The zonal and seasonal CO2 marginal emissions factors for the Italian power market

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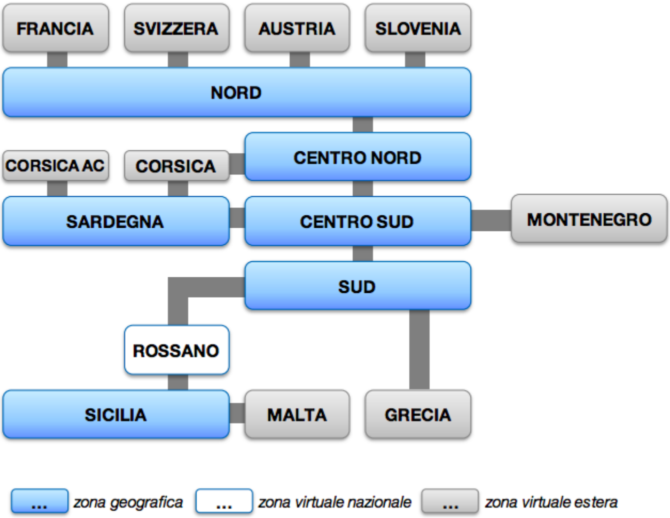
Outline

Motivation

- Increasingly ambitious targets for carbon emissions reduction.
- The penetration of *Renewable Energy Sources* (RES) in power markets enables to displace the carbon-intensive thermoelectric generation $\Longrightarrow$ *European Green Deal Investment Plan.*
- Policy. Average Emission Factors (*AEFs*) are not reliable tools to inform well-oriented policy interventions for carbon emissions reduction. AEFs ignore the variability of electricity production, the merit-order technology mix and the carbon intensity of marginal units.
- Target. Marginal change in carbon emissions (tCO_2) following a marginal change in electricity generation (MWh) $\Longrightarrow$ *Marginal Emission Factors* (*MEFs*).

Figure 1: The Italian wholesale power market configuration in 2018. *Source*: Terna, the Italian Transmission System Operator (TSO).



Contribution

✓ Use of an intra-day approach that allows to capture the dynamics of economic and social activity, for a more intuitive interpretation of results for MEFs.

✓ Identification of seasonal patterns and spatial analysis in the context of zonal pricing. Seasonal and regional differences can be identified and used for policy purposes.

✓ Our *FCVAR* model allows to extend the classic cointegration approach by Engle and Granger (1987) and Johansen (2008).

Literature

US Fixed-Effects model (Holland and Mansur (2008); Callaway and Fowlie (2009)):

$$E_{hrt} = \beta_{hr} G_{hrt} + \alpha_{hr} + \epsilon_{hrt} \quad (1)$$

Contribution by Hawkes (2010, 2014) for the UK power system:

$$\Delta E_{hrt} = \beta_{hr} \Delta G_{hrt} + \epsilon_{hrt} \quad (2)$$

ARFIMA Fixed-Effects model (Beltrami et al., 2020):

$$\Phi_p(L)(1 - L)^d (E_{th} - \beta_h G_{th}) = \alpha_h + \Theta_q(L)\epsilon_{th} \quad (3)$$

Empirical strategy: intra-day vs. inter-day approach

Intra-day approach

- Subsequent settlement periods
- Time-dependence
- Higher frequency of data

✓ Shocks from the demand-side
✓ Shocks from the supply-side
✓ Concatenation of hours
✓ Technical constraints of plants
× Complex data management

Inter-day approach

- Individual settlement periods
- Time-independence
- Lower frequency of data

✓ Simplified data management
× No concatenation of hours
× Neglects technical contraints
× General loss of information

Zonal *MEFs*

1. Zonal institutional market setting;
2. Inclusion of RES in generation data (Li et al., 2017);
3. Flexible econometric approach to deal with the complexity of high frequency time-series data.

Integrated econometric approach

We allow $E_{h,z}$ and $G_{h,z}$ to be fractionally cointegrated $\rightarrow$ $FCVAR_{d,b}$ model. The co-movement between them in the sample period might actually be a partial co-movement (Jones et al., 2014; Carlini and Santucci de Magistris, 2019).

$FCVAR_{d,b}$ methodology

$$\Delta^d(X_t - \mu) = \alpha\beta'\Delta^{d-b}L_b(X_t - \mu) + \sum_{i=1}^{k}\Gamma_i\Delta^d L_b^i(X_t - \mu) + \varepsilon_t \quad (4)$$

Description

The coefficients $d, b \in R_+$ with $0 < b \leq d$ are estimated through maximum likelihood on seasonally-adjusted time-series data.

