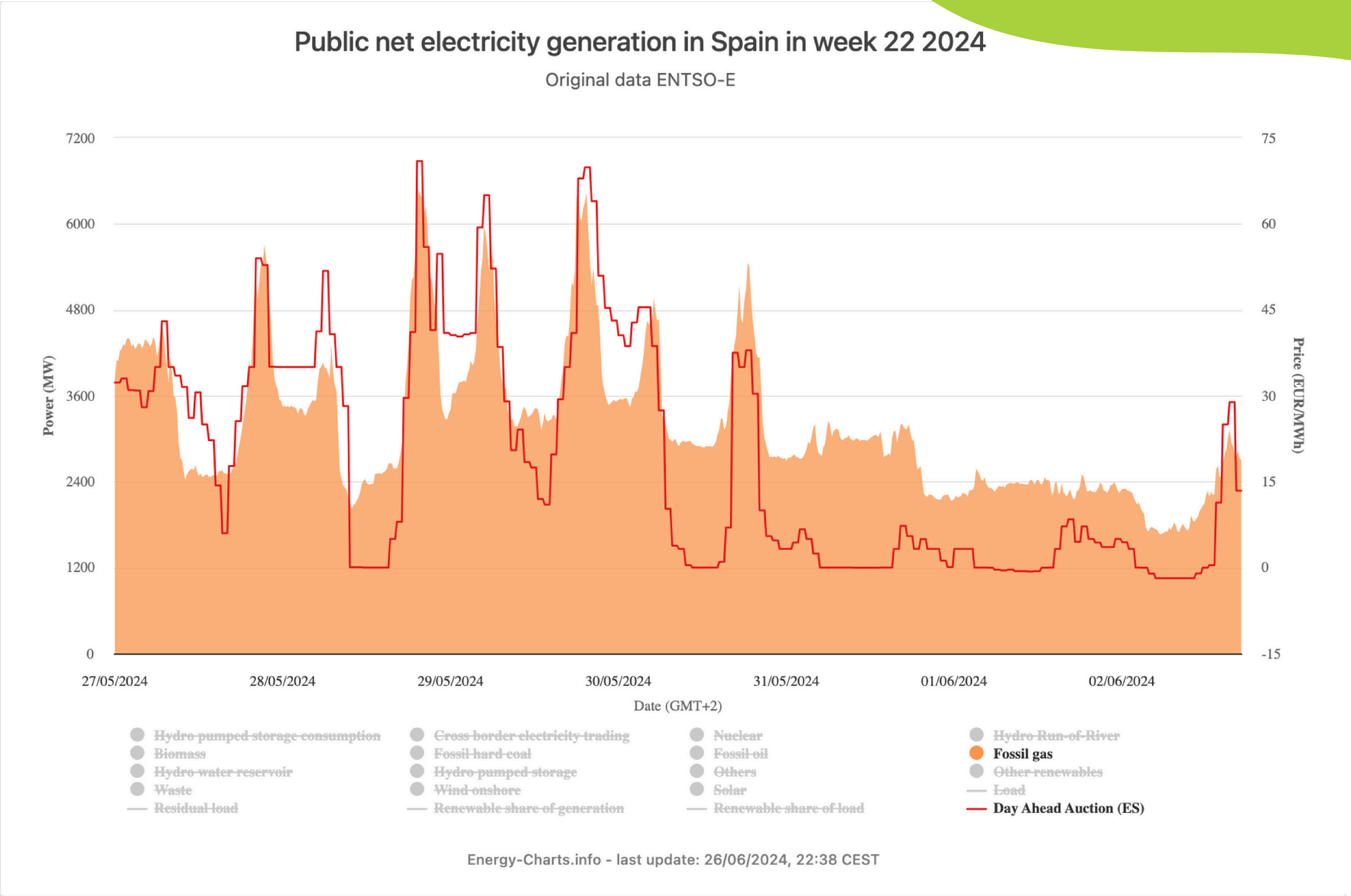
Dispatchable vs non-dispatchable energy

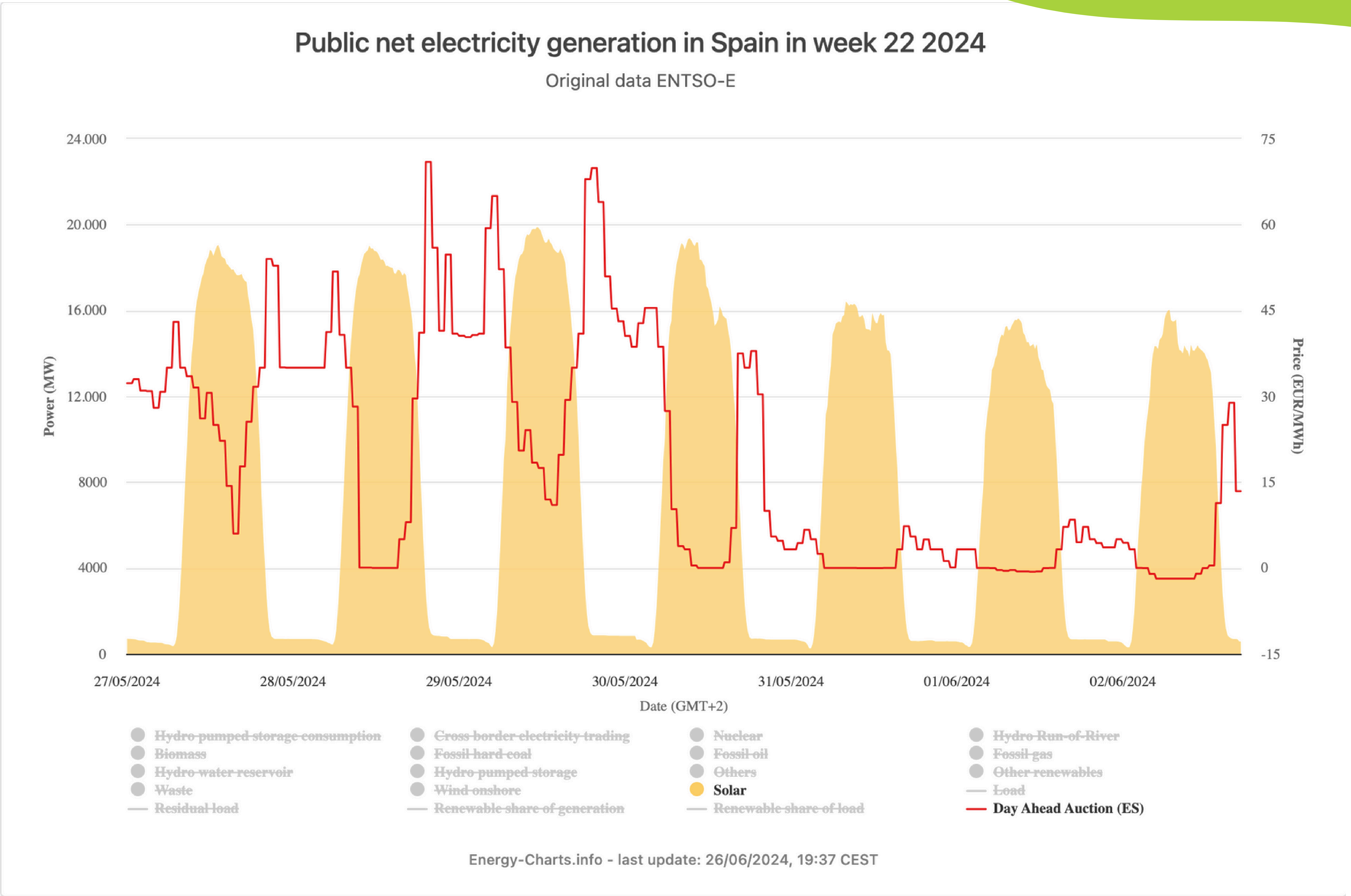





Electricity production and spot prices in Spain in June 2018
35.000
30.000
25.000
20.000
15.000
10.000
5000
0
Power (MW)
70
60
50
40
30
20
10
0
Price (EUR/MWh, EUR/tCO2)
01/06/2018
05/06/2018
09/06/2018
13/06/2018
17/06/2018
21/06/2018
26/06/2018
30/06/2018
Date (GMT+2)
Hydro pumped storage consumption
Renewable
Cross border electricity trading
Load
Nuclear
Day Ahead Auction (ES)
Non-Renewable
CO2 Emission Allowances, Auction EU
Energy-Charts.info - last update: 16/05/2024, 23:51 CEST


Electricity production and spot prices in Spain in June 2024
42.000
36.000
30.000
24.000
18.000
12.000
6000
0
Power (MW)
240
200
160
120
80
40
0
-40
Price (EUR/MWh, EUR/tCO2)
01/06/2024
05/06/2024
09/06/2024
13/06/2024
17/06/2024
21/06/2024
26/06/2024
Date (GMT+2)
Hydro pumped storage consumption
Cross border electricity trading
Nuclear
Non-Renewable
Renewable
Load
Day Ahead Auction (ES)
CO2 Emission Allowances, Auction EU
Energy-Charts.info - last update: 26/06/2024, 21:38 CEST


Public net electricity generation in Spain in week 22 2024
Original data ENTSO-E
Power (MW)
Price (EUR/MWh)
7200
6000
4800
3600
2400
1200
0
75
60
45
30
15
0
-15
27/05/2024
28/05/2024
29/05/2024
30/05/2024
31/05/2024
01/06/2024
02/06/2024
Date (GMT+2)
Hydro pumped storage consumption
Biomass
Hydro water reservoir
Waste
Residual load
Cross border electricity trading
Fossil hard coal
Hydro pumped storage
Wind onshore
Renewable share of generation
Nuclear
Fossil oil
Others
Solar
Renewable share of load
Hydro Run-of-River
Fossil gas
Other renewables
Load
Day Ahead Auction (ES)
Energy-Charts.info - last update: 26/06/2024, 22:38 CEST

