The long-run relationship between the Italian day-ahead and balancing electricity prices*

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Abstract

We study the convergence of day-ahead prices and balancing prices for the Italian power market. The zonal time-series of the prices are evaluated, seasonally adjusted and tested to assess their long-run properties. We focus on the dynamic behavior of the four continental zones of Italy (North, Central-North, Central-South and South). Using a sample of data that spans the last decade and applying the fractional cointegration methodology, we shows the existence of long-run relationships. This signals the existence of convergence between prices in each zone but zone Central-South, where prices are divergent. We also measure the average price difference, and analyse how it evolves over time. Price differentials dynamically reduce for all zones except for Central-South. We comment the results in terms of increasing efficiency, and provide an interpretation for the differences across zones. We also discuss policy consequences for both Italian and other markets.

Keywords: zonal prices; balancing prices; price convergence; fractional cointegration; long-run equilibrium.

J.E.L. codes: Q40, Q41, C32, C51

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1 Introduction

In liberalized power systems, power producers and users (suppliers and retailers) exchange electricity at the wholesale level in markets that are close to real-time delivery, the so-called *Day-Ahead* (DA) markets. However, in real time, it can occur that the amount of electricity effectively injected (or withdrawn) differs form the scheduled amount. Hence, an imbalance occurs. This happens whenever the schedule that results from the DA market (and possibly adjusted in the Intraday Markets) is modified by the occurrence of some event that entails the need for more (or less) power. In this case, the *Transmission System Operator* (TSO)[1] must intervene to maintain the stability of the system by calling additional electricity generators to supply the electricity that was lacking, or curtailing the excess supply, and charging the cost of the imbalance to the subject that created it.

Real-time prices are calculated in different ways around the world. On the one hand, they are obtained by the TSO solving an optimal power flow problem calculated on the basis of pre-received bids for given short time slots (generally every five minutes), eventually taking into account transmission constraints. This is the way real-time prices are fixed in all major ISOs in US, such as New England, New York, the PJM Interconnection (in Pennsylvania, New Jersey, Maryland and a number other eastern states), the Midwest, Texas, and California. In these markets electricity prices are calculated at each node, both at the DA and real-time level (and include the shadow cost of power transmission on congested power transmission lines, called *Locational Marginal Pricing*). On the other hand, it is possible to establish explicit markets in which power producers and load serving entities trade with the TSO electricity for balancing needs. This is what happens in the real-time German Balancing Power markets (Ocker and Ehrhart, 2017) and in the Italian Ancillary Services markets (called *Dispatching Services Market* - MSD). In the latter case, secondary and tertiary reserves and electricity for balancing are exchanged between qualified sellers and the TSO through a set of explicit auctions and priced with a dual pricing system. The price of negative imbalances (due to excess load or lack of supply in real time) is not less than the system marginal price that emerged at the DA level, while the price of positive imbalances (the excess supply of electricity or the reduction in the real-time load) is not higher than the system marginal price.

In this paper, we study the long-run relationship between DA and real-time prices in a market where the latter are established through explicit auction sessions, such as the Italian one. We want to establish if data confirm the hypothesis of price convergence, which should occur in mature markets where arbitrage oppor-

[1] In this paper we refer to the TSO as a general term, regardless of whether it is an Independent System Operator - ISO - as in the USA or a proper Transmission System Operator as in Europe.

tunities are already exploited. Indeed, several articles confirm such a hypothesis, focusing on the relationship between DA and real-time pricing in the US markets (Borenstein et al., 2001, Arciniegas et al., 2003, Longstaff and Wang, 2004 and Jha and Wolak, 2013). However, there are considerably fewer studies for European markets. Boogert and Dupont (2005) study the profitability of trading strategies across the DA and real-time (balancing) market in the Netherlands. Asan and Tasaltin (2017) explicitly measure the impact of the introduction of dual pricing rule on the convergence of DA and real-time prices in Turkey. A related stream of literature focuses on balancing prices and the role that external factors can have on them. Indeed, the price convergence can be influenced by the strategic behavior of agents acting in the balancing market, that can exploit their market power by strategically withholding capacity (Heim and Goetz, 2013). Market power can be enhanced by the design of the balancing market, such as auction formats, settlement rules, limited participation (Ocker et al., 2018a,b, Muesgens et al., 2014). The market structure can also influence price convergence, and in particular the role played by Renewable Energy Sources (RES). The impact of RES on DA prices has received a vast attention (see, among others, Gelabert et al., 2011, Mauritzen, 2013, Mulder and Scholtens, 2013, Sapio, 2015, and Woo et al., 2011). A more recent stream of literature has focused on the institutional design of balancing under increasing RES penetration (Hirth and Ziegenhagen, 2015, Ocker and Ehrhart, 2017, and Brijs et al., 2015) and on the condition for RES to participate to balancing markets (Sorknæs et al., 2013, Fernandes et al., 2016, and Müsgens et al., 2014). Closely related works have been undertaken by Gianfreda et al. (2016), who study the impact of RES generation in the Italian DA, intraday and balancing prices and of Gianfreda et al. (2018), who evaluates the impact that RES penetration has had on the balancing costs for the Italian TSO.[2]

Considering all hours of the day, we study the long-run relationship between balancing prices and DA over a long time period in the four continental zones of the Italian market.[3] Such an approach allows us to capture the existence of a common long run behavior between the series, if present. Indeed, even if RES penetration can impact both balancing and DA prices, this might not be the only relevant factor, and the common long-run behavior can be related to other elements. For instance, Bigerna et al. (2016) show that an increasing RES penetration can enhance market power; this can turn into increasing prices in both markets. Furthermore,

[2]There are a number of relevant differences between these works and our contribution. In Gianfreda et al. (2016, 2019) they focus on four hours of the day. In the Gianfreda et al. (2016) work they consider two zones. In the Gianfreda et al. (2016) paper they consider the long-run dynamics using weekly median prices of these four hours, while we use deseasonalized hourly prices.

[3]As explained in the Section 3, our dataset does not allow us to test the long-run relationships for the two islands of Sardinia and Sicily.

de Menezes et al. (2016) and Gianfreda et al. (2019) assess the importance of fuel prices on DA, intraday and balancing costs, for the European and Italian markets, respectively. These are common elements that can influence both DA and balancing prices. However, before focusing on a single determinant of the price in a given market, our purpose is to assess whether data confirm the existence of price convergence between DA and balancing, within a given market.

To carry out our study, we need to take into account the seasonal nature of power prices. Electricity prices are subject to a complex seasonal structure, at the daily, weekly and annual level. There is a large stream of literature focusing on the seasonality of wholesale electricity prices (see Weron, 2007, Caporin et al., 2012, Janczura et al., 2013, Nowotarski and Weron, 2016, Uniejewski et al., 2018, among many others). We take seasonality into account in the empirical analysis evaluating the characteristics of the deterministic patterns of electricity prices at both the DA and the balancing level. We first compare, with a descriptive view, the periodic patterns in the two markets in each zone, pointing out similarities and differences. Then, we apply a filtering methodology that allows to remove the periodic components of the data and later focus on the analysis of seasonally adjusted prices, to verify if they converge to a common long-run trend.

From an econometric perspective, price convergence calls for the presence of cointegration. We proceed in steps and first discuss the integration properties of the seasonally adjusted zonal prices. Our analysis shows that the prices are not characterized by unit roots, thus excluding the possible presence of cointegration in the classic sense, that is associated with the long-run equilibrium between non-stationary stochastic processes characterized by unit roots. However, since all the price series (filtered from the periodic patterns) show evidence of long range dependence, or long memory, we cannot exclude the possible presence of *fractional* cointegration, see Robinson and Yajima (2002) and Johansen (2008) among others. The latter feature allows for the presence of a long-run link among price series that have long memory. Therefore, we first estimate the memory properties of the price series and then determine if the latter are fractionally cointegrated.

