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Price regimes in an energy island: Tacit collusion vs. cost and network explanations

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ABSTRACT

In this paper, we explore the determinants of wholesale electricity prices in an energy island such as Sicily, by estimating regime switching models with fixed and time-varying transition probabilities on daily data in the 2012–2014 period. Explanatory variables used alternatively in the price equation and in the switching equation include power demand, the supply of intermittent renewables, the residual supply index, and a congestion indicator. Four competing hypotheses on the determinants of price regimes are tested (arbitrary market power, cost profile, tacit collusion, congestion) in order to understand why, despite the general trend of declining prices induced by renewables in southern Italy, Sicilian prices stood high. The pattern of estimated coefficients is consistent with a tacit collusion story.

1. Introduction

The integration of electricity markets in Europe is among the main goals of the 2030 Climate-Energy Package, approved by the European Council in October 2014. The existence of *energy islands* is identified as one of the main impediments towards the single electricity market. Understandably, the investment targets outlined in the package are influenced by geopolitical considerations, motivating the focus on the Baltic States, that are integrated with the Russian grid but not sufficiently with the EU partners. Not less relevant in economic and geopolitical terms are the bottlenecks that separate the Iberian peninsula from France, Ireland from Great Britain, and Sicily from the Italian mainland. Ten years after market liberalization, in 2014 Sicily was separated for about 80% of the hours from the rest of Italy. From a purely geographical viewpoint, the Sicilian interconnection problem is rather similar to the Irish one and Sicily is a potential bridge towards Northern Africa just like the Iberian countries (see Cambini and Rubino, 2014). Yet, Sicily faces less workable southward interconnection opportunities, due to the Libyan civil war and Tunisia's slow post-revolutionary recovery, than those facing Spain and Portugal (Morocco, a rather stable and favorable destination for FDIs).

The energy isolation of Sicily may lie behind its less than satisfactory price performance. Following the subsidized boom in new renewable energy investments, the annual reports of the Italian Power Exchange (IPEx) have shed light on the declining trend in the wholesale price in the renewable-rich southern regions, leading prices south of Rome to undercut the historically lower northern ones (see GME, 2012, 2013). Sicily strikingly departs from this trend, despite its large wind and solar penetration rates. Between 2011 and 2012, the price in Sicily increased by 2.2%, in line with Sardinia (+2.2%) and the South zone (+1.9%) and below the other market zones (GME, 2012). Yet, the pronounced price plunges observed between 2012 and 2013 (from −16.8% in the North zone to −24.7%

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in Sardinia) were not replicated in Sicily (−3.4%) (GME, 2013). While the average national price fell below 50 Eur/MWh in the summer of 2014, Sicilian prices reached 95 Eur/MWh on average in July and 108 Eur/MWh in August, roughly twice the price in the neighboring South zone. Therefore the win–win outcome of renewables support (stable revenues for subsidized producers, lower prices for wholesale purchasers) is not available in Sicily, causing an equity issue that needs to be solved by providing policy-makers with sound information about the roots of such price dynamics.

In this paper, we explore the determinants of wholesale electricity prices in Sicily by estimating regime switching models, using daily data in the 2012–2014 period. Explanatory variables included in the price equation and in the switching equation are power demand, the supply of renewable energy, a measure of market power, and a congestion indicator. Testing theoretical hypotheses on price regimes is rife with potentially fruitful insights, in view of the high policy-making returns from appropriate modeling of the price process. Indeed, the regime switching model has been successfully applied to the electricity market (e.g. in Huisman and Mahieu, 2003; Weron et al., 2004; Mari, 2008; Karakatsani and Bunn, 2008; Janczura and Weron, 2010 among others), thanks to its fit performance and its possible consistency with multiple equilibria and tacit collusion rooted in repeated interaction among oligopolistic power generating companies (since Green and Newbery, 1992; von der Fehr and Harbord, 1993).

Finding price regimes in Sicily could testify to the role of tacit collusion in the observed upward trend. Yet, while persistence in a high-price regime would be consistent with a collusive focal point, it may alternatively occur because of congestion, which may keep the price in a high regime even if generators fail to collude. The high frequency of congestion episodes is a powerful limit to competition on the island, in line with the pioneering theoretical analysis performed by Liu and Hobbs (2013), showing how strategic (de)congestion and the generators' ability to anticipate the moves by the transmission system operator sustain collusion. Joint ownership at both sides of the transmission line can also exacerbate the collusive temptations (Boffa and Scarpa, 2009).[1] Consistently, one may interpret sky-rocketing prices in the summer of 2014 as the attempt of generating companies to reap large profits before the expected upgrade of the Sorgente-Rizziconi cable linking Sicily with the Italian mainland, that was scheduled to be completed in 2015. At the same time, generators in Sicily face highly volatile residual demands, as renewable supply is growing and the paucity of hydropower resources implies limited flexibility and storage. Coupled with a contractionary demand trend after the financial crisis, volatility defies the otherwise clear expectation that Sicilian generators would easily sustain a tacit collusion agreement.[2]

The tacit collusion hypothesis, empirically assessed e.g. by Fabra and Toro (2005) and Sweeting (2007), needs to be tested against alternative hypotheses, grounded in the existing empirical literature. Besides congestion, previously mentioned (Haldrup and Nielsen, 2006a,b; Sapio, 2015a,b), regime transitions may result from electricity demand fluctuations spanning a kinked market-wide cost function, even in the absence of market power (Kanamura and Ohashi, 2008). In a quite popular class of models (Huisman and Mahieu, 2003; Janczura and Weron, 2010), the price in the "high" regime is a random draw from a probability distribution, as if generating companies exercised an *arbitrary* market power, as Karakatsani and Bunn (2008) put it.