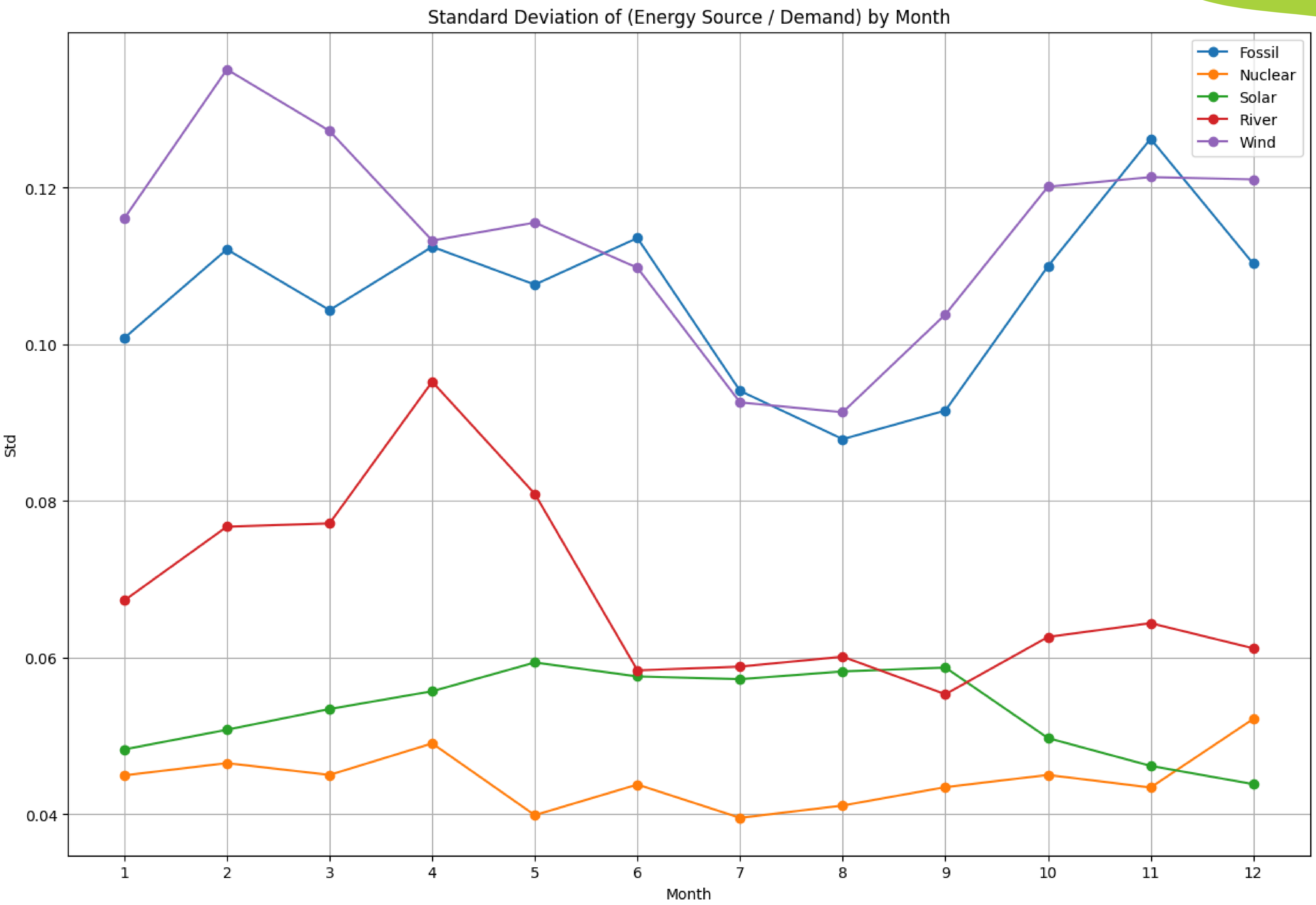

Public net electricity generation in Spain in week 22 2024
Original data ENTSO-E
Power (MW)
24.000
20.000
16.000
12.000
8000
4000
0
Price (EUR/MWh)
75
60
45
30
15
0
-15
27/05/2024
28/05/2024
29/05/2024
30/05/2024
31/05/2024
01/06/2024
02/06/2024
Date (GMT+2)
Hydro pumped storage consumption
Cross border electricity trading
Nuclear
Hydro Run-of-River
Biomass
Fossil hard coal
Fossil oil
Fossil gas
Hydro water reservoir
Hydro pumped storage
Others
Other renewables
Waste
Wind onshore
Solar
Load
Residual load
Renewable share of generation
Renewable share of load
Day Ahead Auction (ES)
Energy-Charts.info - last update: 26/06/2024, 19:37 CEST

Monthly Statistical Analysis

Data grouped by month

Mean percentage of demand of energy

Standard deviation of demand of energy



Standard Deviation of (Energy Source / Demand) by Month
Fossil
Nuclear
Solar
River
Wind
Std
0.04
0.06
0.08
0.10
0.12
Month
1
2
3
4
5
6
7
8
9
10
11
12

Key Results

June vs December

4,4%

Lowest standard deviation from **Nuclear** in June

11%

Highest standard deviation from **Fossil** in June

Key Results

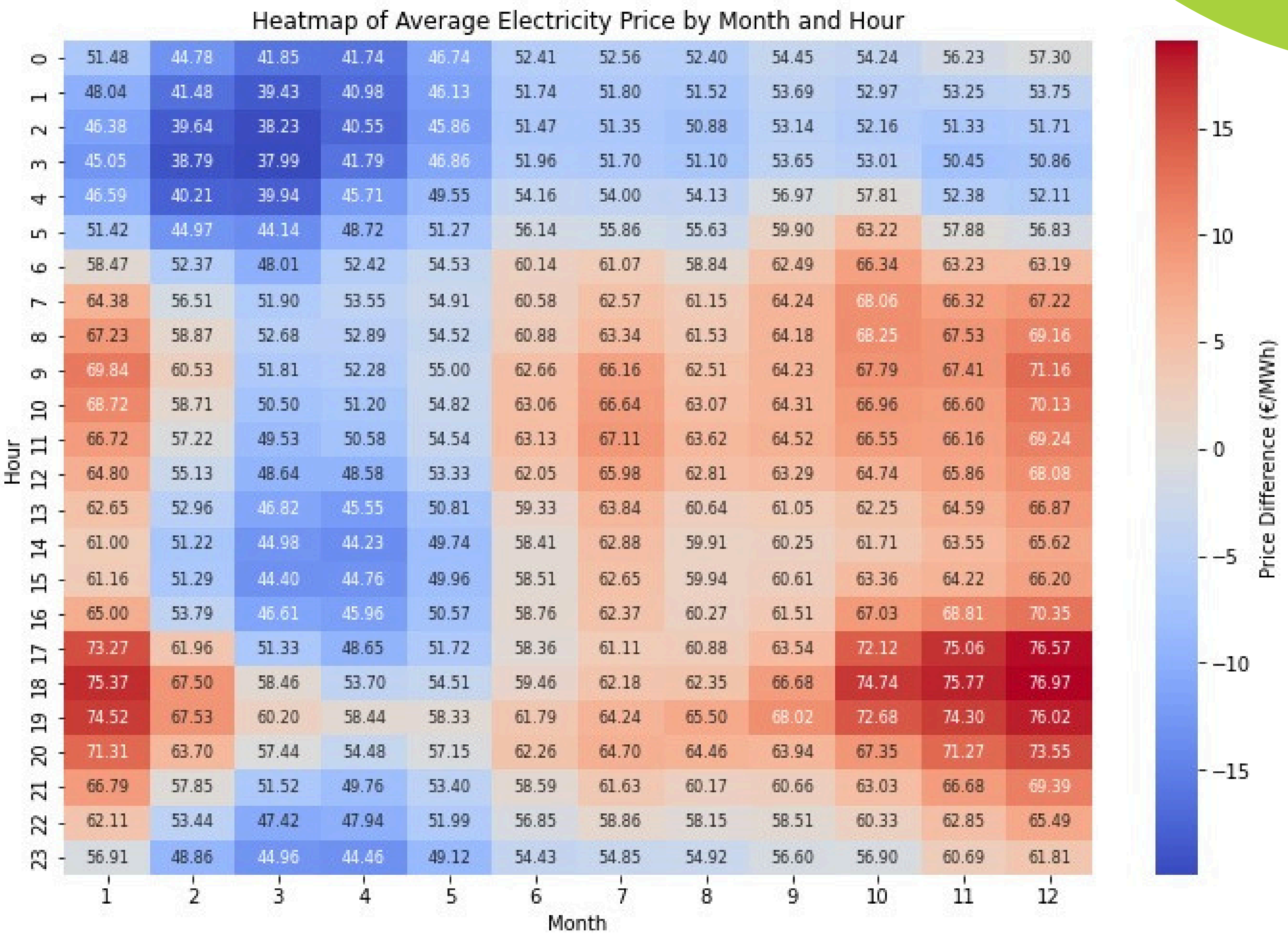
June vs December

4,4%

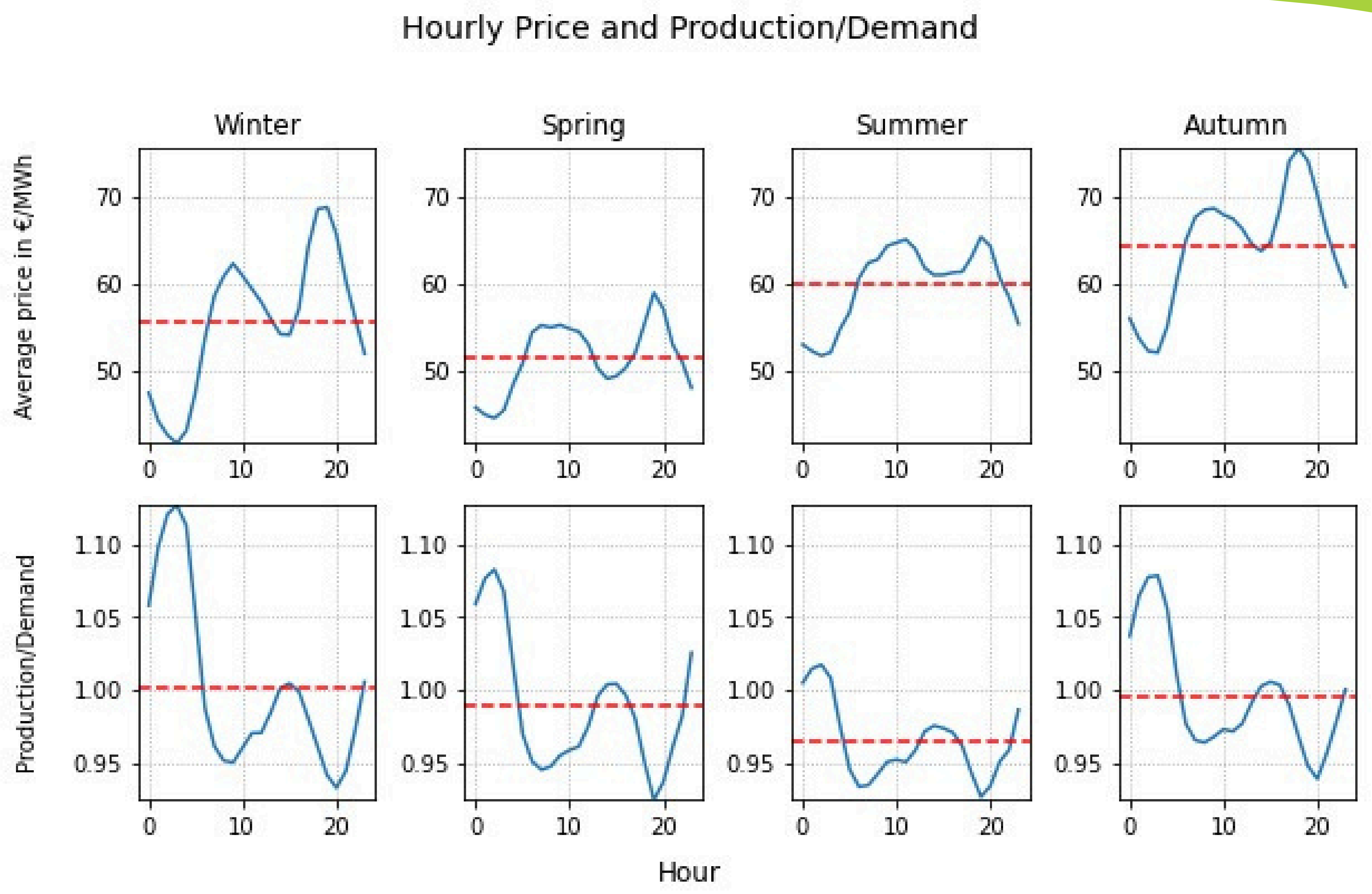
Lowest standard deviation
from **Solar** in December