The data allow us to focus on the four Italian continental zones, namely, North (NO from now onward), Central-North (CN), Central-South (CS) and South (SO). We show that the wholesale and the balancing markets are linked in the long-run; however, each zone has its specific behavior. In particular, evidence of price convergence is stronger for the NO zone, less so for CN and SO, while there is evidence of divergence between the series in CS. The price difference between DA and real-time is a measure of the difference in the electricity cost provision, thus providing the magnitude of markets' inefficiency. Price convergence implies that such a difference should reduce over time. To further investigate the dynamics of convergence over time, if any, we study how does the price difference between the series evolves in each zone throughout yearly rolling windows. We show that in NO and CN zones, the average price difference converges to zero, even though in an unstable way. In the SO zone it quickly converges to zero in the latest period, while in zone CS it tends to diverge over time. Overall, the zone that shows higher efficiency in terms of price convergence is the NO zone, followed by CN and more recently SO. In CS there are increasing arbitrage opportunities, which suggest that a more careful assessment of the market efficiency of this zone is needed. Overall, our analysis shows that even in market that share the same regulation and common institutional factors, local specific factors (that can be related to the structure of the grid or of the power supply) are the key elements that affect market efficiency.

The paper is structured as follows. In section 2, we present the main features of the Italian DA and ancillary services markets. In Section 3 data is discussed and analyzed. Section 4 introduces the methodological approach followed. Results are presented in section 5. Policy implications are discussed in Section 6. References follow. Furthermore, a supplementary document contains additional empirical results.

2 The Italian Day-Ahead and ancillary service markets

The Italian Power Exchange (IPEX), managed by the Gestore del Mercato Elettrico (GME), is organized in several markets, depending on products delivered and on the time horizon of the delivery. For the purpose of this analysis the relevant markets are the following:

a) The DA Market (Italian acronym MGP, Mercato del Giorno Prima), where producers, wholesalers, and eligible final customers may sell/purchase electricity for the next day;

b) The ancillary service market (Italian acronym MSD, Mercato del Servizio di Dispacciamento - Dispatching Services Market), where the Italian TSO (Terna s.p.a.) provides the dispatching services needed to manage, operate, monitor and control the power system. The Italian MSD consists of the scheduling stage (ex-ante MSD), and of the Balancing Market (BM). In the ex-ante MSD, the TSO accepts demand bids and supply offers in order to relieve residual congestion, and to create reserve margins. In the BM, the TSO secondary and tertiary reserves are exchanged between generators and the TSO, to perform secondary regulation and maintain the system balanced.

Both the MGP and the MSD have a zonal configuration. There are 6 (physical) market zones: North (NO, in Italian *Nord*), Central-North (CN, in Italian *Centro-*

nord), Central-South (CS, in Italian *Centro-sud*), South (SO, in Italian *Sud*), Sicily (SI, in Italian *Sicilia*) and Sardinia (SA, in Italian *Sardegna*).[4] Unfortunately, the patterns of the data, characterized by missing observations, instability in the seasonal patterns, presence of structural breaks in the mean as well as in the variance do not allow us to analyse the two zones of Sicily and Sardinia.[5]

At the DA level, generators participate making offers at plants level. With the exception of plants with production larger than 10MW, the offers of RES-sources are grouped by GSE (the Italian public company managing all activities related to RES) and are submitted at zero prices to the market. These have priority dispatching. Instead, only a subset of plants that participate to the DA market are allowed to participate to the ancillary service markets, namely, the large thermal and hydro and water plants with production above 10 MW, which can offer secondary and tertiary reserves. A relevant difference between the MGP and the MSD is related to the equilibrium pricing rule in the auction. The DA market, MGP, works with uniform auctions, that fix the system marginal price at each hour. The winning bidders receive the system marginal price of the zones in which they are located. The load pays a weighted average, namely, the average of the (possibly) different prices originated at the zonal level weighted by the volume of effective exchanges (net of purchases for pumping and from virtual foreign zones). This is called *Single National Price* (Italian acronym PUN *Prezzo Unico Nazionale*).

The equilibrium pricing rule of the MSD is a pay-as-you-bid-rule. Firms receive the price they have offered/demanded, if their offer to sale/purchase ancillary services to/from the TSO has been accepted. More precisely, power plants make offers to rise or reduce the power they had already offered at the MGP. For instance, a plant sells power to the TSO whenever the latter forecasts the need of more power than the one bought at the DA Market to relieve a congestion or preserve a sufficient reserve margin. These are called sales offers, or *up-regulation* offers. Similarly, power plants sell to the TSO offers to reduce production (called purchase offers or *down-regulation* offers) if the TSO faces, for instance, an imbalance due to an excess supply of power for a given hour and zone. The TSO cashes in the accepted down regulation offers, and pays accepted up regulation offers. The MSD

[4] There exists also limited production poles, which are production areas with null or negligeable load that are constrained by relevant export congestions, and foreign and virtual zones.

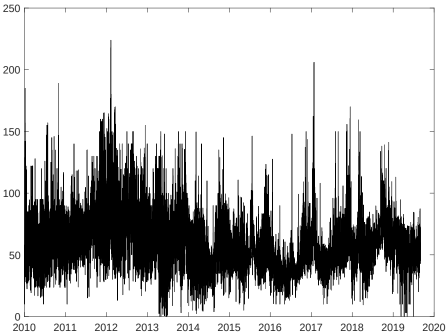
[5] The zones of the two islands Sardinia and Sicily are scarcely interconnected with the continent. Furthermore, their interconnection capacity has been changing throughout the sample period. Markets in these islands have their own peculiarities. In Sardinia there are no gas-fired power plants since there are no natural gas pipelines. This is a sharp difference compared with the rest of Italy, where natural gas fired plants are the majority of thermal power plants. In Sicily, balancing prices have been administratively set under a special regime from 2016 onward, due to the lack of sufficient thermal capacity in the MSD. Due to their peculiarities, we believe that there is no lack of generality from not having these two zones analysed.

includes two markets where bid and offers are structurally different. In the first market, the MSD ex-ante, there are offers to buy the power needed (ex-ante) to reduce the predicted zonal congestion and therefore to create reserve margin. In the second market, the Balancing Market, offers are made to provide secondary and tertiary reserves.

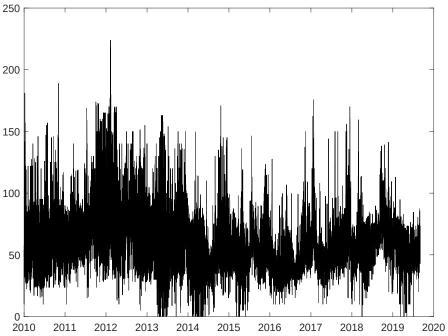
The prices at MSD are given for every hour of the day and for every zone of the Italian electricity market. Each sale (or purchase) offer that is accepted in the MSD is then priced at its own price (pay-as-you-bid). Therefore, no proper single price arises at the MSD level. However, the market operator provides data of weighted average of accepted up and down regulation offers, in which each price is weighted by the amount of power that has been effectively purchased. In order to calculate the net cost of balancing in a given hour and zone, we calculate the weighted average of all the up and down regulation offers, for every hour and for both MSD ex-ante and MB. The up regulation has a positive sign denoting that this is a cost for the SO, while the negative sign of the down regulation signals that the SO cashes in those offers. The algebraic sum of the (weighted average of all accepted) offers represents the effective cost for the electricity system of the provision of ancillary services that are needed because of aggregated imbalances in a given hour and zone. This net imbalance price corresponds to the imbalances cost due to the differences between the predicted DA quantities and the quantities needed by the TSO to maintain the system balanced. In other words, it represents the social costs (for the electricity system users) of having the electricity system balanced by the TSO.

3 Data description and analysis

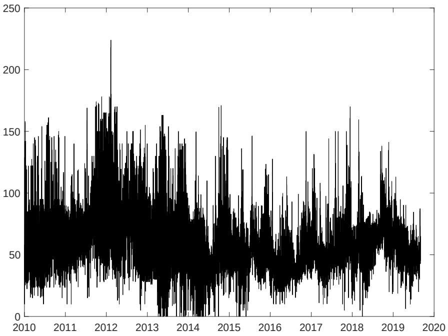
We use publicly available data provided by GME on its website. The prices are hourly, zonal, ranging from 1st January 2010 to 31st August 2019, for a total of 84,720 observations for each zone in each market. The MGP prices are the system marginal price of each zone and hour. For the ancillary service prices, we take the weighted averages of accepted (non-revoked) offers of the ex-ante MSD and add to each weighted average the price of the BM in that hour and zone, weighted by the respective volume, if present. Then, we calculate the net difference between prices of up and down regulation per each zone and hour. The resulting price, which measures the net balancing costs in a given hour and zone, can be positive or negative. In the former case, there would be an excess demand, that is a need of power for balancing purposes since the amount exchanged at the DA level is less than the actual quantity needed. The opposite for negative prices.