[1] The former monopolist, Enel, operates thermal power and hydropower plants in both Sicily and Calabria.

[2] Collusive incentives are pro-cyclical according to Green and Porter (1984). Renewable energy producers receive a regulated tariff, hence they have no incentive to join in the collusion game.

The regime-switching model that we build is able to encompass the abovementioned four hypotheses. Depending on the signs of the parameters in the price equation and in the switching equation, one can obtain four different models, nested in the general one, that correspond to the competing hypotheses. Unlike Fabra and Toro (2005), we allow all coefficients in the mean price equation to vary across regimes, not just the constant, and consider the possible effects of intermittent renewables and network congestion. In our analysis, persistence in a high-price regime will be attributed to sustained tacit collusion only if the whole set of estimated parameters rules out alternative interpretations.

We empirically identify two regimes – high and low – and find that in each regime, the electricity price in Sicily can be explained by positive drivers (demand, market power, congestion) but its level is mitigated by the supply of renewables, confirming the merit order effect shown by a number of works (Sensfuss et al., 2008; Guerci and Sapio, 2012; Ketterer, 2014; Paraschiv et al., 2014; Veraart, 2015 and references therein). Market power, thus, does not translate into occasional random spikes, ruling out the arbitrary market power hypothesis. The cost profile hypothesis, too, is discredited, as price levels reflect something more than cost information. Both the high and low regimes are strongly persistent, consistent with both the congestion and tacit collusion hypotheses. The congestion indicator helps predicting the regime transitions, but it displays statistically significant variation within each regime, suggesting that it is not the main explanation for price regimes. Supporting the tacit collusion hypothesis, the transition probability from the high to the low regime increases when demand, market power, and congestion are relatively low, and when RE supply is relatively high. This is consistent with the theoretical conditions triggering price wars (see Ivaldi et al., 2003).

The paper is structured as follows. After a literature review, Section 2 outlines the competing hypotheses to be tested through the model described in Section 3. Section 4 presents the dataset and the empirical results, discussed in the concluding Section 5.

2. Literature review and hypotheses

Regime switching models are built for a variety of goals, from improving the forecast performance of power price models, to the valuation of electricity-based contracts, to the detection of price wars in repeated games. Accordingly, those different approaches put the stress on different underlying drivers of the regime dynamics, such as strategic behavior, distribution of marginal costs, tacit collusion, and network congestion. We shall organize the following literature review on regime switching models along these lines.

2.1. Strategic behavior and market power

A first class of models defines a *base regime*, wherein the electricity price is driven by a mean-reverting autoregressive process and/or by fundamentals, a *spike regime*, corresponding to a random draw from a given probability distribution, and sometimes a *drop regime*, in which the price drops in a similarly random fashion. A three-regime model has been estimated by Huisman and Mahieu (2003) and Janczura and Weron (2010). Karakatsani and Bunn (2008) found it to be a superior representation of the price process in peak periods, whereas Huisman and Kiliç (2013) employed a two-regime model. The switching process is usually Markovian; the fit is usually improved by assuming transition probabilities that depend on time-varying variables, i.e. load and the reserve margin (see Mount et al., 2006; Mari, 2008) or by positing self-exciting dynamics (Lucheroni, 2012).

Modeling price in the spike regime as a purely random variable, without any serial correlation and no relationship with fundamentals, is consistent with a view of an arbitrary strategic behavior on the part of power generating companies, or one that cannot be rationalized by using public information alone. The drop regime is interpreted as the outcome of unexpected technical events that cause a sudden shortfall in supply (see Janczura and Weron, 2010). Although not in a regime switching framework, the empirical model in Orea and Steinbuks (2012) assumes firm-specific, random conduct parameters, allowing for a market power exercise that is gradually changing and unpredictable.

A debated issue in this literature is whether the functional form of the price equation in the base regime should be linear or log-linear. While it provides a superior empirical fit, e.g. in Janczura and Weron (2010), the assumption of linearity is consistent with a uniform distribution of marginal costs across power generating units —an assumption that underlies some theoretical approaches (e.g. the supply function equilibrium model of Baldick et al., 2004), but it is empirically tenable only if it is consistent with the underlying distribution of marginal costs. This leads to a second possible determinant of price regimes.

2.2. The distribution of marginal costs

Suppose marginal costs of power generation are uniformly distributed in a positive range, and suppose that all units are offered in the market at full capacity and at their marginal costs. Then, the resulting supply stack will be linear, with a null intercept, and with a slope that depends on the marginal cost of the least efficient unit in the system.

Under some (admittedly restrictive) assumptions (no entry of new units, no time variation in marginal costs, no intermittent capacity, no strategic behavior), the electricity price is only a function of power demand because of the market clearing requirement, and due to linearity, the marginal effect of demand on price is constant. Hence, no regime appears. By the same token, no regime emerges if the supply stack is approximated by a continuous function with stable parameters.