12%

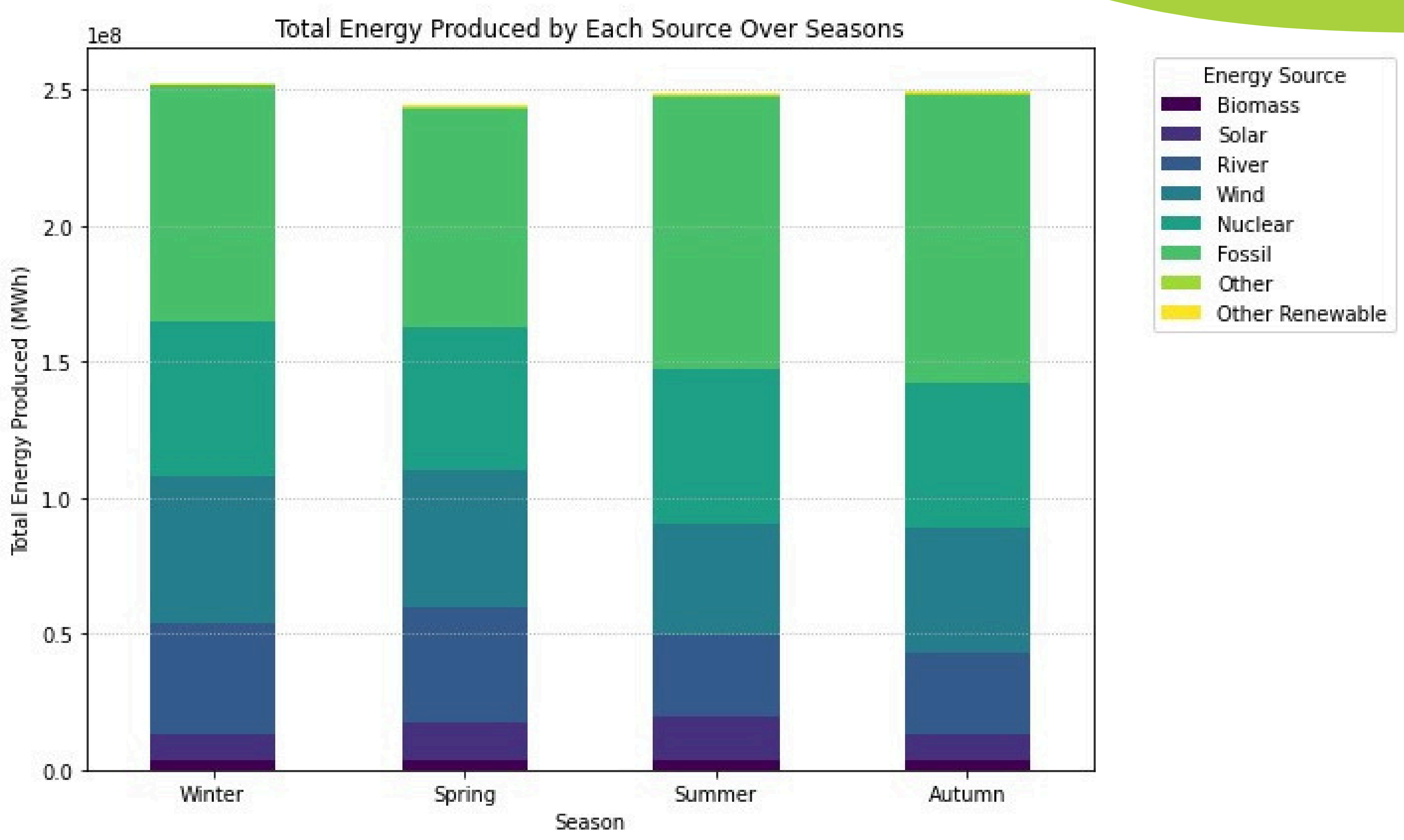
Highest standard deviation
from **Wind** in June



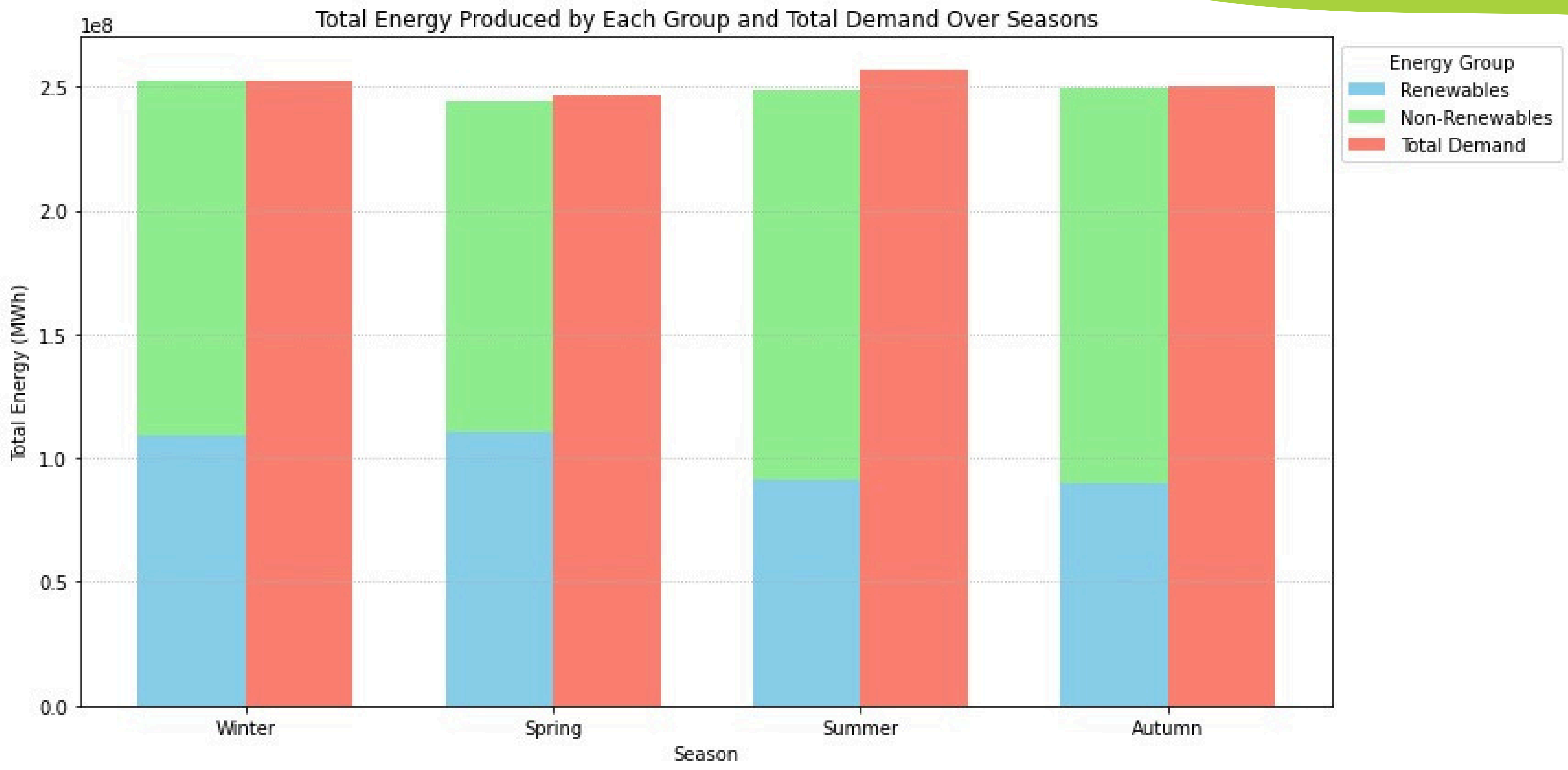
Analysis of the electricity price



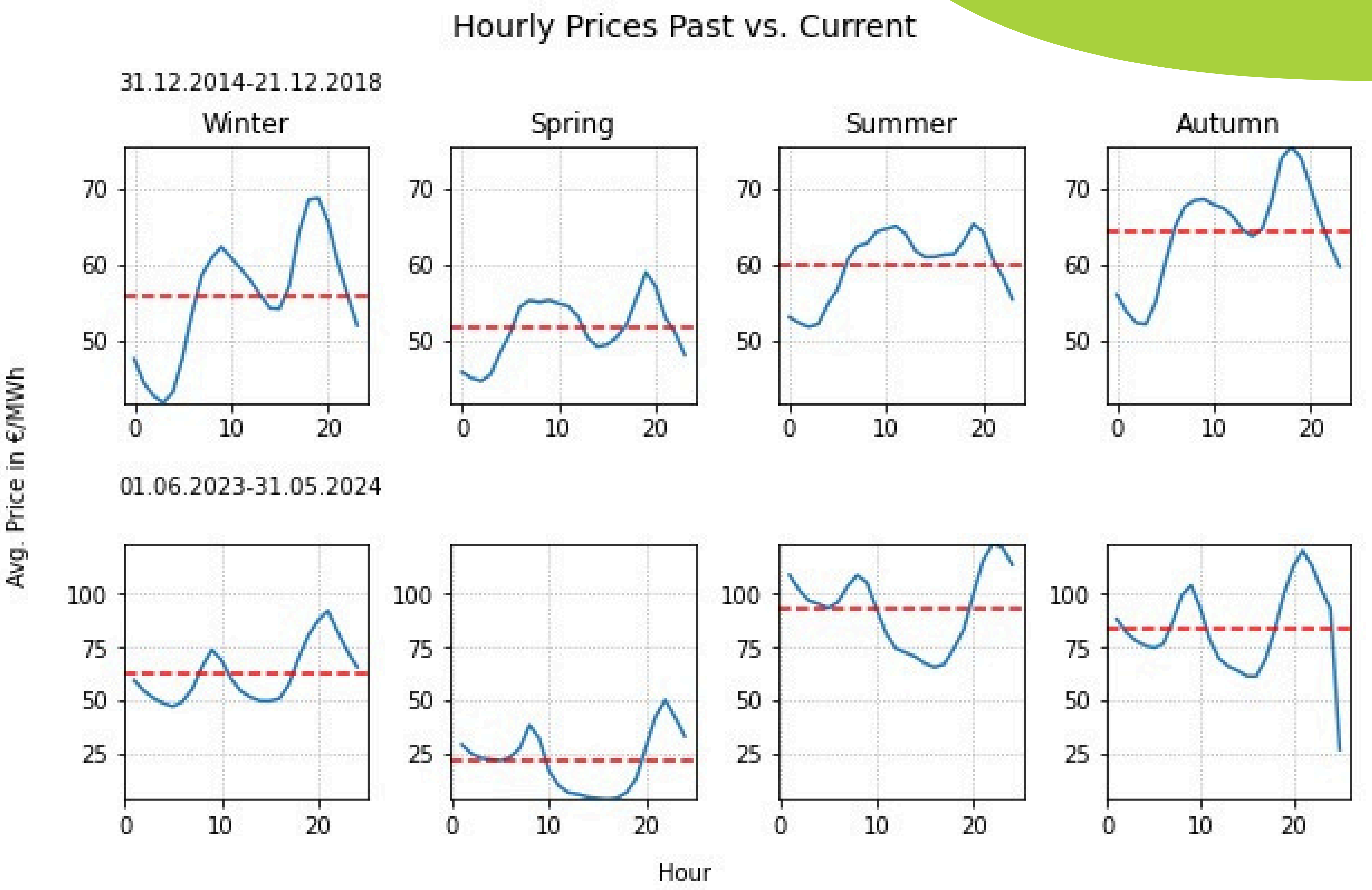
Hourly Price and Production/Demand
Winter
Spring
Summer
Autumn
Average price in €/MWh
Production/Demand
70
60
50
1.10
1.05
1.00
0.95
0
10
20
Hour



Total Energy Produced by Each Source Over Seasons
1e8
2.5
2.0
1.5
1.0
0.5
0.0
Total Energy Produced (MWh)
Winter
Spring
Summer
Autumn
Season
Energy Source
Biomass
Solar
River
Wind
Nuclear
Fossil
Other
Other Renewable



Total Energy Produced by Each Group and Total Demand Over Seasons
1e8
2.5
2.0
1.5
1.0
0.5
0.0
Total Energy (MWh)
Winter
Spring
Summer
Autumn
Season
Energy Group
Renewables
Non-Renewables
Total Demand


Hourly Prices Past vs. Current
31.12.2014-21.12.2018
Winter
Spring
Summer
Autumn
01.06.2023-31.05.2024
Avg. Price in €/MWh
Hour