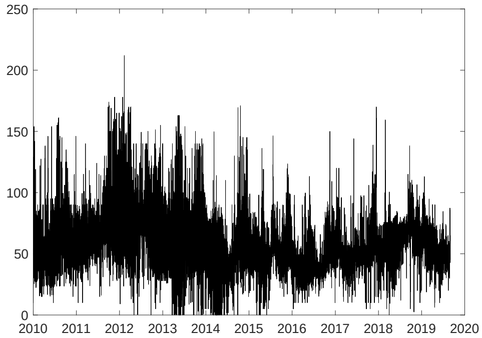
(a) MGP - NO



(b) MGP - CN



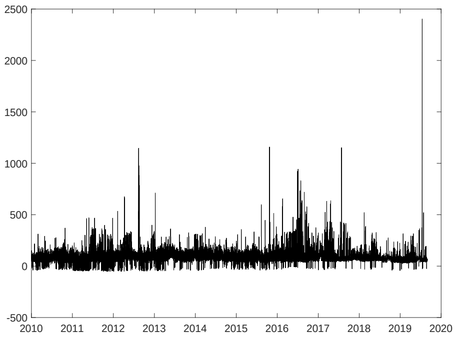
(c) MGP - CS



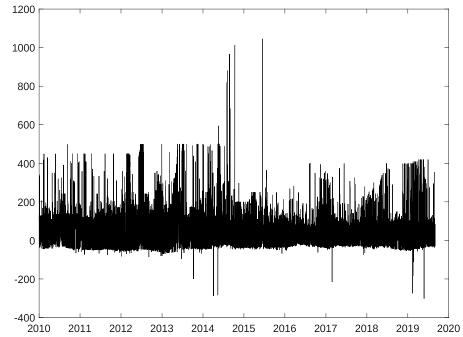
(d) MGP - SO

Figure 1: Time series of MGP. The figure reports the time series of the MGP prices for the four zones, North (NO), Central-North (CN), Central-South (CS), South (SO).

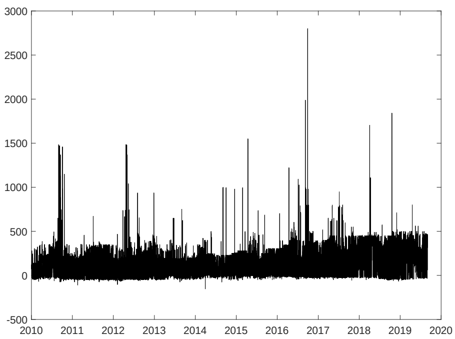
Figures 1 and 2 report the time series of MGP and MSD for the four areas. From a visual inspection of Figure 1, it appears that MGP and MSD have a mean-reverting and stationary behavior, with MSD displaying larger dispersion around the mean. Furthermore, by looking at the same price series in the four different areas, we notice common dynamic patterns, which will be studied in Section 4 in terms of fractional cointegration. Table 1 reports descriptive statistics for MGP and MSD prices by zone. There are clear differences between MGP and MSD. Zones are quite different in terms of price values, as well as with respect to the presence of zeros or negative values. For what concerns the MGP prices, the median values are around 55 in all cases. Instead, we observe larger differences between zones for the MSD. First, the median values highly differ across zones and also in relation with the median MGP value. In the NO zone, the median is



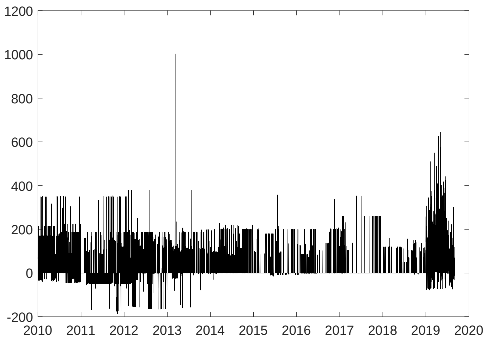
(a) MSD - NO



(b) MSD - CN



(c) MSD - CS



(d) MSD - SO

Figure 2: Time series of MSD. The figure reports the time series of the MSD prices for the four zones, North (NO), Central-North (CN), Central-South (CS), South (SO).

50% higher than the corresponding MGP value, while in the CN zone the MSD price is only slightly higher than the MGP price. On the contrary, the MSD price is almost twice as much as the MGP price in CS. This is due to the frequent need of costly *up regulation*. For the SO zone, the median MSD price is zero, which is associated with the large fraction of zeros included in the data on SO, except for very recent periods.

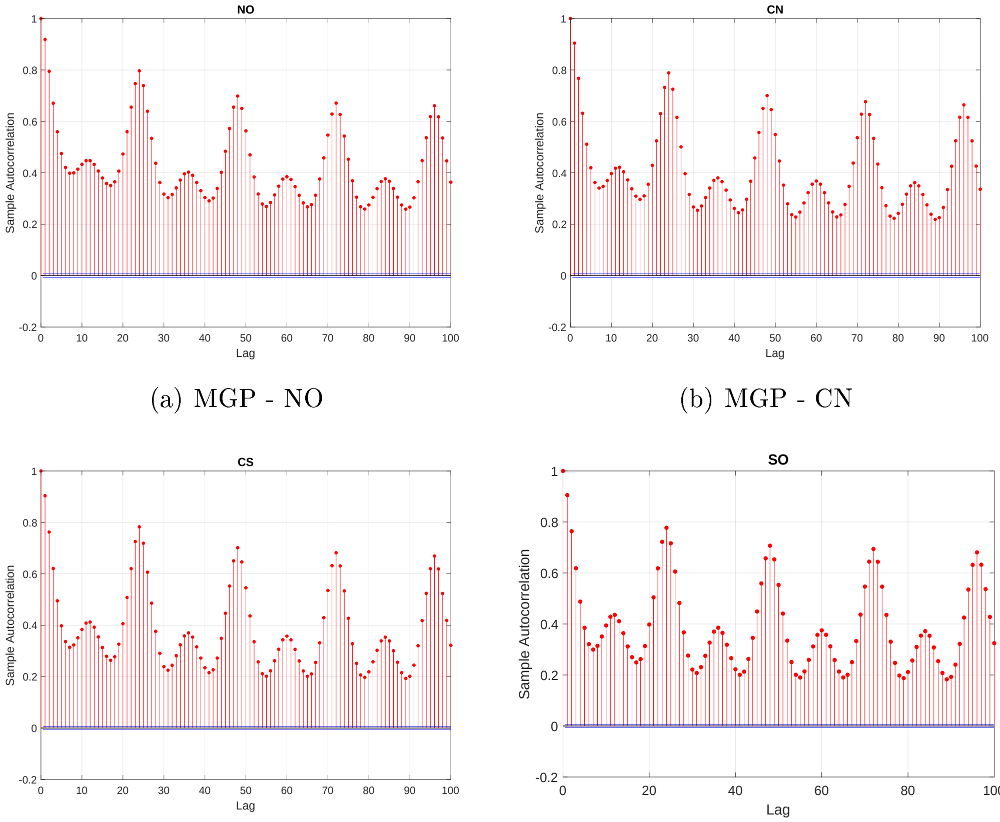
It is worth recalling that these prices are effectively social costs paid by the TSO, which are then transferred to the end consumers through a specific tariff component. Negative figures therefore are negative costs, namely, net gains for the TSO, that arise whenever the willingness of generators to pay to reduce power outweighs their willingness to be payed to generate. This occurs if the zone is long on power, and generators cannot adjust quickly enough their production. Note that negative prices can also depend on the level of competition among producers, since the higher the competition the more producers are forced to bid fiercely among themselves in the market. Negative prices can be observed in a limited number of cases, less than 2% for NO, while for CN and CS, the percentage of negative prices reaches much larger frequencies, about 21% and about 12.5%, respectively. This signals the fact that, in the observed period, these zones went long more frequently than the others, and generators had difficulties to reduce their scheduled programs. The fraction of zero prices is also a relevant quantity, as the distribution of zeros across zones shows in which zones dispatching services were less used in the sample period. NO is the only zone without zero prices in the sample. Recalling that a zero price signals that ancillary services are not needed in that hour and zone (and therefore have null value), it follows that NO needs a continuous balancing of power. Differently, zeros are a relevant fraction for CN (about 19%), and a more limited fraction of the sample for CS (about 6%).