The modeling strategy of Kanamura and Ohashi (2008) generates price regimes through a piece-wise linear supply stack without relaxing the abovementioned restrictive assumptions. This is equivalent to assuming that marginal costs are uniformly distributed with support $[0, c']$ within a given capacity interval, and follow another uniform distribution (with support $[c', c'']$) in the capacity interval including the least efficient units. As demand fluctuates in a mean-reverting fashion, price regimes emerge because of a kink in the market-wide marginal costs curve and do not necessarily reflect market power exercise.

As an implication of the assumed supply function structure, Kanamura and Ohashi show that transition probabilities depend on exogenous fundamental variables, such as the long-term trend in demand, the temporary deviations of demand from its trend, and the gap between current demand and the supply threshold that triggers the regime switch. This would match the empirical observation that price spikes are more frequent when demand is relatively high. The shape of this relationship reflects the probability distribution function of the error term in the price equation, which the authors assume to be Gaussian without loss of generality.

The Kanamura–Ohashi model lends itself to an alternative interpretation, one in which marginal costs are uniformly distributed across the whole capacity, but once demand grows beyond a certain threshold, power generating companies add a markup that is linearly increasing with demand — thus shifting up the supply stack slope. Indeed, the kinked profile of the supply stack can be exacerbated by market power, as noted by Wolak and Patrick (2001). If so, the model would suggest cost structures and strategic behaviors as joint determinants of price regimes, but here strategic behaviors would be partly predictable (increasing with demand) and thus not arbitrary as in the previously reviewed class of models.

2.3. Tacit collusion

The regime switching models just reviewed are often quite generic about the source and type of market power exercised by power generating companies. As argued by Karakatsani and Bunn (2008), the base regime can be conceived as a focal point in a repeated game, with an autoregressive structure that is meant to capture the learning processes involving power generating companies. Repeated electricity market games are increasingly analyzed in the literature, from the early attempt by Fabra (2003) to more recent works (Boffa and Scarpa, 2009; Liu and Hobbs, 2013), moving away from single-stage game representations (reviewed in Ventosa et al., 2005). Simulation models, such as Bunn and Martoccia (2005), Tellidou and Bakirtzis (2007), and Anderson and Cau (2009), have highlighted the role of learning in the build-up and support of the collusive strategies. Motivating evidence of price patterns consistent with tacit collusion includes Macatangay (2002) and Sweeting (2007) on the England & Wales market, Harvey and Hogan (2000) and Borenstein et al. (2002) on the California crisis.

The link between regime switching models and multiple equilibria in electricity markets is explored by Fabra and Toro (2005), whose time-varying Markov regime switching model explains Spanish price levels in the *collusive* and *price war* regimes through duopolistic production levels and costs; the regime switches are triggered by changes in market shares, in concentration, in company-level revenues or in average prices. A move from a high-price to a low-price equilibrium is interpreted as a price war, and one of the duopolists (Iberdrola) is identified as the responsible for the deviation, in line with the predictions of repeated games (as outlined e.g. in Ivaldi et al., 2003, Green and Porter, 1984).

In Fabra and Toro (2005), only the constant term of the price equation is subject to switches, hence the marginal effect of cost and production variables is the same across regimes. Their empirical results show that the electricity price positively depends on the marginal costs and production of the largest generator (Endesa), while supply from fringe generators has a negative impact. Market concentration is theoretically and empirically shown to be higher in the price war regime, because a deviation from the collusive agreement causes the asymmetry in market shares to increase.

2.4. Network congestion

The above models were based on *latent* regimes. Indeed, the demand and supply conditions that trigger market power exercise are only imperfectly observed (Sections 2.1 and 2.3), and similarly for the kink in the supply stack (Section 2.2), although bid-based data could be used to estimate the latter.

However, the price determinants and their effects can change when the transmission capacity of the grid is saturated. Consider a country whose power grid consists of two zones, connected through a transmission line of given capacity. Whenever the power flows from either zone exceed the transmission capacity, the line is congested. This allows to distinguish between two different regimes: a *congested regime* and a *non-congested regime*.

In the congested regime, zonal prices differ, and the price in each zone is determined by local demand, local supply and the amount of electricity imported (if the local price is relatively high) or exported (if it is relatively low). In the non-congested regime, the zones are fully integrated, hence zonal prices are equal and are both determined by the national demand and supply for electricity. The shape of the relationship between the price and its determinants in each zone changes across regimes; the sets of plants involved in the computation of the zonal price differ, and the cost information related to them, too. The congested regime is supposedly more prone to market power exercise, because zonal generating companies are shielded from competition, yet the causality may be reversed, especially if the same company runs units at both sides of the possible bottleneck, leading to a sort of multi-market contact issue (Boffa and Scarpa, 2009), and can strategically cause or relieve congestion by means of capacity withholding.

Unlike latent determinants of price regimes, congestion is observable using market-level data. Regime switching models with *known* regimes identified by congestion episodes have been built by Haldrup and Nielsen (2006a,b). The authors (in their 2006b article) estimate the transition probabilities from the observable congestion events in the NordPool area, as empirical frequencies of changes in grid states (from congested to non-congested and vice versa), and model the (log of) the price ratio between neighboring zones. In all cases, autoregressive models are estimated, allowing for fractional integration. In the no congestion regime, the log of the price ratio is zero, because prices are equal, hence all coefficients are restricted to zero, only to switch to non-zero values whenever congestion arises, according to the transition probabilities previously estimated. For a given status of the grid (congested in import/congested in export/noncongested), the price equation coefficients are constant, hence any latent regime trigger is assumed away. The long-memory properties of the series differ across regimes and grid locations.