Model Hourly Electricity Price

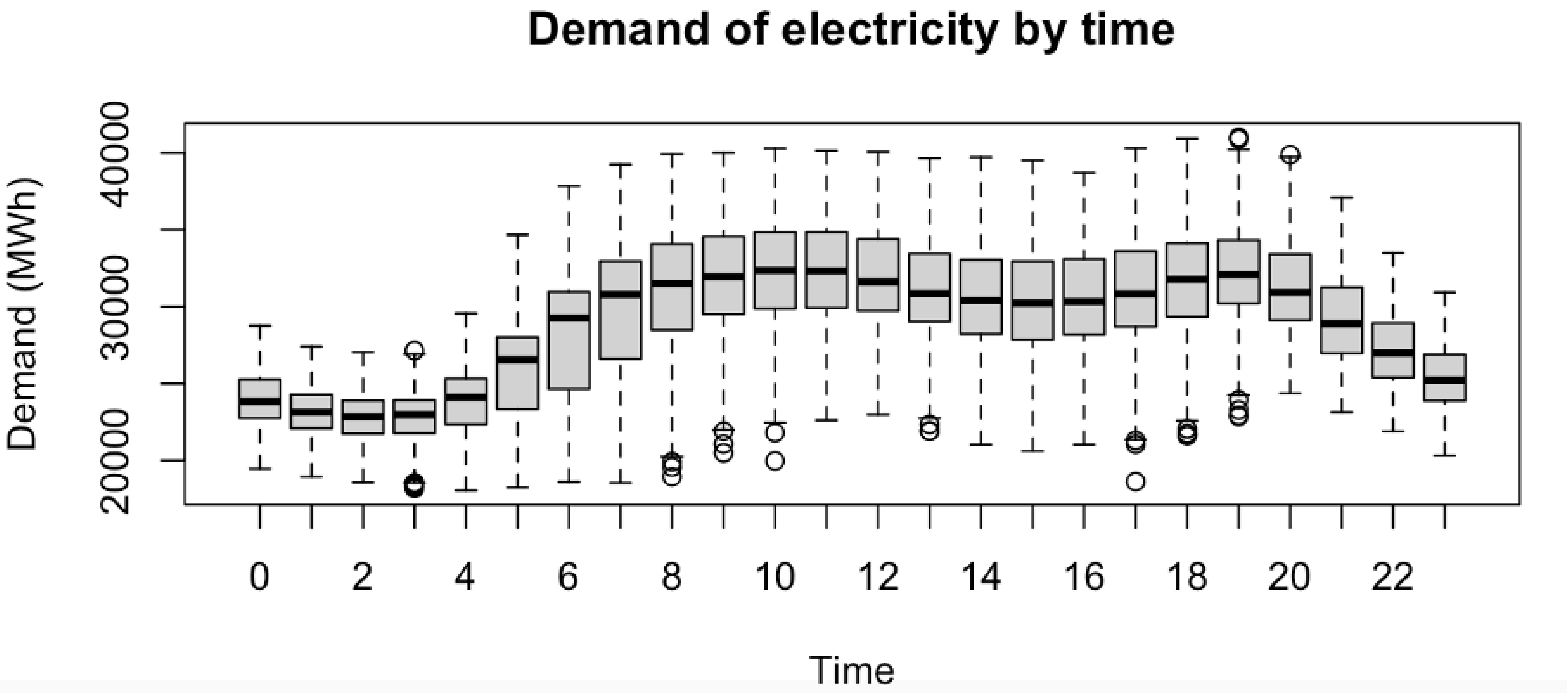
Linear model

$$\bar{P}_t = p_0 + H(t) + M(t)$$

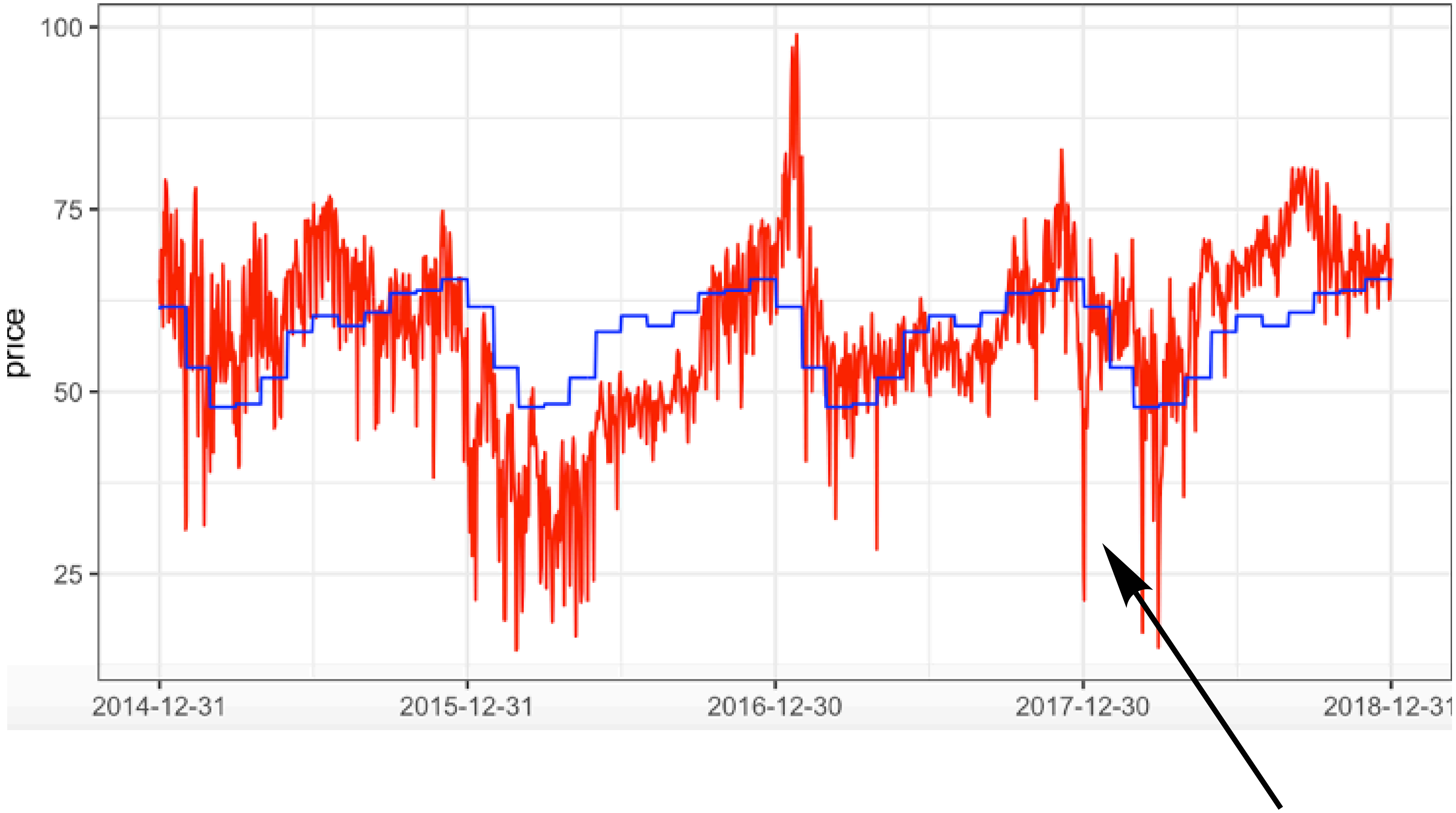
$$H(t) = \begin{cases} H_1 & \text{Hour} = 1 \\ H_2 & \text{Hour} = 2 \\ \vdots \\ H_{23} & \text{Hour} = 23 \end{cases}$$

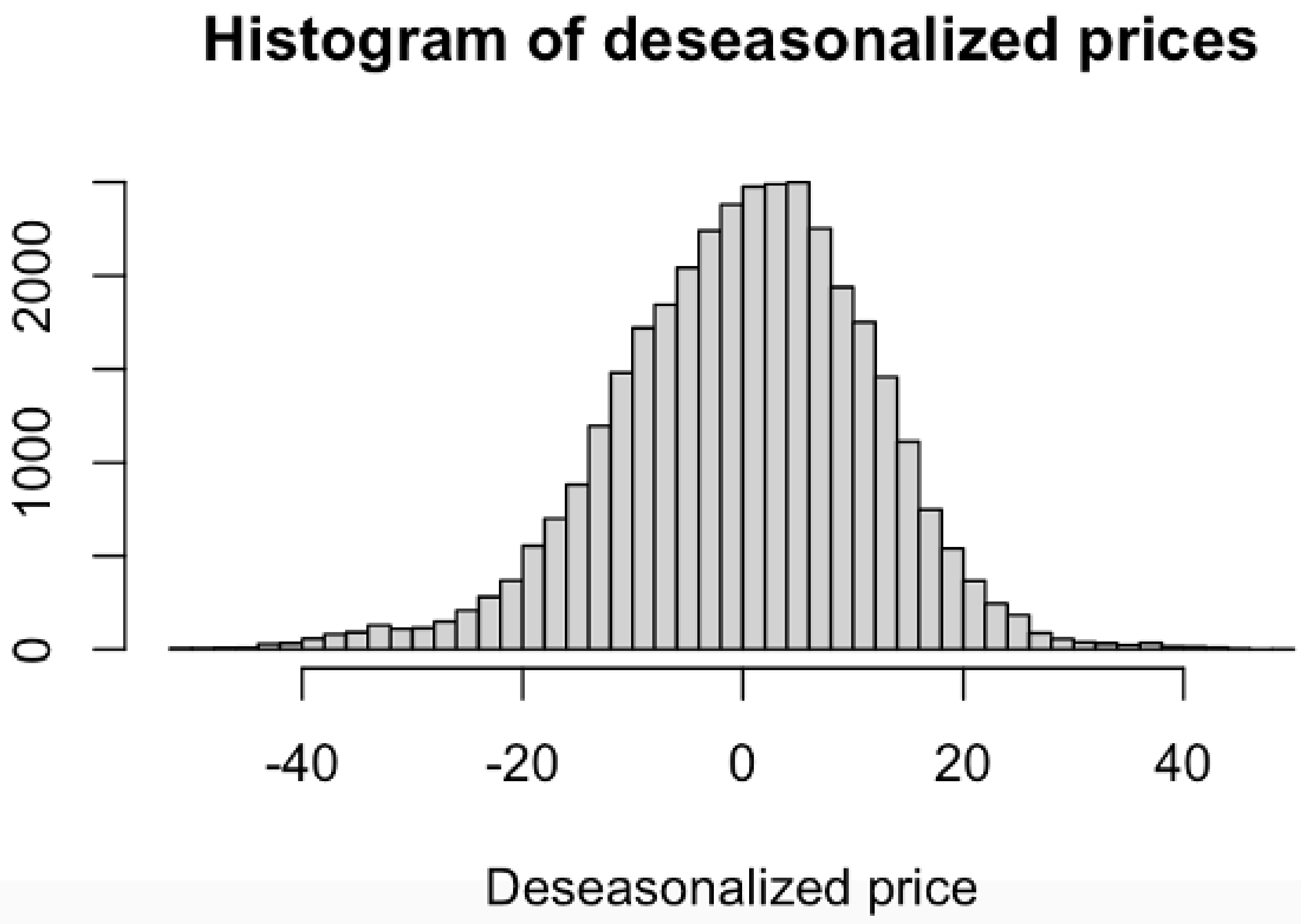
$$M(t) = \begin{cases} M_2 & \text{Month} = \text{February} \\ \vdots \\ M_{12} & \text{Month} = \text{December} \end{cases}$$