Zone	Min	Q(5%)	Q(25%)	Median	Q(75%)	Q(95%)	Max	% of < 0	% of 0	Range	IQR
						MGP					
NO	0.00	31.16	45.46	57.29	69.27	89.76	224.00	0.00	0.00	224.00	23.81
CN	0.00	31.00	45.00	56.97	69.27	90.00	224.00	0.00	0.00	224.00	24.27
CS	0.00	30.13	44.01	55.61	68.54	89.85	224.00	0.00	0.00	224.00	24.53
SO	0.00	29.67	43.00	54.32	66.68	85.01	212.00	0.00	0.00	212.00	23.68
						MSD					
NO	-52.70	44.15	59.23	74.21	97.07	155.29	2403.71	1.30	0.00	2456.41	37.84
CN	-301.61	-39.00	0.00	57.93	95.00	169.07	1045.00	21.07	19.40	1346.61	95.00
CS	-153.94	-26.61	58.35	104.16	194.50	372.80	2800.75	12.52	6.05	2954.69	136.14
SO	-185.55	0.00	0.00	0.00	0.00	142.56	1003.00	3.51	82.10	1188.55	0.00

Table 1: Descriptive analysis of MGP and MSD prices. The table reports, by zone, minimum and maximum values, the 5%, 25%, 50%, 75% and 95% quantiles, the fractions of null and negative prices, the Max-Min range and the interquartile range.

3.1 Seasonality

The seasonality in the MGP and MSD prices might derive from the superposition of several cyclical patterns: the diurnal ones, due to the differences in electricity demand between day and night; the weekly pattern, with different demands during workdays and week-ends (with holidays usually behaving as Sunday); the yearly one, due to the alternation of seasons and summer breaks in the industrial activities. To study the level of temporal dependence in the time series of MGP and MSD, we look at the the sample auto-correlation function (ACF). Figures 3-4 display the ACFs of the MGP and MSD prices for the four zones and highlights



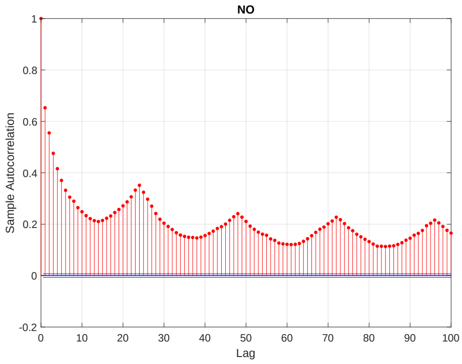
(a) MGP - NO (b) MGP - CN

(c) MGP - SO (d) MGP - CS

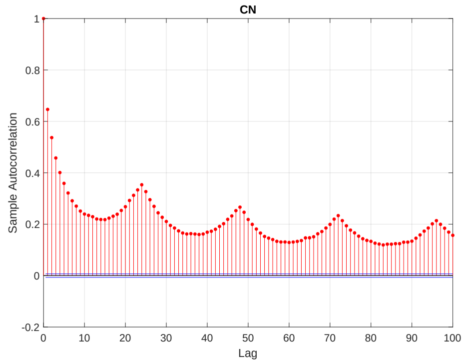
Figure 3: ACF of MGP. The figure reports the ACF of the MGP prices for the four zones, North (NO), Central-North (CN), Central-South (CS), South (SO).

their strong seasonal patterns.

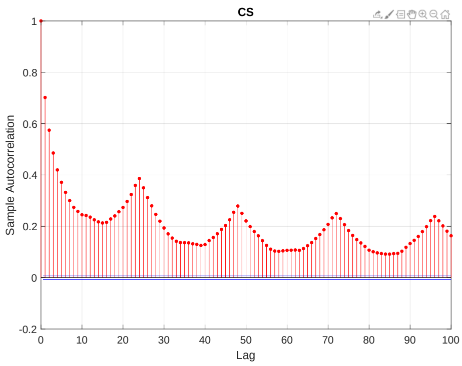
To deal with the complex cyclical pattern we follow, among the various methods proposed in the literature, the approach by Bernardi and Petrella (2015) that introduce a flexible exponential smoothing method to capture seasonal cycles in time series. Their model allows to deal with monthly, weekly and intra-daily patterns. Note that by adopting the method of Bernardi and Petrella (2015) and given the existence of a yearly cyclical pattern in the series, the filtering procedure leads to a reduction of the length of the series by one year (the year 2010 in our case). We follow Bernardi and Petrella (2015) and estimate the following model on the zonal prices. Let y_t be the series of interest (like MGP or MSD prices for



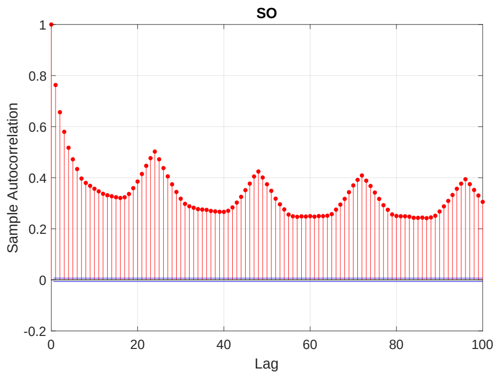
(a) MSD - NO



(b) MSD - CN



(c) MSD - CS



(d) MSD - SO

Figure 4: ACF of MSD. The figure reports the ACF of the MSD prices for the four zones, North (NO), Central-North (CN), Central-South (CS), South (SO).

a given zone), observed from $t = 1, 2, \dots T$ at a hourly frequency, then

$$
\begin{aligned}
y_t &= \mu_{t-1} + \sum_{j=1}^{J} \lambda_j d_{j,t} + \sum_{i=1}^{I} x_{i,t} s_{i,t-24} + \varepsilon_t && (1)\\
\mu_t &= \mu_{t-1} + \alpha \varepsilon_t && (2)\\
s_{i,t} &= s_{i,t-24} + \left(\sum_{j=1}^{I} \gamma_{i,j} x_{j,t} \right) \varepsilon_t, \quad i = 1, 2, \dots I && (3)\\
\varepsilon_t &= \sum_{i=1}^{p} \phi_i \varepsilon_{t-i} + \sum_{i=1}^{q} \theta_i \zeta_{t-i} + \zeta_t. && (4)
\end{aligned}
$$