The role of fundamentals that may make congestion more or less likely, however, is best understood by making transitions endogenous. Lucheroni (2010) builds a stochastic model in which price spikes occur when the oscillations of a periodic driver cross a threshold, and distance from the threshold is interpreted as distance from congestion. In Sapio (2015a,b) an endogenous switching mechanism is considered, whereby the congestion probability depends on the relative balances between supply and demand in each zone as well as on the transmission capacity, using Sicily as the test case. Congestion is found to be significantly related to power demand and renewable energy supply both in import and in export.

In this modeling strategy, price regimes can emerge even without strategic behaviors, e.g. when renewable energy supply changes suddenly and faster than demand. This does not deny that market power can be a price determinant. Indeed, the results from the vector autoregression analysis performed by Sapio (2014) suggest that zonal market power exercise (proxied by the residual supply index or by the Herfindahl–Hirschmann index) is higher when the grid is congested. In fact, market power can be a determinant also in the low-price regime, e.g. if the reserve margin at the national level is thin, but the transmission capacity is large enough to guarantee market integration.

2.5. Building hypotheses

Based on insights from the above literature review, four alternative hypotheses can be outlined in an empirically testable form, concerning the ultimate determinants of the regime structure of electricity prices: the *arbitrary market power*, the *cost profile*, the *tacit collusion*, and the *congestion* hypothesis. For the sake of simplicity, these hypotheses shall be built under the assumption that electricity prices undergo a 2-regime dynamics, although statistical tests may indicate otherwise. We shall refer to the two regimes as the high-price regime and the low-price regime (high and low in short). We could have called them the spike and drop regimes, as in Janczura and Weron (2010), or the collusive and price war regimes (Fabra and Toro, 2005); yet, our goal is precisely to assess the empirical plausibility of the alternative interpretations of price regimes, which the mentioned terminologies are associated with. The four hypotheses are schematized in Table A.1, summarizing the expected impact of some relevant variables (demand, RE supply, market power, and congestion indicators) on price levels in the two regimes as well as on the transitions between regimes.[3]

In the **arbitrary market power** hypothesis, a transition from the high to the low regime is caused by changes in fundamentals: increasing demand, market power, and congestion would have the system shift to and persist in the high regime, whereas a larger supply of renewables would favor a transition to the low regime and persistence in it. Yet the magnitude of strategic behavior in the high regime, as mirrored in the price level, is entirely random (as with the spike regime in Janczura and Weron, 2010). Hence, in the high regime, we expect all coefficients associated with fundamentals in the price equation to lack statistical significance. The price level in the low regime, instead, depends on demand and supply fundamentals.

The **cost profile** hypothesis postulates that the transition probabilities and the price levels in both regimes depend on demand, on RE supply, and on congestion, as the switching dynamics is only dictated by the presence of a kink in the cost-reflective supply stack. Within regimes, demand and congestion are expected to act as positive drivers, whereas the merit order effect previously theorized and detected in the literature a suggests a negative impact of renewables. Demand, however, need not be significantly associated with the electricity price if the supply stack is nearly flat, as it could occur in the low regime. An increase in the supply of renewables would cause the location of the kink to shift rightwards, leading to higher persistence in the low regime. Congestion, instead, would determine a regime switch by changing the very shape of the supply stack, e.g. by limiting the import of low-cost electricity from a neighboring zone. In a perhaps simplified reading of the proposition in Kanamura and Ohashi (2008) that assumes away the interplay among fundamentals, market power has no role to play: it does not trigger switches and it does not affect price levels within regimes.

The core of the **tacit collusion** hypothesis lies in the conditions that trigger price wars (Ivaldi et al., 2003, Fabra and Toro, 2005). When colluding generators face a below average residual demand, they expect to receive lower collusive profits. This may happen because of low demand as well as because of a relatively high supply of renewables. Uncertainty in the available amount of the renewable resource makes coordination difficult, as shown in the simulation analysis by Banal-Estañol and Ruperez-Micola (2011). Evidence of profitability thinning due to wind power has been produced by Sioshansi (2011) and Hirth (2013). Compliance with a collusive agreement would be less attractive in those circumstances. A more concentrated market, with less competitors or with a pivotal supplier would instead enforce collusion and increase persistence in the high price regime. Anderson and Cau (2011) have theoretically shown that the collusive potential is maximized at intermediate levels of market power, and less likely in competitive and symmetric duopolistic settings. By limiting competition, network congestion goes in the same direction of sustaining tacit collusion. Liu and Hobbs (2013) provide perhaps the first theoretical analysis of how transmission constraints affect collusive incentives, inspired by the evidence of strategic exploitation of loop flows (Cicchetti et al., 2004). Once the price enters a certain regime, demand, market power and congestion are positive drivers of the price level, whereas the merit order effect associated to RE supply acts as a mitigating factor. In this hypothesis, too, the impact of demand may vanish in the low regime because of a flat supply stack.

Finally, under the **congestion** hypothesis, congestion is the only driver of regime transitions; demand, renewables, and market power do not exert any independent effect on regime switches. In turn,

[3] All tables and plots are in the Appendix.

congestion triggers market power exercise in the high regime (which is likely to correspond to a congested grid and hence to a more concentrated zonal market). If regimes were perfectly predicted by congestion, a congestion indicator (such as the number of congested hours in a day) would display very little variance, if any, within each price regime. Hence, the congestion hypothesis predicts that the coefficients associated to congestion in both regimes would not be statistically significant. All other fundamentals are expected to affect the price within regimes as in the tacit collusion hypothesis.