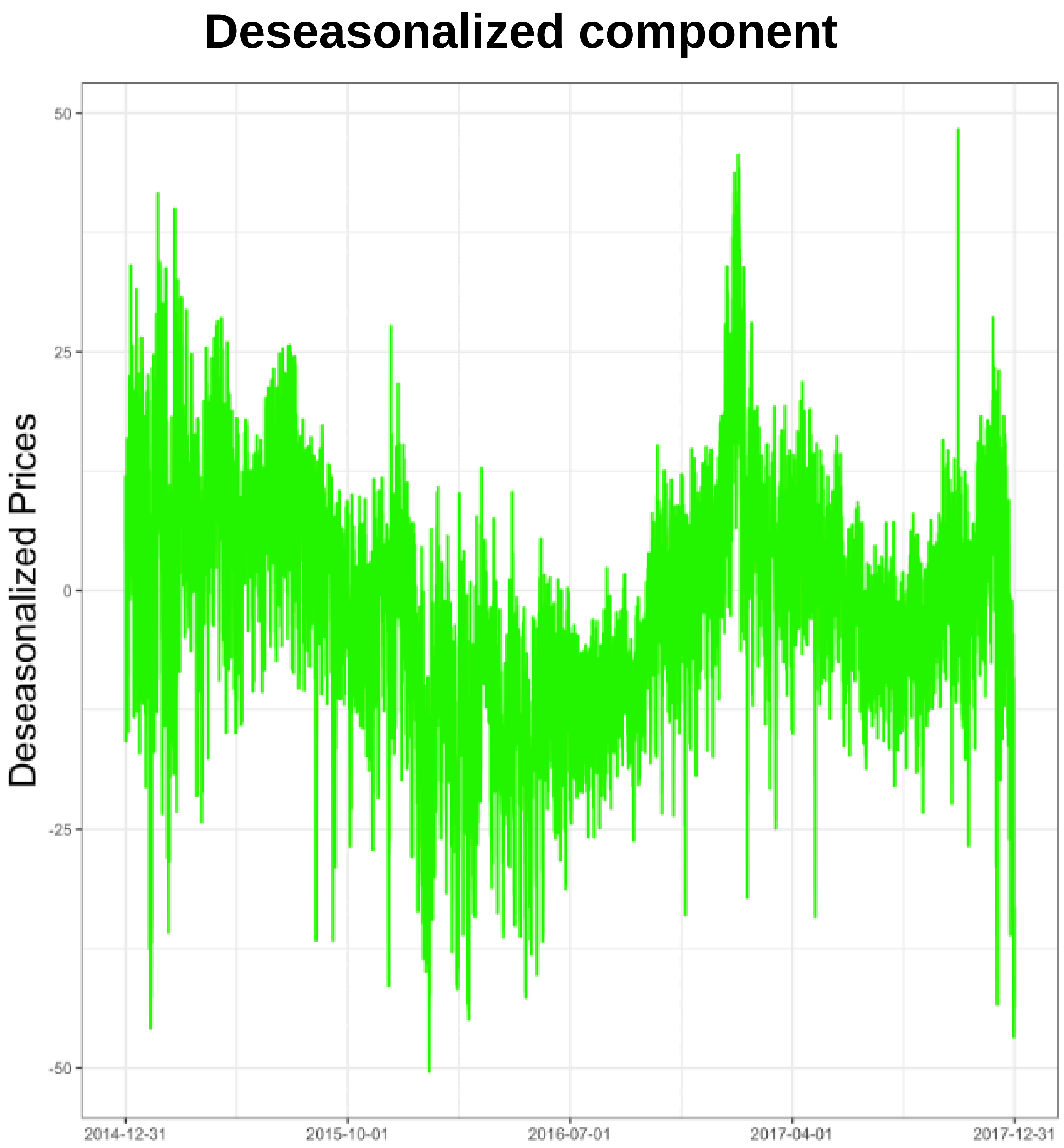
$$\tilde{P}_t = P_t - \bar{P}_t$$


Demand of electricity by time
Demand (MWh)
20000
30000
40000
0
2
4
6
8
10
12
14
16
18
20
22
Time

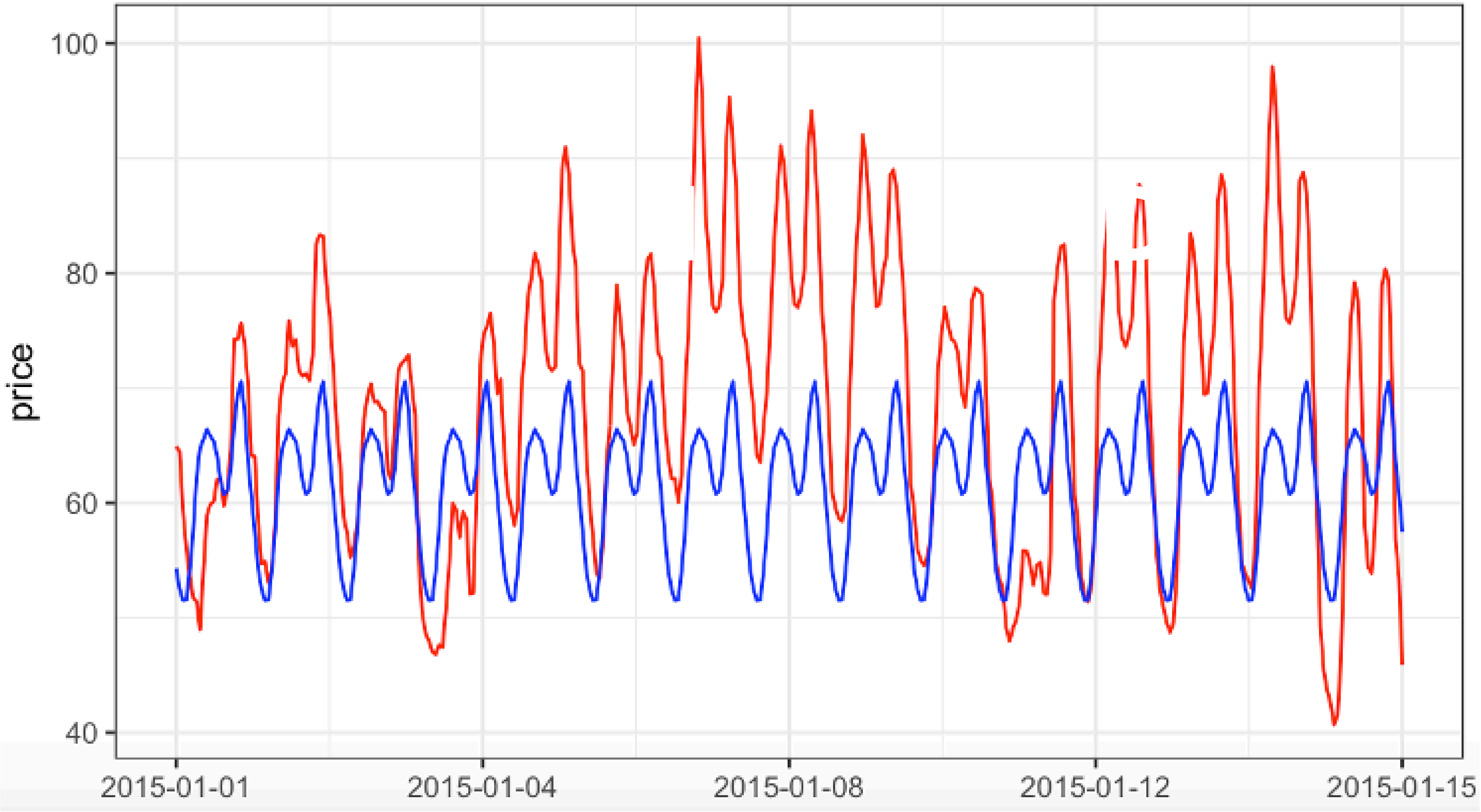
Realized prices vs seasonality component




Histogram of deseasonalized prices
0
1000
2000
-40
-20
0
20
40
Deseasonalized price


Deseasonalized component
Deseasonalized Prices
50
25
0
-25
-50
2014-12-31
2015-10-01
2016-07-01
2017-04-01
2017-12-31

Realized prices vs seasonality component: weekly view



Modelling the de-seasonalized prices:

Autoregressive process with one lag [AR(1)]

$$\tilde{P}_t = \phi \tilde{P}_{t-1} + \varepsilon_t$$

- **Main idea:**

Stepping stone for modelling

- **Important assumption:**

Persistence in time

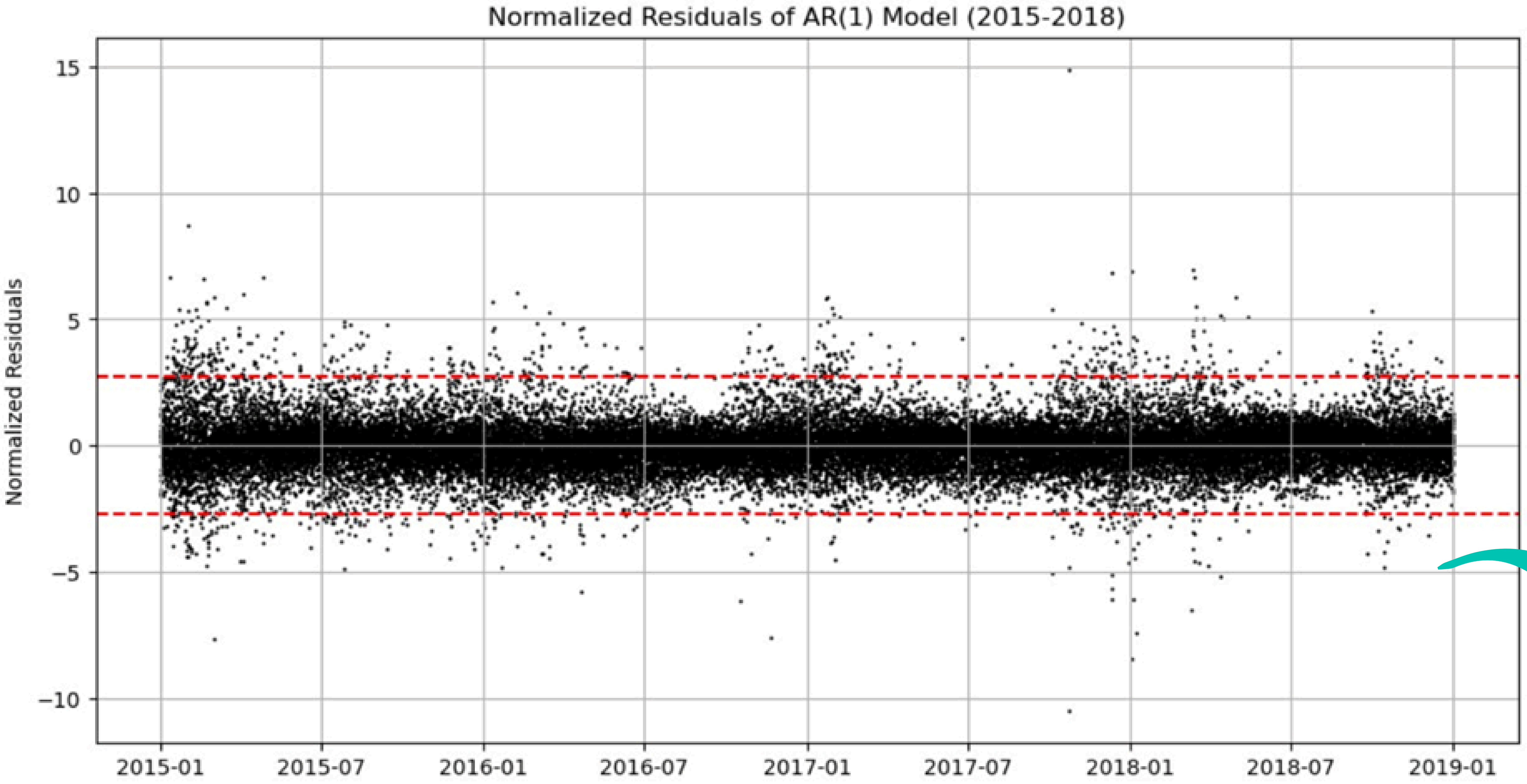
Model fit output in Python:

```
                      AR - Constant Variance Model Results
==============================================================================
Dep. Variable:     deseasonalizied_time_series   R-squared:                   0.946
Mean Model:                                 AR   Adj. R-squared:              0.946
Vol Model:                   Constant Variance   Log-Likelihood:           -84961.9
Distribution:                           Normal   AIC:                       169928.
Method:                     Maximum Likelihood   BIC:                       169945.
                                                 No. Observations:            35063
Date:                         Wed, Jun 26 2024   Df Residuals:                35062
Time:                                 19:38:59   Df Model:                        1
                               Mean Model
==========================================================================
                    coef    std err          t      P>|t|  95.0% Conf. Int.
--------------------------------------------------------------------------
dese...ies[1]     0.9726  1.397e-03    696.417      0.000 [  0.970,  0.975]
                          Volatility Model
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
sigma2         7.4511      0.110     67.848      0.000 [  7.236,  7.666]
========================================================================

Covariance estimator: White's Heteroskedasticity Consistent Estimator
```

if $|\phi| < 1$ process is stationary !

Checking the residuals:



Volatility clusters spotted

Checking the residuals:

Two-Sample Kolmogorov-Smirnov Test

```
p-value is 3.268838697781156e-21
The null hypothesis is rejected
```

- Residuals do not have an identical distribution
- Variance is not constant (Heteroskedasticity)
- AR(1) is not an optimal model

But how do we account for heteroskedasticity?