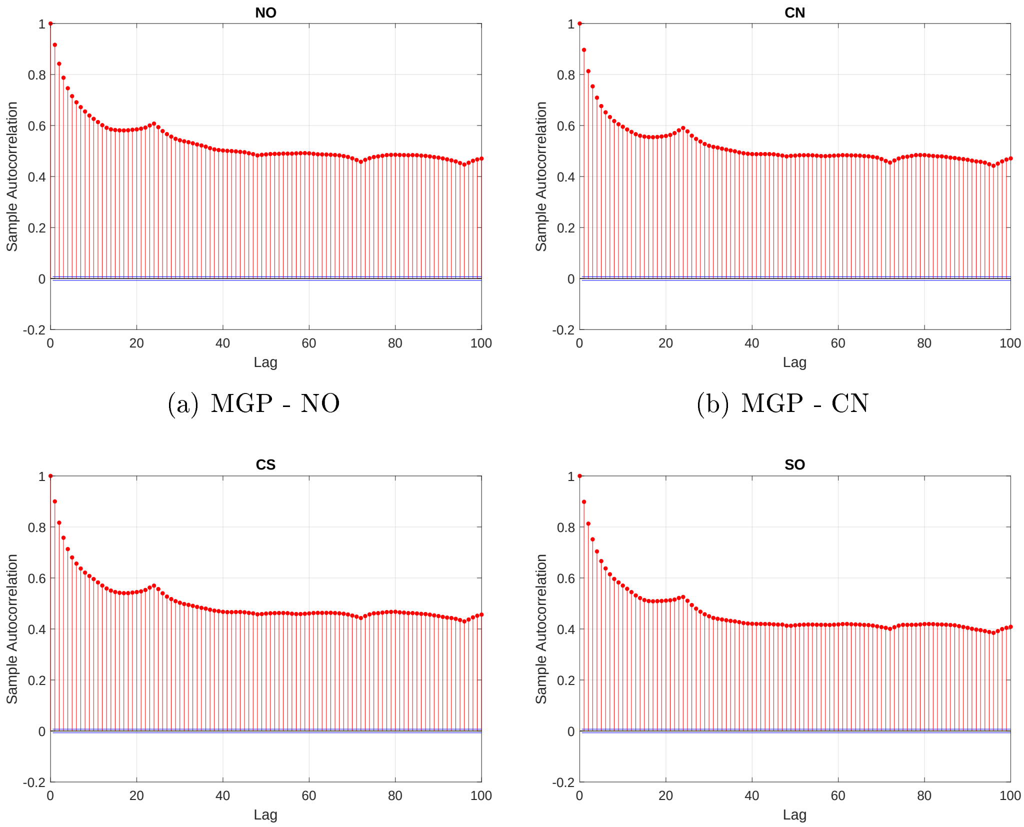
The model includes several components. First, μ_t is the long-run evolution of the series, the trend component, following a random walk plus noise specification. The variables $d_{j,t}$ with $j = 1, 2, \ldots J$ are monthly dummies taking value 1 if a given day belongs to month j, but note that we might set the monthly dummies such that we have $J \leqslant 12$ dummies, thus J different monthly effects. The collection of $s_{i,t}$, $i = 1, 2, \ldots I$ represents the cyclical component of the model. It captures the differences in the daily patterns across days of the week, with $1 \leqslant I \leqslant 7$ different patterns. Note that each $s_{i,t}$ follows a daily seasonally integrated process with a multiplicative error term. In the latter, the variables $x_{l,t}$ are dummies taking value 1 if the observation at time t falls within one of the I intra-weekly seasonal cycles. The error term ε_t follows an ARMA process whose innovations are assumed to be Normally distributed with mean zero and unit variance.

For details on the implementation and estimation of the model we refer to Bernardi and Petrella (2015). In our analysis, we set $I = 5$ different day types, setting Tuesday, Wednesday and Thursday to share the common intra-daily seasonal cycle. In terms of monthly dummies, we borrow them from the analysis of Bernardi and Petrella (2015) that consider the electricity demand in Italy from 2004 to 2014, and consider five monthly patterns, $J = 5$, where the first group of months include January, March, June, September and October, the second group comprises November and December, April and May constitutes the third group while February and July the fourth. Finally, August is separately considered given its peculiar behavior. Similarly to Bernardi and Petrella (2015), we also separately consider irregular days (holidays). For the innovation term, we specify a simple autoregressive process of order 1. Once the parameters of the model are estimated, the seasonally adjusted (filtered) series are computed as

$$\tilde{y}_t = y_t - \sum_{j=1}^{J} \hat{\lambda}_j d_{j,t} - \sum_{i=1}^{I} x_{i,t} \hat{s}_{i,t-24}, \tag{5}$$

where we remove the cyclical behaviors only, while maintaining the long-term component and the irregular component.

The empirical ACFs of the seasonally adjusted series, reported in Figures 5 and 6, show evidence of two phenomena. First of all, the filtered prices of MSD (and to a lesser extent also of MGP) appear still slightly contaminated by a seasonal behavior, as highlighted by the mild periodic pattern of the correlograms, with an oscillation with a period of 24 observations (one day). This suggests that some residual stochastic periodic component is still present in the filtered series. Secondly, all series display long range dependence, as the ACF slowly decreases toward zero and it is still highly significant after 100 lags in all cases. This indicates that the adjusted price series might follow a stationary and predictable process with long memory and not, as usually expected for prices in financial markets, a



(a) MGP - NO (b) MGP - CN

(c) MGP - CS (d) MGP - SO

Figure 5: ACF of the filtered MGP. The figure reports the ACF of the filtered MGP prices for the four zones, North (NO), Central-North (CN), Central-South (CS), South (SO).The filtering has been performed following the method of Bernardi and Petrella (2015).

random walk process; see, among many others, (Fama, 1965).

3.2 Long memory

The existence of common trends in prices points at the existence of a long-run relationship. In particular, the classic way to determine whether two or more series are linked in the long-run and to verify if there is an equilibrium relation between them (with non persistent deviations from it) is by means of the well known concept of cointegration. Unfortunately, the concept of cointegration is typically restricted to $I(1)$ time series, whose dynamic behavior resembles that

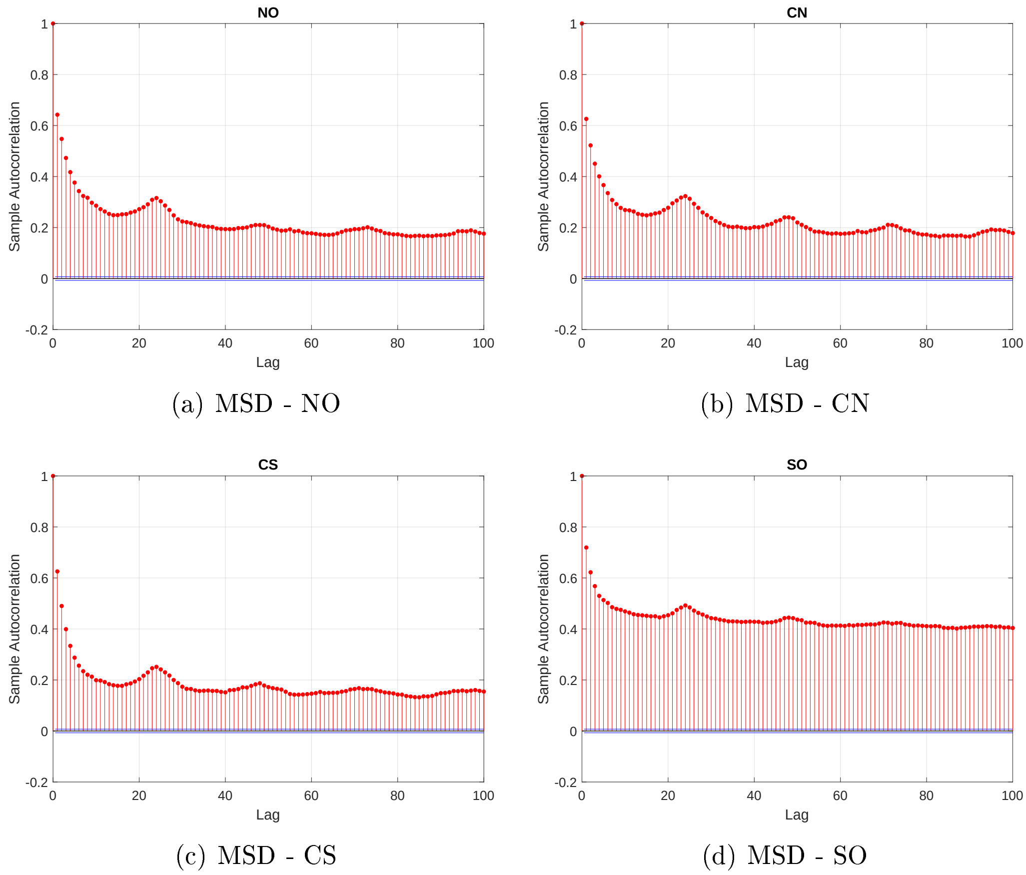


Figure 6: ACF of the filtered MSD. The figure reports the ACF of the filtered MSD prices for the four zones, North (NO), Central-North (CN), Central-South (CS), South (SO). The filtering has been performed following the method of Bernardi and Petrella (2015).

of a random walk. Thus, we first carry out the augmented Dickey-Fuller and Philips-Perron tests to verify if the filtered zonal MGP and MSD prices are unit root processes. The results of the tests (not reported) are concordant in strongly excluding that the dynamics of the two series are coherent with those of a unit root process. Consequently, the prerequisite for the classic definition of cointegration is missing, i.e. the series are not $I(1)$. However, such a finding does not completely exclude the possible presence of long-run links among the variables of interest. In fact, all series share a relevant feature; they are all characterized by strong persistence. This suggest that a specific form of long-run relation might exist, the one associated with the concept of *fractional* cointegration, which arises between series that are not $I(1)$ (or $I(2)$), but are nevertheless characterized by long-range dependence. The latter thus becomes a prerequisite for fractional cointegration.