3. The model

Testing the hypotheses formulated in the previous section requires the set up of a rather general regime-switching model with time-varying transition probabilities, including the same set of explanatory variables both in the price equation and in the transition probabilities equation. Following Filardo (1998), the coefficients of the price process and of the switching process in the time-varying transition probability model can be consistently estimated via a maximum likelihood estimator (MLE) if, given the current price, the trigger variables are conditionally uncorrelated with the regime.[4] This condition holds even if the trigger variables are included as regressors in the price equation; moreover, the nonlinear relationship between the variables included in the price equation and those in the transition probability equation is sufficient to identify the parameters. One difficulty may arise if there is reverse causality in the transition equation — say, if generating companies induce congestion in order to achieve a regime switch. Since regimes are unobserved, direct verification of reverse causation is not possible (Filardo, 1998).

However, our attempts at estimating the full model were upset by computational issues, presumably due to the relatively large space of explanatory variables that we deal with, and resulting in the lack of convergence of the MLE algorithm. Therefore, we were constrained to follow an alternative approach: trying to learn as much as possible from models that are nested into the "general" one. At first, we estimate a regime-switching model with fixed transition probabilities:

$$\begin{aligned} p_t =& \mu(s_t) + \sum_{i=1}^{4} \boldsymbol{\beta}_i p_{t-i} + \alpha(s_t) d_t + \delta(s_t) r_t \\ &+ \lambda(s_t) m_t + \theta(s_t) c_t + \sigma(s_t)\varepsilon_t, \qquad (t \in \mathbb{T}), \end{aligned} \tag{1}$$

$$\mu(s_t) = \sum_{i=l}^{h} \mu^{(i)} \mathbf{1}\{s_t = i\} \quad \text{and} \quad \sigma(s_t) = \sum_{i=l}^{h} \sigma^{(i)} \mathbf{1}\{s_t = i\} \tag{2}$$

where $p_t = (\text{price}_t), d_t = (\text{demand}_t), r_t =$(renewable energy supply$_t$), $m_t =$ (market power$_t$) and $c_t =$ (congestion$_t$). All these variables are in natural logarithms. Autoregressive terms (up to four lags) are considered. Therefore, the parameters vector of the mean price Eq. (1) is defined by $\mu^{(i)}$ and $\sigma^{(i)}$, $(i = l, h)$ which are real constants, the autoregressive terms $_{i=1}^{4}\beta_i$, and the parameters α, δ, λ, and θ, which measure the impact of demand, renewable energy supply, the residual supply index and congestion, respectively.

$\{\varepsilon_t\}$ includes i.i.d. errors with $\mathsf{E}(\varepsilon_t) = 0$ and $\mathsf{E}(\varepsilon_t^2) = 1$, and $\{s_t\}$ are random variables in $\mathbb{S} = \{l, h\}$ that indicate the unobserved state of the system at date t. Throughout, the regime indicators $\{s_t\}$ are assumed to form a Markov chain on $\mathbb{S}$ with a transition probability matrix

$$\Pi = \begin{bmatrix} \pi_{ll} & 1-\pi_{ll} \\ 1-\pi_{hh} & \pi_{hh} \end{bmatrix} \tag{3}$$

where $\pi_{ij} = \Pr(s_t = j | s_{t-1} = i)$, and $0 < \pi_{ll}, \pi_{hh} < 1$. It is also assumed that $\{\varepsilon_t\}$ and $\{s_t\}$ are independent.

Both the mean and the conditional variance of the price process are assumed to vary across regimes. Due to convexity of the supply stack, the mean price and the variance are expected to move together, so that a high-price regime is also likely to be a high-variance regime.

This model, despite assuming away any effect of fundamental variables on regime transitions, allows to discriminate among the hypotheses we have outlined. Indeed, each hypothesis entails a distinct pattern of restrictions on the price equation (see Table A.1). In particular, we reject the arbitrary market power hypothesis if significant parameters in the high-price regime equation are found, i.e. if prices in the high regime are predictable; the cost profile hypothesis is rejected if the coefficients of market power are significant in both regimes; whereas the tacit collusion hypothesis is supposed to hold if all fundamentals are significantly associated with prices, with the possible exception of demand in the low regime. Finally, one rejects the congestion hypothesis if, within regimes, congestion is significant.

We then undertake the estimation of a non-ergodic Markov switching process by allowing the transition probabilities to be function of demand, renewables, market power, and congestion, and assuming that these variables only affect electricity prices through transition probabilities. The conditional mean equation has the following specification:

$$p_t = \mu(s_t) + \sum_{i=1}^{4} \boldsymbol{\beta}_i p_{t-i} + \sigma(s_t)\varepsilon_t, \qquad (t \in \mathbb{T}), \tag{4}$$

$$\mu(s_t) = \sum_{i=l}^{h} \mu^{(i)} \mathbf{1}\{s_t = i\} \text{ and } \sigma(s_t) = \sum_{i=l}^{h} \sigma^{(i)} \mathbf{1}\{s_t = i\}. \tag{5}$$