GARCH(1,2)-Model for volatility

Residuals not identically distributed

Use GARCH to model volatility clusters

Model composition:

$$\varepsilon_t = \sigma_t u_t$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2$$

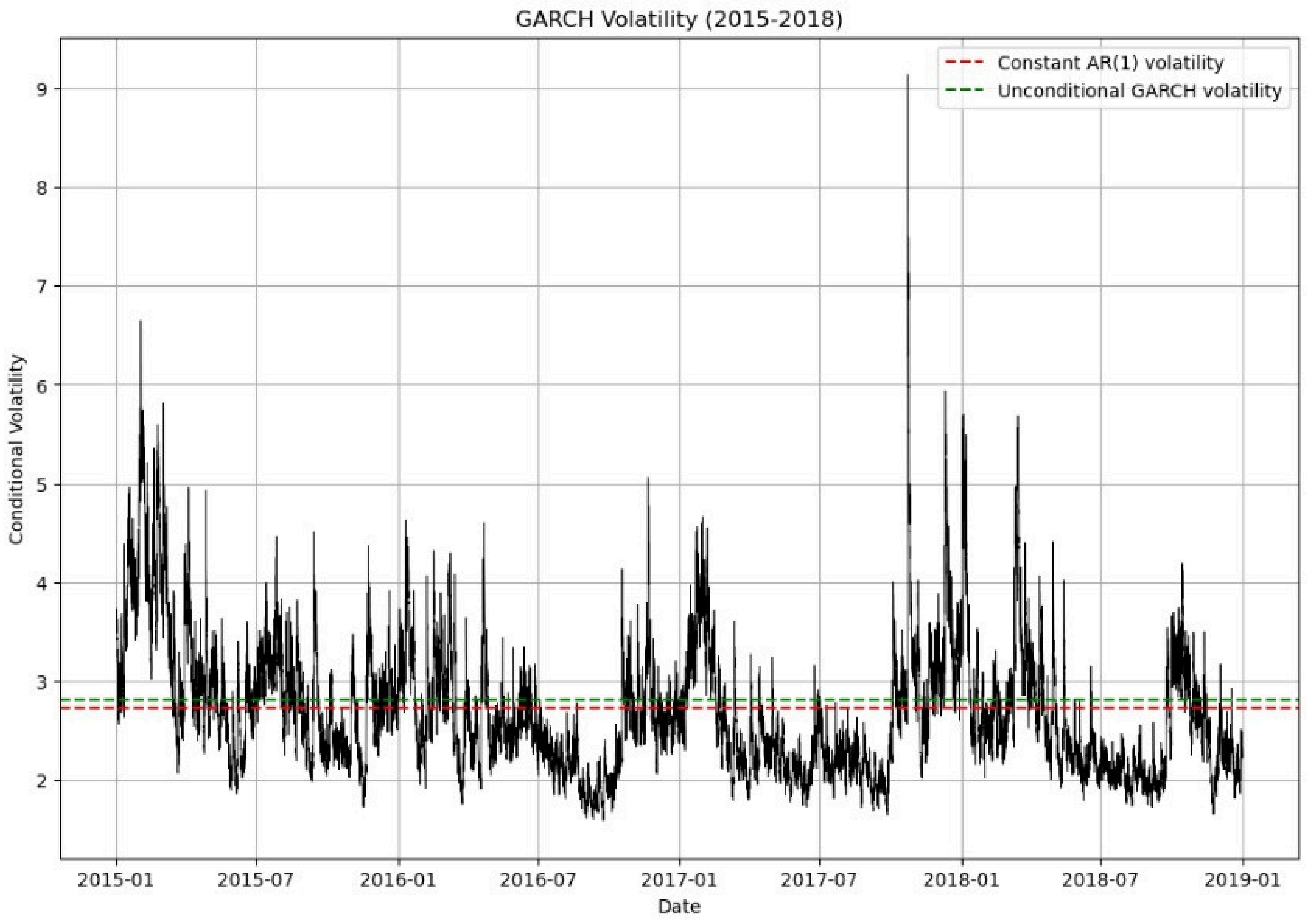
$$u_t \sim \mathcal{N}(0,1)$$

Our fitted values show persistence

Parameter	Value	p-value
omega	0.0412	1.072e-03
alpha_1	0.0379	1.437e-12
beta_1	0.2177	1.300e-07
beta_2	0.7392	3.650e-70

$$\alpha_1 + \beta_1 + \beta_2 = 0.995$$

Process is **stationary**


GARCH Volatility (2015-2018)
Constant AR(1) volatility
Unconditional GARCH volatility
Conditional Volatility
9
8
7
6
5
4
3
2
2015-01
2015-07
2016-01
2016-07
2017-01
2017-07
2018-01
2018-07
2019-01
Date

Test shows:
Our model still needs improvement

Let’s take a look at the residuals and our assumptions

Kolmogorov-Smirnov 2 sample test:
Normalised residuals are now identically distributed!

BUT: Not normally distributed!

$$\varepsilon_t = \sigma_t u_t \quad u_t \sim \mathcal{N}(0,1)$$

$$u_t = \frac{\varepsilon_t}{\sigma_t} \sim \mathcal{N}(0,1)$$

While the volatility was improved, the residuals don’t fit the model yet!

Gaussian Mixture Distribution

Let's consider a **Gaussian mixture model** for the GARCH normalized residuals, i.e.

$$u_t \sim B \cdot (\mu_1 + \sigma_1 Z_1) + (1 - B) \cdot (\mu_2 + \sigma_2 Z_2)$$

where $B \sim \text{Bernoulli}(p)$, while Z_1 and Z_2 are standard normal. All are assumed to be independent.

Our goal is now to **find the optimal parameters combination** for this distribution in order to **better explain the GARCH residuals.**

Why Gaussian Mixture?

Flexibility

Non normality of residuals

Capturing different volatility regimes

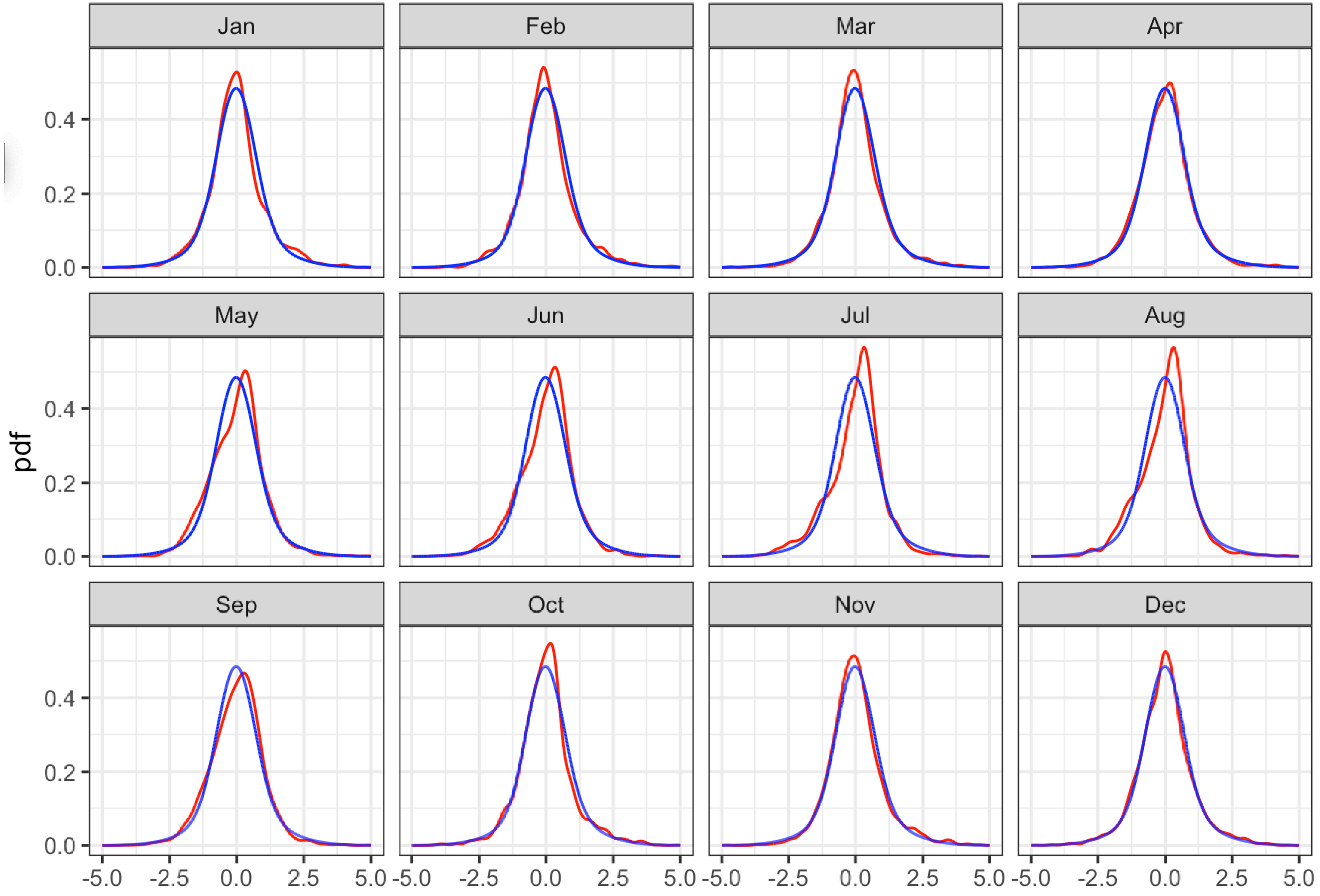
Improved risk assessment

Key results for yearly parameters fitting

μ_1	μ_2	σ_1	σ_2	p_1	$1-p_1$	log-lik	$\mathbb{E}\{u_t\}$	$\mathbb{S}d\{u_t\}$
0.04521	-0.02346	1.489	0.6885	0.3015	0.6985	-48452	-0.00272	1

If B takes the **extreme values**, i.e. 1 or 0:

- High volatility vs. Low volatility periods
- Positive shocks vs. Negative shocks
- Normal market vs. Abnormal market