- $X_t = (X_{1,t,z}; X_{2,t,z}) = (E_{h,z}; G_{h,z})$;
- μ is the restricted constant (Johansen and Nielsen, 2016);
- d is the fractional parameter ($d \leq 1$). X_t is $I(d)$ process;
- b is the degree of fractional cointegration. In the estimation stage, we assume $d = b$;
- The value of β is the estimated *MEF* and α is the speed of adjustment towards the equilibrium cointegrating relationship.

Robustness checks

$$
\begin{aligned}
R_{\psi}\psi &= r_{\psi} \\
R_{\alpha} vec(\alpha) &= 0 \\
R_{\beta} vec(\beta^{*}) &= r_{\beta}
\end{aligned}
\tag{5}
$$

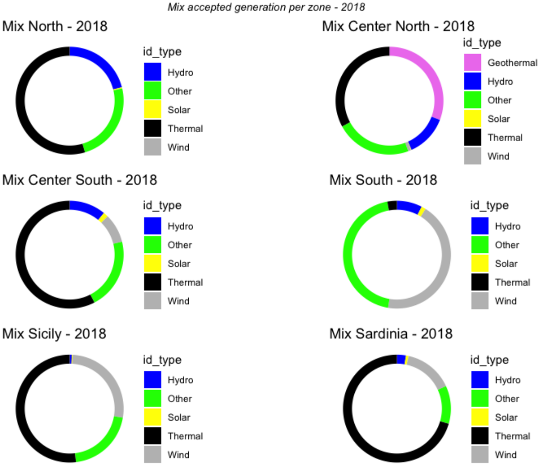
Hypothesis tests

1. $\mathscr{H}_d^1$: is it statistically correct to adopt a $FCVAR_{d,b}$ rather than a standard CVAR ($d = b = 1$)?
2. $\mathscr{H}_\alpha^1$ and $\mathscr{H}_\alpha^2$: long-run exogeneity tests on the single variables. Test on the coefficient α;
3. $\mathscr{H}_\beta^1$: does the emission variable belong to the cointegrating equilibrium relationship? Test on the coefficient β.

Data

- Italian day-ahead wholesale power market (*MGP*). 6 physical market zones: North, Center North, Center South, South (excluded), Sicily and Sardinia.
- Electricity generation ($G_{h,z}$) from the analysis of bids in the day-ahead market by zone. Year: 2018 (*source*: GME, the Italian Market Operator).
- Carbon emissions ($E_{h,z}$) calculated from data on the efficiency of thermoelectric power plants and the hourly fuel consumption. Year: 2018 (*sources*: REF-E, ISPRA).
- Data treated with R. Algorithm for FCVAR: Matlab.

Figure 2: Italian zonal power generation mix resulting from the day-ahead power market. *Source*: own elaboration from GME data.



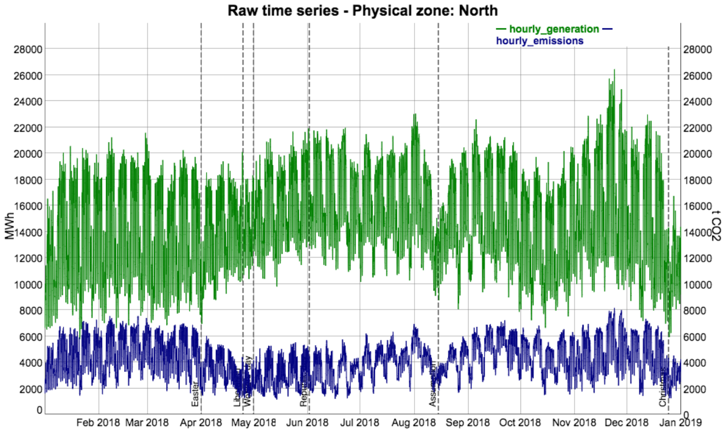


Figure 3: Raw time-series data of hourly generation (MWh) and carbon emissions (tCO_2) for the zone North in 2018. *Source*: own elaboration.

Preliminary unit root and stationarity tests

- Full year 2018. The unit root (ADF, DF-GLS, PP, ZA) and stationarity (KPSS and RKPSS) tests indicate fractional integration for our individual seasonally-adjusted time series variables for all zones. Data exhibit a process with long memory.
- Quarters 2018. The unit root (ADF, DF-GLS, PP, ZA) and stationarity (KPSS and RKPSS) tests indicate fractional integration for our individual seasonally-adjusted time series variables for all zones, except for Sardinia. Data seem to point out towards fractional cointegration.