The conditional mean value (μ^l for prices in the low regime and μ^h for prices in the high regime) follows an independent regime-shifting process (Diebold et al., 1994) with the transition mechanism governing $\{s_t\}$ given by the following time-varying transition probabilities:

$$\begin{aligned} \pi_{ll,t} &= \frac{\exp\left(k^l + \alpha^l d_t + \delta^l r_t + \lambda^l m_t + \theta^l c_t\right)}{1 + \exp\left(k^l + \alpha^l d_t + \delta^l r_t + \lambda^l m_t + \theta^l c_t\right)}, \\ \pi_{hh,t} &= \frac{\exp\left(k^h + \alpha^h d_t + \delta^h r_t + \lambda^h m_t + \theta^h c_t\right)}{1 + \exp\left(k^h + \alpha^h d_t + \delta^h r_t + \lambda^h m_t + \theta^h c_t\right)} \end{aligned} \tag{6}$$

where $\pi_{ij,t}$ denotes the probability of a transition from regime i to regime j at time t, such that $\pi_{ll,t} + \pi_{lh,t} = 1$ and $\pi_{hh,t} + \pi_{hl,t} = 1$. Demand ($d_t$), renewable energy production (r_t), market power index (m_t) and congestion (c_t) are variables that are now allowed to affect the transition probabilities rather than the mean equation as in Eq.(1). The smoothed probabilities derived from the time-varying transition probability model are defined as $Pr(s_t = i|\psi, I_T)$, where $I_t = \{p_{t-1}, p_{t-2}, p_{t-3}, p_{t-4}, d_t, r_t, m_t, c_t\}$ be the set of explanatory variables at time t, and $\psi = \{\mu^i, \beta_1, \beta_2, \beta_3, \beta_4, \sigma^i, k_i, \alpha^i, \delta^i, \lambda^i, \theta^i\}$, with $i \in \{h, l\}$.

Note that, since $\partial\pi_{hh,t}/\partial d_t$ $(\partial\pi_{hh,t}/\partial r_t, \partial\pi_{hh,t}/\partial m_t, \partial\pi_{hh,t}/\partial c_t)$ has the same sign as $\alpha^h(\delta^h, \lambda^h, \theta^h)$, $\alpha^h > 0(\delta^h > 0, \lambda^h > 0, \theta^h > 0)$ an increase in d_t (r_t, m_t, c_t) increases the probability of remaining

[4] This, indeed, allows to concentrate out of the likelihood function the parameters of the trigger variables processes and yield ML estimators with desirable properties.

in the state characterized by a high price. Similarly, $\alpha^l > 0(\delta^l > 0, \lambda^l > 0, \theta^l > 0)$ implies that an increase in d_t (r_t, m_t, c_t) will increase the probability of remaining in the low regime (low price). Coefficients k^h and k^l characterize the behavior of the transition probabilities in the theoretical instance when all explanatory variables or their coefficients are null.[5]

Based on the coefficient patterns implied by our hypotheses (Table A.1), this estimation strategy does not allow to distinguish between arbitrary market power and tacit collusion; yet the cost profile and congestion hypotheses can be assessed.

Admittedly, coefficient estimates may be biased in both modeling strategies, as we omit relevant variables, whose effects may however be taken up by the autoregressive terms if lagged prices are correlated with fundamentals. It is worth noting that our hypotheses are formulated in terms of signs and significance of the coefficients, hence any potential bias is not of concern for our analysis. Nonetheless, the implications of omitting variables in regime switching models are not well understood,[6] and taking into account a regime-dependent conditional variance is expected to alleviate that issue.

Taken together, the whole set of estimates (from fixed and time-varying probability models) shall guide us on the empirical validity of the proposed hypotheses. Table A.2 outlines how information from the estimates of the two models shall be used to reject any hypothesis. For each model, we identify the hypotheses that cannot be rejected. Let NR_f and NR_{tv} denote the set of hypotheses that cannot be rejected, respectively, by the estimates of the fixed and time-varying transition probability models. We shall consider the results to be consistent only with the hypotheses that neither model can reject, i.e. with hypothesis H such that $H \in NR_f \cap NR_{tv}$.

4. Empirical analysis

4.1. Data sources

Day-ahead wholesale trading of electricity takes place in the Italian Power Exchange (IPEx), managed by State-owned Gestore dei Mercati Energetici (GME). The IPEx day-ahead market is a closed, non-discriminatory, uniform-price double auction. Each day, market participants can submit bids and offers valid for each hour of the next day, used by GME to clear the market using a merit order rule.

If transmission constraints do not bind, all day-ahead supply offers are remunerated by the same price, the System Marginal Price (SMP), except for holders of long-term contracts, who receive the contract price, and subsidized plants, receiving the regulated tariffs. The optimal dispatch solution involves the calculation of zonal prices when lines are congested, in which case the Italian grid is segmented into up to 6 market zones (North, Center-North, Center-South, South, Sicily, and Sardinia) and 5 limited production poles.[7] Sicily is the zone most frequently separated and is only connected with the South zone through the Rossano production pole.[8]

Data on the wholesale day-ahead electricity market have been collected from the IPEx website (www.mercatoelettrico.org) for the period Jan.1, 2012–Dec.31, 2014. These data are recorded with a hourly frequency and include: zonal prices (Eur/MWh), zonal purchased quantities (MWh) and the residual supply index (RSI). In the econometric analysis, we focus on the Sicily zone and we aggregate these hourly variables on a daily horizon, by taking daily averages (in the case of zonal prices) or the sum across hours (purchased quantities). The daily purchased quantity on the day-ahead market is a good proxy for the overall electricity demand in Sicily, considering the high liquidity of the IPEx market (roughly between 60% and 70% in the sample period; sources: GME, 2012, 2013 and website). Moreover, one can safely consider demand as price-inelastic. End users who have not switched to competitive retailers are served by the publicly-owned company Acquirente Unico (single acquirer), and the available evidence cast doubts on the efficacy of existing demand responsiveness programs, despite the relatively good diffusion of meters in Italy.[9]