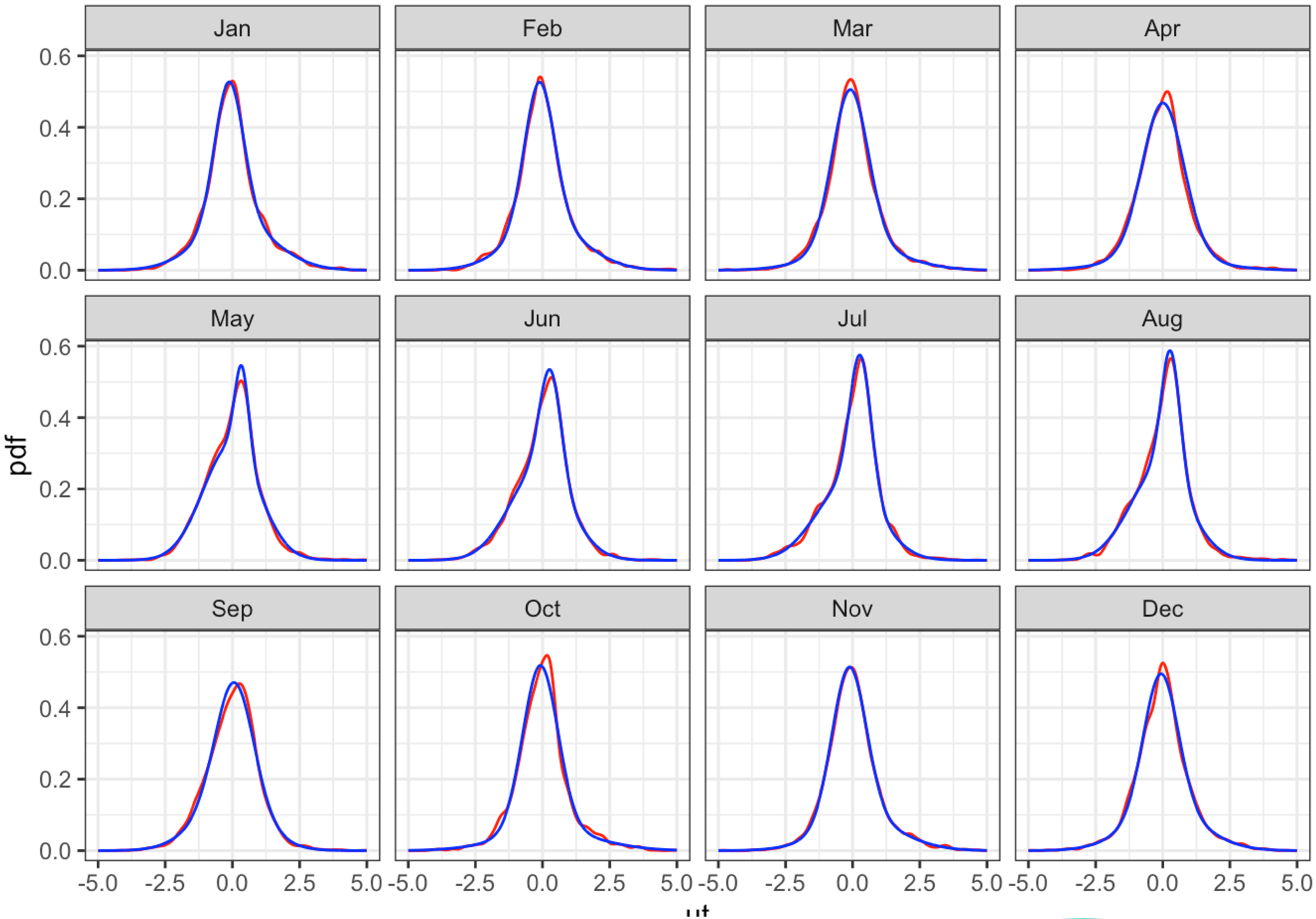


Yearly Gaussian Mixture vs Empirical monthly densities

Fitting for monthly parameters

Month	μ_1	μ_2	σ_1	σ_2	p_1	$1-p_1$	log-lik	$\mathbb{E}\{u_t\}$	$\mathbb{S}d\{u_t\}$
Jan	0.1491	-0.129	1.41	0.54	0.46	0.54	-4177	-0.00087	1.09
Feb	0.1506	-0.118	1.40	0.56	0.43	0.57	-3761	-0.00184	1.05
Mar	0.2573	-0.094	1.62	0.67	0.25	0.75	-4067	-0.00492	1.02
Apr	0.0069	-0.040	0.77	1.73	0.83	0.17	-3971	-0.00112	1.00
May	0.3486	-0.059	0.26	1.05	0.16	0.84	-4097	0.00614	0.95
Jun	0.2982	-0.131	0.39	1.12	0.30	0.70	-3945	-0.00369	0.96
Jul	0.2912	-0.203	0.40	1.17	0.38	0.62	-4021	-0.01530	0.97
Aug	0.2965	-0.136	0.35	1.10	0.31	0.69	-3966	-0.00302	0.91
Sep	0.0779	-0.145	0.70	1.25	0.62	0.38	-3916	-0.00692	0.92
Oct	0.2648	-0.083	1.79	0.65	0.24	0.76	-4097	-0.00096	1.11
Nov	0.3298	-0.131	1.49	0.64	0.30	0.70	-3913	0.00749	1.00
Dec	0.1011	-0.071	1.43	0.64	0.37	0.63	-4134	-0.00735	1.02

Monthly Gaussian Mixture vs Monthly Empirical Densities



Simulating Price Processes

$$\bar{P}_t = p_0 + H(t) + M(t)$$

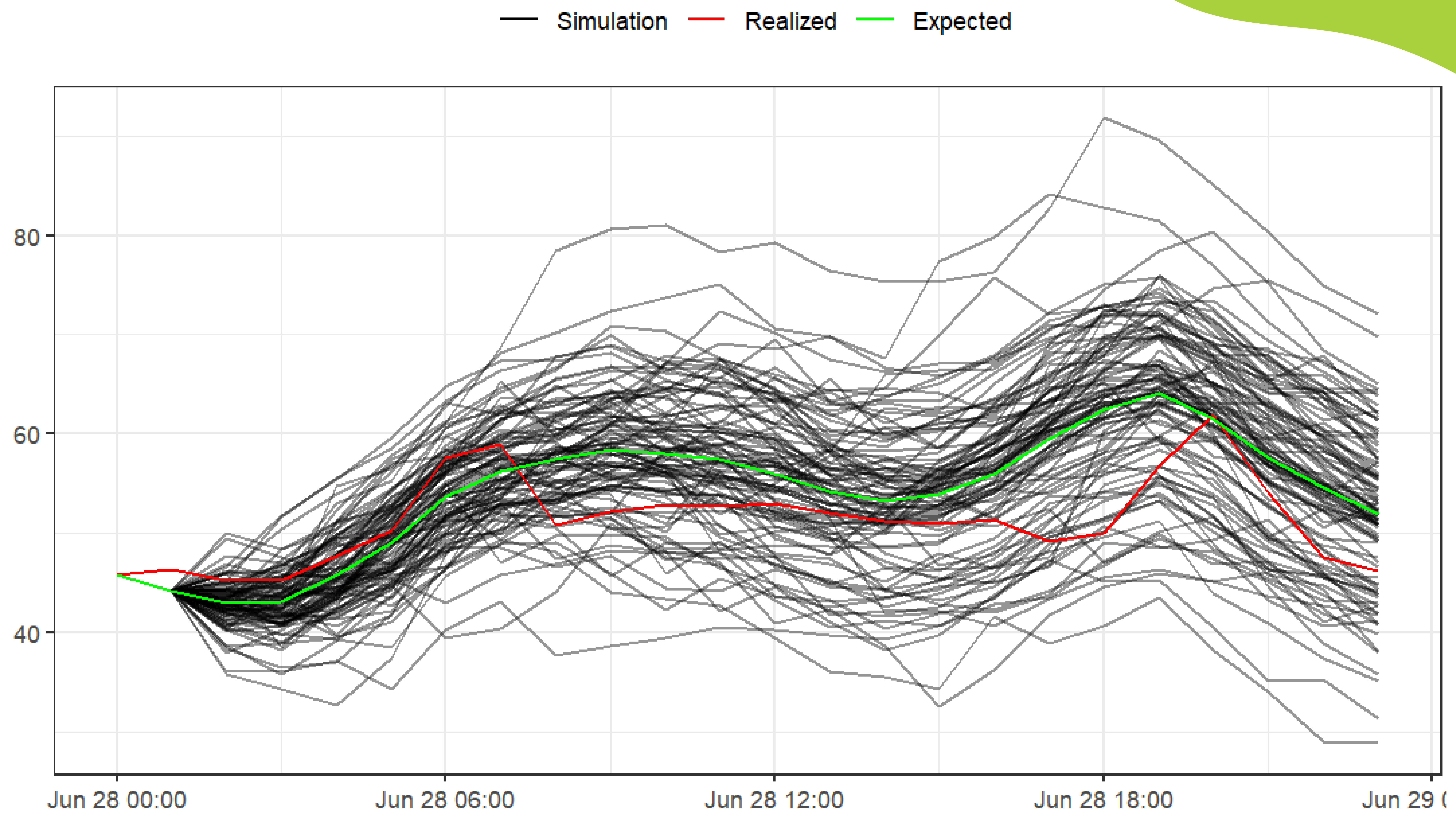
$$\tilde{P}_t = P_t - \bar{P}_t \qquad \tilde{P}_t = \phi \tilde{P}_{t-1} + \varepsilon_t$$

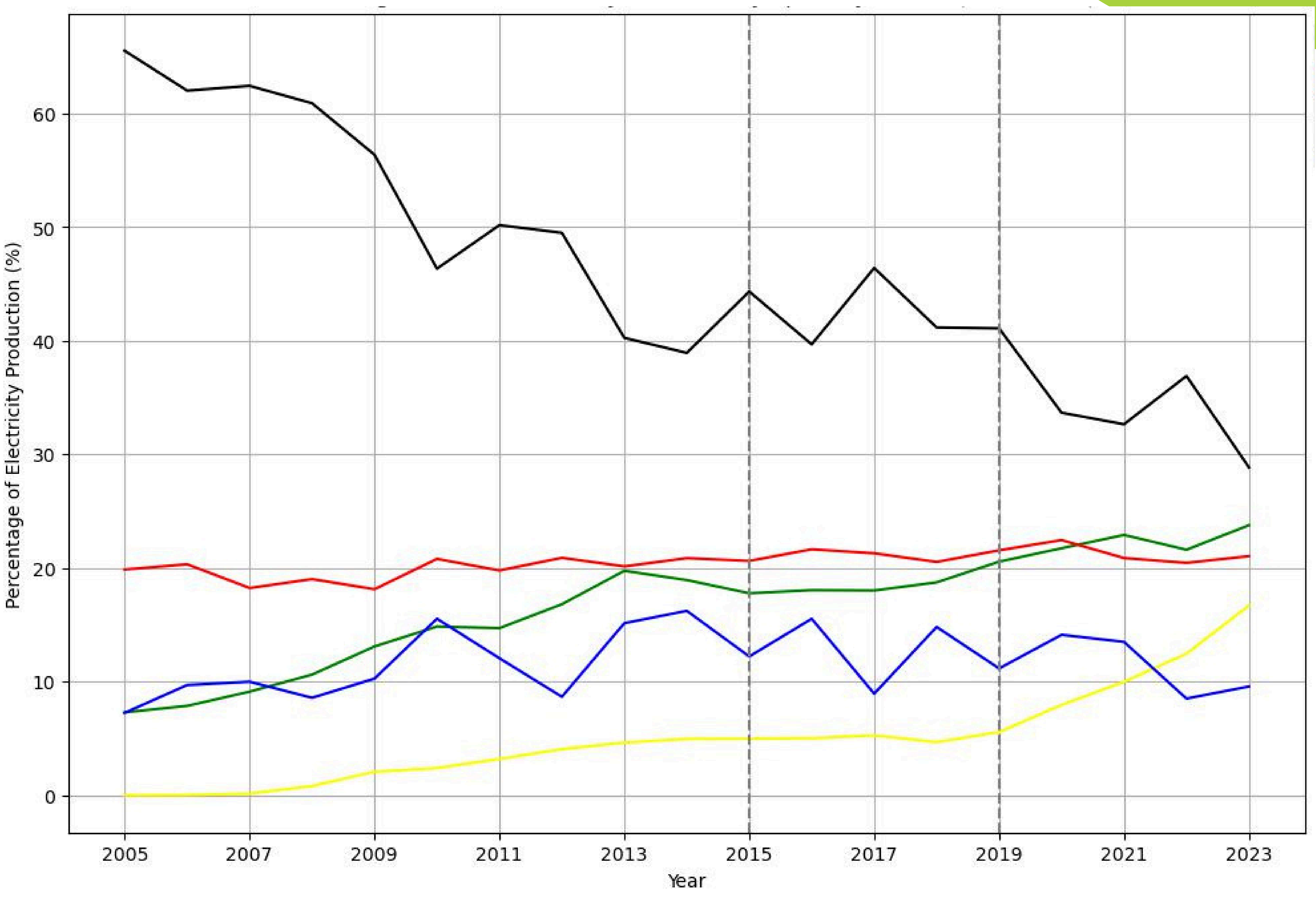
$$\varepsilon_t = \sigma_t u_t$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2$$

$$u_t \sim B \cdot (\mu_1 + \sigma_1 Z_1) + (1 - B) \cdot (\mu_2 + \sigma_2 Z_2)$$