Selected model and main findings

- Full year 2018. FCVAR is appropriate for all zones. Only for Center South there is no evidence of cointegrating relationship (ARFIMA used here).
- Quarters 2018. For quarterly samples, FCVAR model is rejected (and also CVAR is inappropriate) for most of the cases. Hence, ARFIMA is used instead (variables in levels).
- Results. High variability of MEFs across zones. Annual MEF strongly affected by carbon intensity in Q1, except for Sicily where warmer months display higher MEFs as compared to colder months. Moreover, the inclusion of RES reduces MEF by 32% as respect to our computation of the conventional MEF.

Summary of results - Full sample 2018

Table 1: *Marginal emission factors (tCO_2/MWh) and average emission factors (tCO_2/MWh) in 2018 by market zone.*

Zone	*MEF*	*AEF*
North	0.2018	0.2840
Center North	0.4236	0.1234
Center South	0.7022	0.4078
Sicily	0.1460	0.0738
Sardinia	0.7189	0.3001
Italy	**0.3921**	0.2524

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Summary of results - Quarters 2018

Table 2: *Quarterly MEFs (tCO_2/MWh) in 2018 by zone in the Italian day-ahead electricity market.*

	North	Center North	Center South	Sicily	Sardinia
Q1	0.3937	0.6437	0.7358	0.1476	0.8596
Q2	0.3624	0.3313	0.7535	0.2960	0.8102
Q3	0.2738	0.3297	0.6616	0.3214	0.7953
Q4	0.3340	0.3649	0.6315	0.3015	0.7737

Conclusions

- AEFs wrongly assess potentials for carbon offsets.
- *MEFs* estimates produce reliable evaluation of policy measures (ex. subsidies to RES) and of revenues from taxation, being robust indicators to assess the carbon footprint of modern electric grids.
- Zonal *MEFs*. Highly relevant for targeted energy and environmental policy-making $\Longrightarrow$ correct remuneration of alternatives (RES/demand side management/storage) replacing polluting plants.
- Regional differences should be considered when the generation mix varies geographically.

Thank you for your attention.
Any question/comment?

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Plant-level CO_2 emissions

$$E^f_{i,h} = \varepsilon^f * \lambda * g^f_i(Q_{i,h}) \tag{6}$$

- Unit of measure: tCO_2/h.
- Production-based carbon accounting method to estimate carbon emissions through plant-level efficiency coefficients.
- Sources of variability:

1. ε^f is the national carbon intensity from local fuel combustion.
2. λ is the conversion factor from Gcal/h to TJ/h;
3. $g^f_i(Q_{i,h})$ expresses the plant-level fuel consumption model.

National carbon intensity of fuels

$$\varepsilon^f_{i,h} = \varepsilon^f \quad (7)$$

- National average carbon intensities from fuel combustion for power generation. *Source*: ISPRA (2018).

Fuel	CO_2 intensity (tCO_2/TJ)
Coal	95.124
Natural gas	57.693
Oil	76.604
RES technologies	0.0

Plant-level fuel consumption model

$$g_i^f(Q_{i,h}) = \sum \alpha_i^f (c_{2,i}^f Q_{i,h}^2 + c_{1,i}^f Q_{i,h} + c_{0,i}^f) \tag{8}$$

- ELFO++ model developed by *REF-E*. Inverse of the function of technical efficiency.
- Coverage: **Relevant** thermoelectric power plants (>10 MW).
- Sources of variability:

1. $Q_{i,h}$ represents the hourly accepted power generation by plant.
2. $c_{2,i}^f, c_{1,i}^f, c_{0,i}^f$ represent the plant-level efficiency parameters.
3. α_i^f is the fraction of utilisation of fuels (2 fuels at most).

Unit root and stationarity tests - Full sample 2018

Table 3: *Unit root and stationarity tests by each physical zone for the seasonally adjusted emissions (E_t) and generation (G_t) time series. Sample period: 2018. Critical values (C.V.) for each test are shown in the second column.*

		North		Center North		Center South		Sicily		Sardinia	
Test	C.V.	E_t	G_t	E_t	G_t	E_t	G_t	E_t	G_t	E_t	G_t
ADF	-1.95	-6.98	-4.70	-14.01	-4.23	-13.27	-8.38	-20.38	-4.45	-5.56	-2.58
DFGLS	-1.94	-12.19	-9.59	-16.16	-19.06	-15.75	-21.23	-23.24	-11.25	-6.27	-6.29
PP	-2.86	-14.27	-15.95	-22.74	-19.35	-21.39	-20.45	-23.59	-14.35	-7.65	-10.05
KPSS	0.15	4.29	4.35	2.08	2.51	1.91	1.09	0.26	0.22	2.94	2.73
rKPSS	0.15	4.49	4.74	1.93	2.56	1.89	1.12	0.37	0.29	2.88	2.80
ZA	-5.08	-17.79	-18.86	-26.64	-27.72	-24.03	-21.95	-26.42	-14.93	-11.50	-10.18

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