As it is well known, power markets are imperfectly competitive, with strategic exploitation of market power opportunities leading to higher than marginal cost clearing prices. Traditional measures of market power (Lerner index, concentration measures) have been shown to be less than satisfactory in a sector, such as electricity, characterized by non-storability, capacity constraints, and network congestion (Borenstein et al., 1999). The residual supply index (RSI) is a more appropriate measure, aiming to catch the ability of a generator to impede market clearing through the threat of capacity withholding (Sheffrin, 2002; Swinand et al., 2010). The RSI published by the IPEx is defined as the sum of the overall quantities offered by sale, minus the number of the operators multiplied by the difference between the sum of the overall quantities offered by sale and the sum of the overall quantities sold.[10] We use the daily median, which is to be preferred to the mean because of the very skewed within-day distribution of the hourly RSI values.

Network congestion, a major determinant of price dynamics in Sicily, is measured as the daily number of hours when prices in Sicily and in the South zone differed. The coefficient associated to the number of congested hours can be seen as the effect of an additional hour of congestion, directly on the electricity price level or indirectly through transition probabilities.[11] As many congestion measures, this is an imperfect one, since a single congested hour might have a greater impact on the price dynamics than a whole congested day. As a way of capturing this, we could have weighted the different hours by using hourly demand levels, as the impact of congestion is stronger in hours with a tighter balance between demand and supply. Yet, this would induce undesired cross-correlation between explanatory variables.

Besides being an *energy island* in most market sessions, Sicily is also quite rich in renewables, thanks to good insolation and wind speeds. Omitting renewables would undermine the understanding of price dynamics. Data on the actual generation of intermittent

5 In that case, the transition probabilities are fixed and are equal to $\pi_{ll,t} = \frac{\exp k^l}{1+\exp k^l}$ and $\pi_{hh,t} = \frac{\exp k^h}{1+\exp k^h}$.

6 Monte Carlo simulations of a fixed probability model in Hamilton (1996) (assuming omission of a dummy from the “main” equation) suggest a small-sample attenuation bias and the underestimation of standard errors. We are not aware of any similar result applying to omitting variables from the main equation in a time-varying transition probability model.

7 A zone is a subset of the transmission network that groups local unconstrained connections. Zones are defined and updated by the transmission system operator, or TSO (Terna in Italy) based on the structure of the transmission power-flow constraints.

8 In all cases, electricity buyers pay a weighted average of zonal prices, called PUN (Prezzo Unico Nazionale, or single national price), with weights equal to zonal demand shares.

9 By the end of 2009, about 90% of final customers were equipped with smart meters supplied by Enel, the largest generating company in Italy. Time-of-use pricing has had a limited impact, because of fixed, regulated peak-off peak price differences for retail customers (Lo Schiavo et al., 2013).

10 This is the negative of the sum (over companies) of the RSI index presented in Gianfreda and Grossi (2012), hence it is increasing in market power.

11 We have alternatively used the daily change in the number of congested hours, with very similar results.

renewables are downloaded from the Terna website (www.terna.it). We sum the zonal sold quantities for the two available technologies (on-shore wind, photovoltaics) for each hour, and then take the daily sums. Detailed biomass and hydropower production data were not available for the whole sample period, while geothermal is absent in Sicily.

For each variable, 1096 daily data points are available. Table A.3 summarizes the notation, definitions, and sources of the variables used in the econometric analysis.[12]

4.2. Summary statistics

Summary statistics for the sample are given in Table A.4 for the Sicily zone, before applying filters. Sicilian power demand averaged 52,271 MWh per day in the sample period, corresponding to 6.6% of the national power demand. 12,540 MWh per day was accounted for by intermittent renewables. The whole sample statistics about Sicilian electricity prices hide the differences due to network congestion. The line between Sicily and South zones was congested in about 80% of the hourly market sessions; hence, on average, Sicily was separated from the rest of the Italian system about 19 h per day on average. Congestion was nearly always in import, i.e. from the Italian peninsula to Sicily, resulting in higher prices in Sicily (95.41 Eur/MWh on average under congestion, with a maximum of 3000 Eur/MWh in a hourly session, vs. a whole sample average of 51.81 Eur/MWh). The penetration rates of wind and photovoltaics in Sicily were, respectively, 16.0% and 8.2% in the sample period. These figures have been computed by summing the total RE sold quantities in Sicily for each source, and dividing them by the total power demand in Sicily in the sample period. Sicily ranked very high among Italian regions in terms of wind power (20.4% of the national wind power capacity in 2013), and fairly good also in regard to photovoltaic production (a 6.9% capacity share).[13]

Figs. A.1 and A.2 depict the time series of the variables of interest. Fig. A.1 features the daily average electricity prices (top panel) and the daily purchases (bottom panel) in Sicily. The two annual peaks in the demand series correspond to the winter and summer seasons, due to, respectively, heating and cooling needs. The price series retains the seasonal pattern in quite a milder fashion, as its behavior is more erratic and is occasionally punctuated by sudden and short-lived spikes (the tallest one on August 21, 2012, an average daily price of 273.64 Eur/MWh). A downward trend in demand is visible, motivated more by deteriorating macroeconomic conditions than by improvements in energy efficiency, but the price seems to have fallen significantly only during the winter between 2013 and 2014; electricity in the summer of 2014 was on average as expensive as in the summer of 2012, except for the different spike magnitudes.[14]