Simulated Price Processes





$$\bar{P}_t = p_0 + H(t) + M(t)$$

Solar

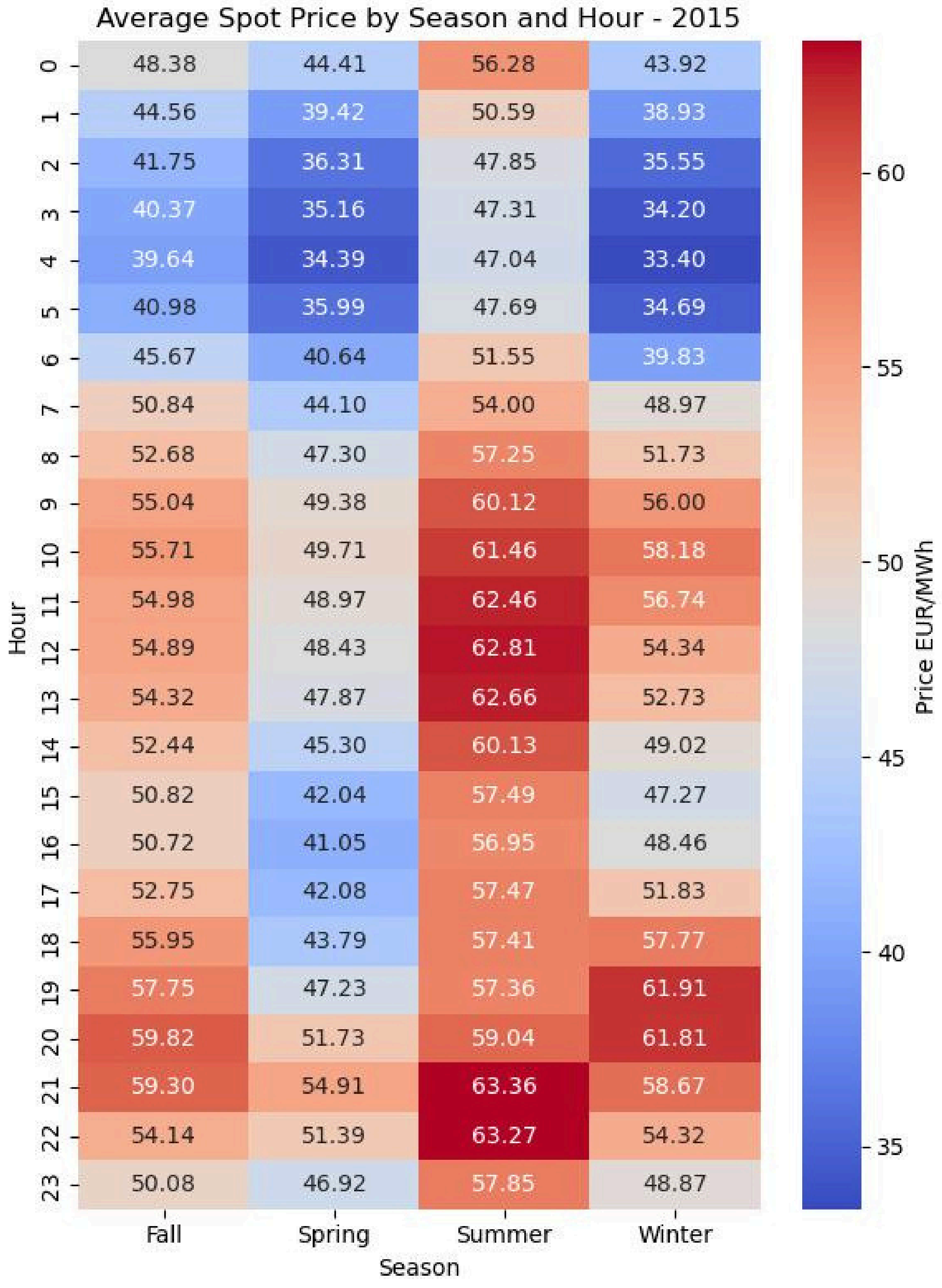
Wind

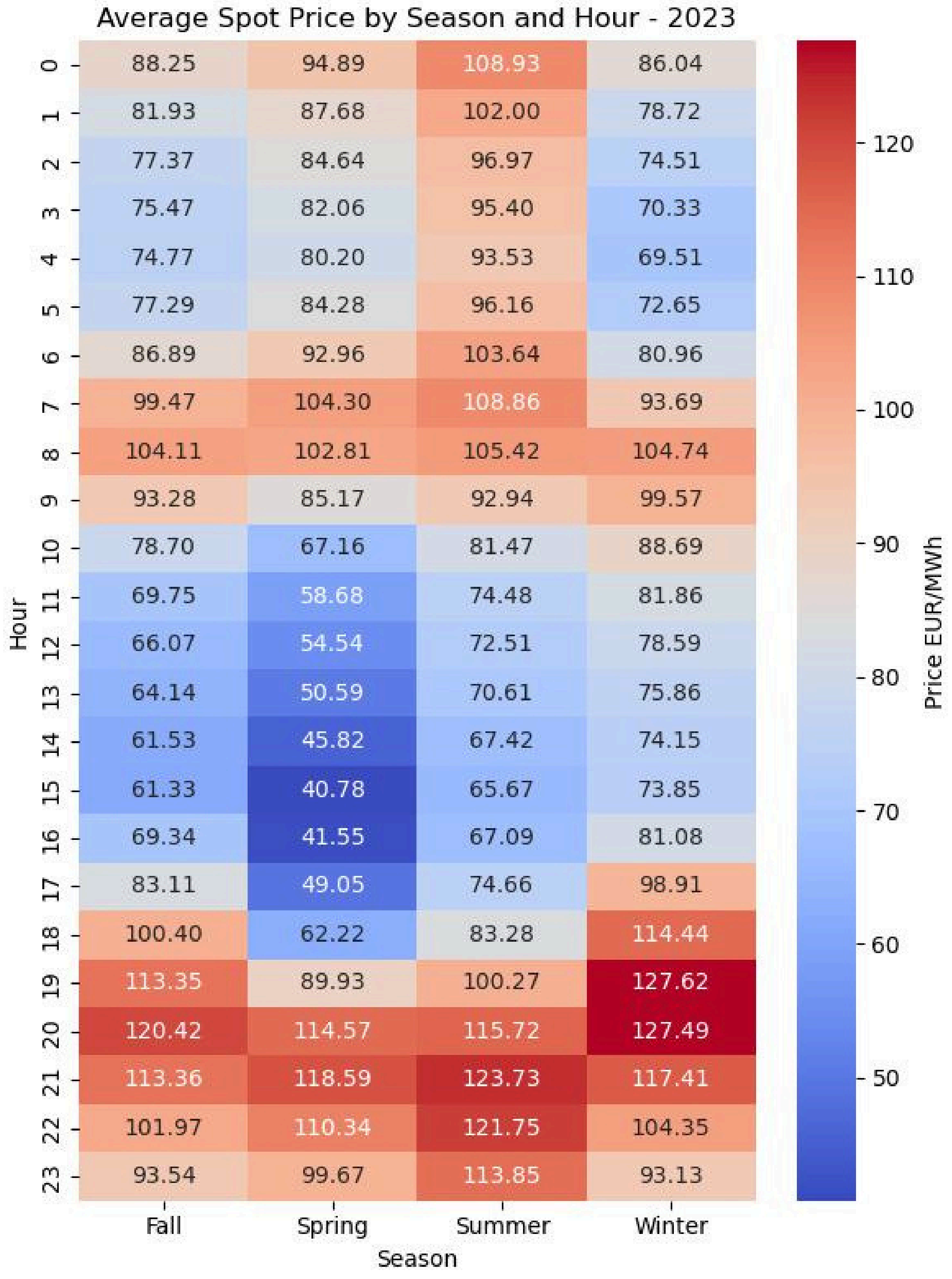
Fossil

Nuclear

Other Renewables

Data from energy-charts.info

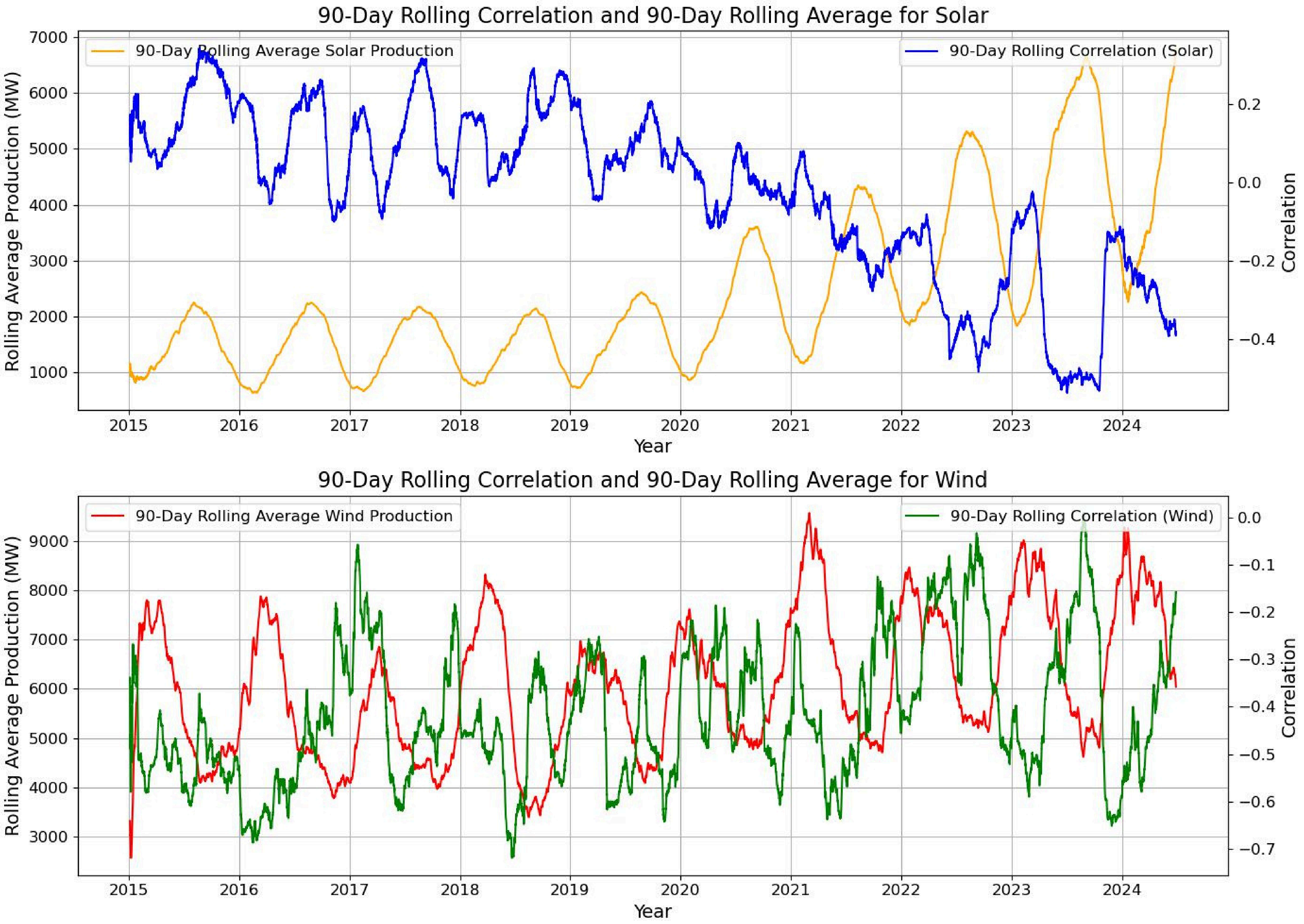




Realized prices vs seasonality component

$$\bar{P}_t = p_0 + H(t) + M(t)$$

Data from energy-charts.info



Correlation Renewables and Prices

Data from energy-charts.info

Future developments

- Price Models with NWP
- Asian Quanto option for solar producers:

$$(K_P - P(t))^+(IR(t) - K_{IR})^+$$

- For an hydro producer:

$$X_{\tau_2}(\tau_1, \tau_2) = (T - RF(\tau_1, \tau_2))^+$$

$$RF(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} R(t)$$

Thank you for your attention!

Giuseppe Bressi, Alessia Fattorel, Bora Callioglu, Sofia Cattani, Sara Farnedi, Alessandro Brancalion, Fabio Ehrenhofer, Max Lichtbau, Jakob Larsen, Mohammadhossein Nikoupour, Nicholaus Augustin, Philipp Lauer, Enora Ndiaye-Martin, Nicolo' Cenciarelli, Reza Hassanzadeh