	$m_d = T^{0.5}$		$m_d = T^{0.6}$	
	MGP	MSD	MGP	MSD
NO	0.56	0.49	0.42	0.38
CN	0.55	0.51	0.42	0.42
CS	0.53	0.52	0.40	0.35
SO	0.53	0.68	0.37	0.55

Table 2: Estimates of the memory parameters on the seasonally adjusted series following the approach of Shimotsu and Phillips (2005) and Shimotsu (2010). m_d denotes the bandwidth chosen for the estimation of the long memory (or fractional) parameter. m_d is set proportional to T (the sample size); see Shimotsu and Phillips (2005).

As a first step, we proceed to the estimation of the degree of persistence (or memory) of the series following the semiparametric approach of Shimotsu and Phillips (2005) and Shimotsu (2010), which is robust to deterministic terms. Table 2 reports the estimated memory coefficients, d. A significantly positive coefficient indicates the presence of long memory (or long-range dependence). In particular, if $d < 0.5$, the series is long memory but stationary. The semiparametric estimator of Shimotsu and Phillips (2005) and Shimotsu (2010) is defined in the frequency domain so that its asymptotic properties (bias and variance) depend on the number of frequencies used in the estimation, namely the bandwidth (m_d). Table 2 reports the estimates for two different bandwidth: in all cases the memory coefficient is positive, and in most of them, the memory coefficient is lower than 0.5 when $m_d = T^{0.6}$, and slightly above 0.5 when $m_d = T^{0.5}$. In general, the long memory parameters of MGP and MSD are very close, thus suggesting that the two series share the same level of long memory. Consequently, we state that all the zonal prices, filtered from the periodic patterns, display significant long memory and are stationary. As a first step, we proceed to the estimation of the degree of persistence (or memory) of the series following the semiparametric approach of Shimotsu and Phillips (2005) and Shimotsu (2010), which is robust to deterministic terms. Table 2 reports the estimated memory coefficients, d. A significantly positive coefficient indicates the presence of long memory (or long-range dependence). In particular, if $d < 0.5$, the series is long memory but stationary. The semiparametric estimator of Shimotsu and Phillips (2005) and Shimotsu (2010) is defined in the frequency domain so that its asymptotic properties (bias and variance) depend on the number of frequencies used in the estimation, namely the bandwidth (m_d). Table 2 reports the estimates for two different bandwidth: in all cases the memory coefficient is

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4 The model

On the basis of the statistical evidence outlined above, we considier a fully parametric model coherent with the presence of a common stochastic trend with long memory, namely fractional cointegration. The goal is to shed further light on the long-run dependence between MGP and MSD in each zone. We adopt a fractional vector error correction model specification to study if the series of de-seasonalized hourly MGP and MSD prices are characterized by common trends in each continental Italian zone. The properties of a fully parametric specification for the analysis of fractionally cointegrated series have been studied by Johansen (2008) and Johansen and Nielsen (2012). In particular, the asymptotic theory of the maximum likelihood estimator for the model parameters has been fully derived in Johansen and Nielsen (2012), thus allowing proper inference on the estimated parameters. The model specification of Johansen and Nielsen (2012) has been adopted by Caporin et al. (2013) in the context of high-frequency financial data, by Bollerslev et al. (2013) to characterize the dynamics of the financial risk premia and by Dolatabadi et al. (2015) in the context of commodity prices. More recently, Carlini and Santucci de Magistris (2019a) have illustrated a potential pitfall in the specification of Johansen (2008) and Johansen and Nielsen (2012), associated with the choice of the number of lags in the short run dynamics. Therefore, Carlini and Santucci de Magistris (2019b) proposed a slightly different version of the fractionally cointegrated model, namely the FVECM$_{d,b}$, which is identified for any choice of number of lags and coitegration rank. The FVECM$_{d,b}$ model is

$$\Delta^d X_t = \xi + \alpha\beta'\Delta^{d-b}L_b X_t + \sum_{i=1}^{k}\Gamma_i\Delta^d L^i X_t + \varepsilon_t \quad \varepsilon_t \sim iid(0,\Omega), \tag{6}$$

where X_t is a p-dimensional vector,[6] α and β are $p \times r$ matrices, where r defines the cointegration rank, while ξ denotes the unrestricted intercept. Ω is the positive definite covariance matrix of the errors, and Γ_j, $j = 1, \ldots, k$, are $p \times p$ matrices loading the short-run dynamics. ε_t is the i.i.d. error term with finite eight moment, see Johansen and Nielsen (2012). The operator $L_b := 1 - (1 - L)^b = 1 - \Delta^b$ is the so called *fractional* lag operator, which, as noted by Johansen (2008), is necessary for characterizing the solutions of the system. The model in (6) has k lags and $\theta = vec(d, b, \xi, \alpha, \beta, \Gamma_1, ..., \Gamma_k, \Omega)$ is the parameter vector. The parameter space of the model is

$$\Theta = \{\xi \in \mathbb{R}^p, \alpha \in \mathbb{R}^{p\times r}, \beta \in \mathbb{R}^{p\times r}, \xi \in \mathbb{R}^p, \Gamma_j \in \mathbb{R}^{p\times p}, j = 1, \ldots, k, d \in \mathbb{R}^+, b \in \mathbb{R}^+, d \geqslant b > 0, \Omega > 0\}.$$

where r is the cointegration rank, such that $p-r$ determines the number of common stochastic trends between the series. We apply the model in (6) to zones (NO, CN, CS, SO). We then consider several model specifications designed to verify convergence between markets at the single zone level. The existence of convergence is associated with the existence of a unique common trend, which requires the existence of one cointegrating relation. In other words, under cointegration, there is a unique long-run equilibrium (attractor) towards which the two series converge to.

5 Estimation results

5.1 Full sample analysis

We estimate the following FVECM$_{d,b}$ model for each pair of (seasonally-adjusted) MSD and MGP prices in each of the four zones for the full-sample of 75,960 hourly prices from 1st January 2011 to 31st August 2019,

$$\begin{bmatrix} \Delta^d MGP_t^i \\ \Delta^d MSD_t^i \end{bmatrix} = \begin{bmatrix} \xi_1 \\ \xi_2 \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} L_b EC_t + \sum_{j=1}^{k*} \Gamma_j \Delta^d L^j Y_t + \begin{bmatrix} \varepsilon_t^{MGP,i} \\ \varepsilon_t^{MSD,i} \end{bmatrix} \tag{7}$$

where $Y_t = [MGP_t^i, MSD_t^i]'$ and the error correction term is $EC_t = \Delta^{d-b} MGP_t^i + \beta_2 \Delta^{d-b} MSD_t^i$, and $i = NO, CN, CS, SO$.

Table 3 reports the estimation results for fractional cointegration between MGP and MSD, in each of the four zones. The estimates of the FVECM$_{d,b}$ signal that

[6] The structure of the FVECM$_{d,b}$ model is very similar to that of the FCVAR$_{d,b}$ model,

$$\Delta^d X_t = \xi + \alpha\beta' \Delta^{d-b} L_b X_t + \sum_{i=1}^{k} \Gamma_i \Delta^d L_b^i X_t + \varepsilon_t \quad \varepsilon_t \sim iid(0, \Omega),$$

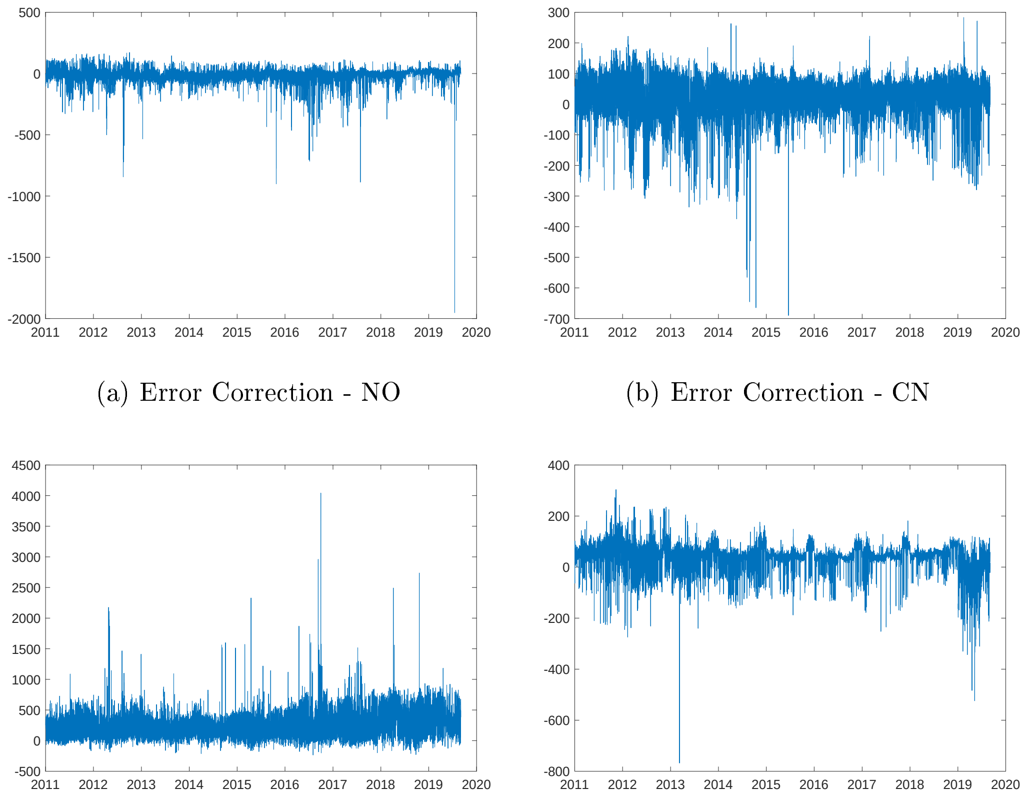
	NO		CN		CS		SO	
	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.
d	0.445	(0.003)	0.418	(0.003)	0.412	(0.003)	0.384	(0.003)
b	0.445	(0.003)	0.418	(0.003)	0.412	(0.003)	0.384	(0.003)
β_2	-0.830	–	-0.703	–	1.461	–	-0.810	–
α_1	-0.002	(0.001)	-0.002	(0.001)	0.001	(0.000)	0.002	(0.001)
α_2	0.082	(0.007)	0.076	(0.009)	-0.068	(0.005)	-0.015	(0.006)
ξ_1	0.237	(0.021)	0.395	(0.028)	0.479	(0.073)	0.345	(0.053)
ξ_2	1.320	(0.144)	-1.072	(0.284)	17.614	(1.100)	0.958	(0.291)
k^*	2	–	2	–	2	–	4	–
LR	0.998	–	0.722	–	0.043	–	0.439	

Table 3: FVECM$_{d,b}$ estimates for the pairs of MGP and MSD of the four main regions (NO,CN,CS,SO). In parenthesis the standard errors. The optimal lag length (k^*) has been found by BIC. LR is the p-value for the test of cointegration rank, $r = 1$. The estimation has been carried out with the MATLAB codes of Nielsen and Popiel (2018). The parameters of the short-run matrices, Γ_i, are not reported due to space constraints.

the strength of the cointegration relation in terms of memory gap is maximal, as $d = b$ in all cases. This means that the EC term is short memory. In addition, the Likelihood Ratio (LR) test for fractional cointegration identifies the presence of cointegration in three of the four zones. The only exception is the CS zone, for which we reject the hypothesis of fractional cointegration. The estimated models are similar in terms of lag length (k^*), with NO, CN and CS zones characterized by two lags and SO by four lags. We attribute this difference to the larger presence of zeros in the SO time series. The intercepts, ξ_1 and ξ_2, are statistically significant for all zones. The parameter β_2 of the NO zone is the closest to -1, while for SO and CN zones it takes slightly lower values. Finally, it is positive and larger than 1 for CS. Thus, the result shows that for the NO zone, a rise of one euro per MWh in the MSD in the long-run is coupled with a rise of 0.83 euro per MWh in the MGP. In other words, there is an average price differential between MSD and MGP of almost twenty cent per MWh whenever price rises in both markets. This differential, which signals the average difference in the cost of electricity exchanged in the MSD vis-a-vis the one in MGP, is slightly higher in CS and SO. In zone CS, data do not show evidence of fractional cointegration and the β_2 coefficient

as it only replaces the fractional lag operator, L_b^i, with the standard lag operator, L^i, in the short run dynamics.

cannot be meaningfully interpreted. However, the absence of cointegration might signal the existence of divergent behaviors in the MGP and MSD prices (for the CS zone), in the sense that a rise of one euro in the MSD implies a more than proportional fall of MSD.



(a) Error Correction - NO

(b) Error Correction - CN

(c) Error Correction - CS

(d) Error Correction - SO

Figure 7: EC term of the four zones. The figure reports the time series for the EC term of the MGP and MGP prices for the four zones, North (NO), Central-North (CN), Central-South (CS), South (SO).

We also look at the estimates of the speed-of-adjustment parameters, α. Despite all parameters α are statistically significant or marginally significant, only the MSD prices significantly move to restore equilibrium. The adjustment is larger for NO and CN while it is much weaker for SO. For CS, the absence of cointegration does not allow interpreting the speed of adjustment parameters. Overall, the evidence suggests that MGP and MSD have common dynamics within NO, CN and SO zones. This result is in favor of price convergence, although for CN and CS the evidence is weaker than for NO. Finally, Figure 7 reports the error correction terms EC_t^i of equation (7) for $i = NO, CN, CS, SO$.[7] We find evidence of a reduction in the persistence over the EC terms compared to what observed among the seasonally adjusted series. This is coherent with the model feature, the presence of fractional cointegration and the associated convergence. In all cases we note some periodic behavior of the residuals, which resembles the remaining seasonality of the filtered series. There are limited differences across zones in the serial dependence of the EC terms, while their volatility is more heterogeneous. The latter is not surprising as there are zonal structural features that also play a role in the deviation from the zonal common trends.

5.2 Dynamic analysis

As a final empirical analysis, we study how the average difference of the two price series, namely MGP and MSD, changes over time. In particular, we investigate if the price differential between MGP and MSD is likely to shrink (or to widen) over time. This allows us to shed further light on the behavior of the price converge. We perform this analysis by means of a rolling estimation of the average price differential based on the following linear time-series regression

$$D_t^i = \alpha_j^i + u_t^i, \quad t = 1, 2, \ldots, 8760 \tag{8}$$

where $D_t^i = MGP_t^i - MSD_t^i$ for $i = NO, CN, CS, SO$ and α_j^i represents the average price differential in the j-th subperiod of 1-year length ($24 \times 365 = 8760$) for the i-th zone. The estimation of α_j is carried out by rolling OLS regression with step equal to 1 day (24 hours), leading to $J = 2800$ estimates, which are plotted in Figure 8 together with the 95% confidence interval.

We note that in the NO zone the average price difference tends to zero, i.e., the prices tend to converge over time. This trend is clearer from 2017 onward. Overall, the analysis of rolling windows confirm that in the NO zone markets are becoming efficient over time. A similar consideration applies for the CN zone, even though the converging trend has been more unstable, with periods of converging trends followed with diverging ones; yet, over time the price difference tends to zero. Zone SO shows a clear indication of convergence over the last part of the sample (from the beginning of 2019), that followed a first phase in which the price differential was rather constant and high. Overall, evidence shows that in this zone markets have recently moved substantially towards efficiency. This can be explained considering that in the SO zone, the limited production poles of Brindisi

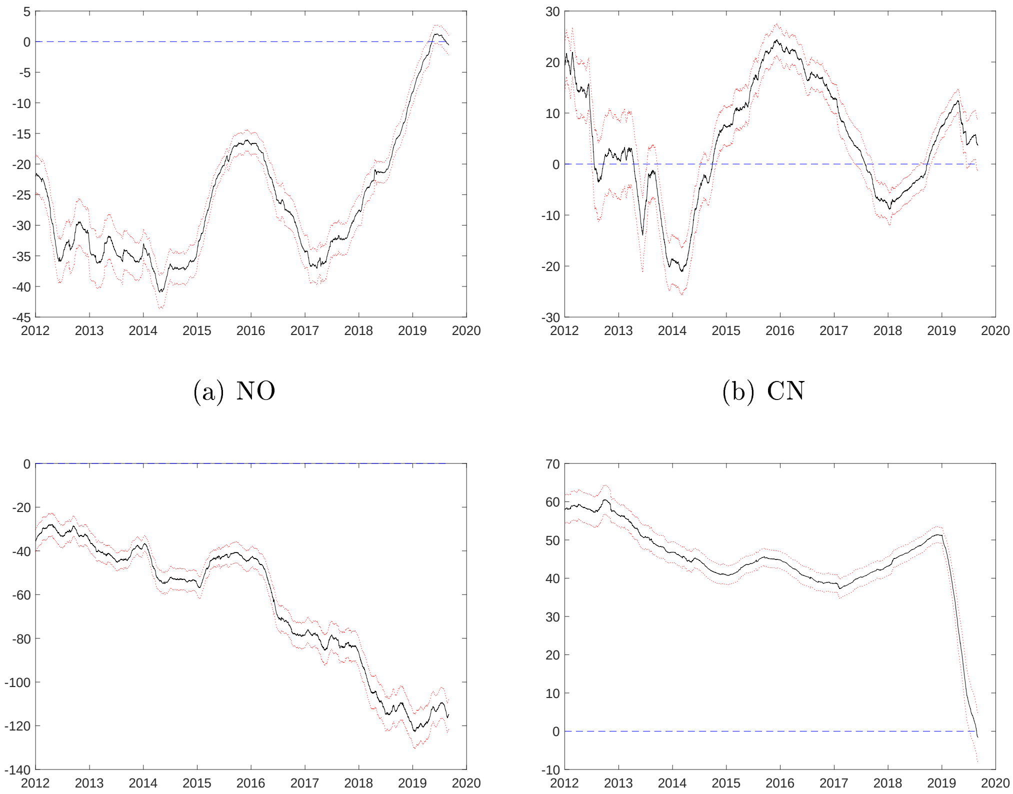
[7] The supplementary material also includes the correlogram of the FVECM residuals and of the error correction terms.

and Foggia disappeared and were included into the SO zone from beginning of year 2019, after the elimination of relevant bottlenecks. Before this period, the capacity that was located in the area of Brindisi and Foggia (which was the largest share of thermal capacity of the Regions that pertain to the SO zone) was kept separate from the SO zone. Thus, the SO zone has started exhibiting a relevant activity in MSD after the incorporation of these limited production poles. The only diverging trend is for CS, where the price differential tends to widen over time. The dynamic analysis confirms the finding of the fractional cointegration analysis on the full sample displayed before. We find a diverging trend between the MSD and the MGP in the CS zone, which has been increasing over time, showing that market inefficiency in the CS zone has been rising throughout the sample.

6 Policy implications and conclusion

In this paper, we have been focusing on the convergence between DA and balancing prices in the four continental zones of Italy. To shed light on this aspect, we first construct a price index for ancillary services, which measures the net social cost of those services for the TSO (and to final customers to which the TSO rebates them). Then, in order to assess the possible long-run correlation hypotheses, we investigate the statistical properties of the time-series and seasonally adjusted them focusing on the statistical properties of the structural component of the series. Afterward, we test the existence of common long-memory of DA prices and balancing costs, and show that MGP and MSD have been subject to converging dynamics within each zone, except for the CS zone, which has exhibited a price diverging path between MSD and MGP prices. Markets are efficient if there are no arbitrage opportunities between DA and real-time markets, arising because of significant price differences. Our results of convergence indicate sufficient market efficiency, since prices in the two markets converge in the long-run and the average price differential tends to reduce over time. This result is in line with previous finding of price convergence between DA and real-time markets (see Arciniegas et al., 2003, Asan and Tasaltin, 2017, Boogert and Dupont, 2005, Jha and Wolak, 2013). However, the empirical evidence also highlights that there are relevant zonal differences. Note that the zones of the Italian market have a common institutional framework, but differ from the structural point of view. Table 4 below shows the installed capacity per type of generation (different RES and thermal) in each of the four continental zone (year 2018, MW in the upper panel, and percentage over the total Italian installed capacity in the lower panel).

The NO zone is the largest zone in terms of installed capacity, while the share



(a) NO

(b) CN

(c) CS

(d) SO

Figure 8: Average difference MGP-MSD for the four zones. The figure reports the rolling OLS estimate of the intercept of the regression of the difference of MGP-MSD prices on an intercept. The length of the estimation window is one year (8760 observations). The black-solid line is the point estimate, and red-dotted lines denote the 95% confidence interval obtained with Newey and West (1987) robust standard errors.

and type of RES for CN and CS is quite similar, even though each zone has its own distribution. There is no clear signal that the CS zone differs from SO or CN in terms of installed non-controllable RES capacity. Yet it is the only zone that exhibit a diverging pattern. This signals that there are other peculiarities that affect market efficiency in each zone. A natural candidate would be the very definition of the zones. They are defined on the basis of permanent congestion on transmission lines, which limit transit across zones. However, there are also relevant congestion within zones that are reflected in the cost of balancing services but that are not apparent since these congestion do not give rise to a separate zone.

Zone	Wind	PV	Hydro	Thermal
		MW		
NO	116.9	8943.5	16789.8	29649.6
CN	145.1	2372.5	1153.3	3647.9
CS	1769.6	2889.4	2772.2	9829.4
SO	4126.4	4643.5	1228.4	12708.1
		% of total inst. cap.		
NO	1.28%	42.51%	72.56%	46.43%
CN	1.59%	11.28%	4.98%	5.71%
CS	19.43%	13.74%	11.98%	15.39%
SO	45.32%	22.07%	5.31%	19.90%

Table 4: Installed capacity in each zone in MW (upper panel) and as percentage of total installed Italian capacity, including Sicily and Sardinia (lower panel).

The existence of local congestion within zones is a well-know characteristics of the Italian system; an example is the area of Naples, which is located in the CS zone, and that sees a limited number of producers that are deemed necessary by the TSO to maintain system stability. This situation clearly increases market power of local producers. In some cases, relevant local congestion were made apparent by means of virtual zones, i.e., zones with production poles without (relevant) load. This was the case of the virtual zones of Brindisi and Foggia, that were kept separate from the SO zone even though this two production poles are physically located within the SO region. These limited production poles disappeared and were included into the SO zone at the beginning of year 2019 upon the resolution of the local congestion, and from that period onward the the SO zone has shown a quick tendency toward price convergence. On the contrary, local congestion in the CS zone could not be solved with a different market design since the area is too big to give rise to a limited production pole yet too small to be considered as an independent market zones (since there are too few producers). Therefore, it seems that local congestion within the CS zone and the increased market power induced by them is what causes the market inefficiency of the CS zone.

Throughout the paper we have shown that there is a tendency towards price convergence in each of the continental zone of Italy but the CS zone. We have also evaluated the relative price difference of those zones where price are converging: we measured the difference in real-time versus DA electricity price, and shown that this average price difference is converging over time. Despite our study referred to the Italian market, we believe that our approach, far from being just an analysis of a given market, can be of interest for other markets as well. It shows a robust methodology that can be applied to evaluate market efficiency in terms of price convergence between DA and real time markets. It also enables us to measure the inefficiency due to the average difference between cost of provision of electricity in real time and forecasted DA figures. Finally, it shows that even under a common institutional framework, the definition of the zone and the existence of relevant congestion within a zone is the crucial parameter that can explain market inefficiency better than the different structural composition of power supply. This latter point can be of relevant importance for policy makers, and in particular for market regulators and for the market surveillance activity. Regulators and policy makers should focus their activity on tackling grids' bottlenecks as this seems to be the crucial parameter affecting competitiveness and price convergence. Monitoring agencies could use the methodology we propose here to have an indication about market price convergence (if any), possible local market power abuse and be aware of which balancing markets they should focus on in order to enhance market efficiency.

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