The time series of daily supply from intermittent renewables (mid-panel of Fig. A.2) shows relatively low and stable amounts only during the summer seasons, meaning that the seasonality is mainly in the variance of the RE generating process and is characterized by an annual frequency. The relatively high volatility of the wintertime RE supply reflects the relatively large availability of wind power, versus the preponderance of the more predictable photovoltaic resource in the summer months. Similarly, the number of congested hours (bottom panel of Fig. A.2) was on average higher and less variable during the summer than in the other seasons. It stayed at its highest (24 h) for several consecutive days during the summer of 2014. An interesting qualitative change is detected in the time series of the RSI index (top panel of Fig. A.2), which after fluctuating wildly and reaching very high values in the first 8 months of 2012, collapsed to values often close to zero with occasional outbursts of lower magnitude than in the past. This was due to entry of new plants (GME, 2012).

In line with the abovementioned trends, seasonals, and spikes, unit root tests (Augmented Dickey–Fuller, Phillips–Perron) performed on the time series of electricity prices, demand, and supply variables reject the null of non-stationary mean. The null of stationarity tested through the KPSS is rejected, too.[15] The logs of price, demand, and supply are thus treated by means of the recursive filter on (log-)prices (RFP) proposed by Janczura et al. (2013).[16] The descriptive statistics of the filtered data are in Table A.5, whereas Table A.6 reports the cross-correlations among variables before and after filtering.[17]

The only cross-correlation of some concern that we find between explanatory variables involves congestion and renewables, and is negative, in line with the findings in Sapio (2015b). Provided that results do not suggest variance inflation, we retain both variables in the model, as their effects on price are interesting for their own sake, and they are not correlated by construction.[18] Other sizable cross-correlations, e.g. between demand and renewables, or demand and the RSI, get weaker after filtering, presumably because the filter removes the common trends that lay behind the cross-correlations.

The null hypothesis of linearity against the alternative of Markov regime switching cannot be tested directly using a standard likelihood ratio (LR) test.[19] Hence we properly test for multiple regimes against linearity using the Hansen (1992) test. The results (Table A.5) support a two-states regime-switching model. The presence of a third state was also tested for and rejected.

As shown in Fig. A.3, the filtered electricity price behaved more erratically in the second and fourth quarters, approximately

12 Data from previous years have not been considered, because the spatial configuration of the grid changed over time: the former Calabria zone was merged with the South zone since January 2009; the SAPEI cable between Sardinia and the Center-South zone was inaugurated in March 2011. Concerning the use of fuel prices, see Footnote 17.

13 Authors' elaborations on data from GSE (2013). Hydropower capacity in Sicily was rather marginal (0.01% of the national hydropower capacity in 2013; hydropower production was 2.3% of the Sicilian electricity demand in 2012). Its exclusion from the analysis should not affect the results.

14 Daily averaging in Fig. A.1 smooths out the otherwise extreme excursions that have been mentioned in the Introduction.

15 The results of the tests are available upon request to the authors.

16 The RFP is an iterative outlier detection method, wherein the outliers are defined in each iteration as the observations lying more than three standard deviations away from the mean of the de-seasonalized prices. The data are de-seasonalized here in two steps: the short-term seasonal is removed by means of 7-day moving averages; then a Daubechies 5 wavelet is computed as the long-term seasonal component and subtracted. Any observation identified as an outlier/spike is replaced by the average offer price for the corresponding week–day.

17 Filtering allows to interpret the data as short-term deviations from seasonals and long-term trends, including the co-integrating relationships between electricity and fossil fuel prices found, among others, by Bunn et al. (2015) (see Janczura and Weron, 2010 for a similar reasoning). In fact, the measure of fuel prices that is most widely used by practitioners in Italy is the ITEC12/REF-E index (published by the energy consultancy company REF-E), a monthly-frequency weighted average of international coal and natural gas prices, adjusted for average thermal efficiencies, with weights corresponding to the average coal and natural gas shares in the Italian generation capacity.

18 Ex-post, this is worrisome for estimation purposes if we find large standard errors, which is not case (see Section 4.3).

19 Standard regularity conditions for likelihood-based inference are violated under the null hypothesis of linearity. Under such circumstances the information matrix is singular.

corresponding to spring and fall, while the amplitude of its fluctuations tended to narrow down in the first and third quarters (winter and summer), with apparently some more serial correlation. Winters and summers are also the time locations of the demand peaks (see the bottom panel of Fig. A.1).

In despiking the data, we follow the industry standard, yet we run the risk of underestimating the effects of our explanatory variables, since all of them could be causing spike occurrences (see evidence in Mari, 2008, and in Hellström et al., 2012). If we retained the spikes, we would need to resort to a different modeling strategy, such as regime spikes (see Huisman and Mahieu, 2003; Mari, 2008; Eichler and Tuerk, 2013). While appropriate in this case, regime spikes are implemented in an autoregressive framework, with minimal inclusion, if any, of exogenous regressors (typically, deterministic trends and seasonals). There is probably a trade-off between the complexity of a model including spike processes along with regimes, and the ability to extract information regarding the price impact of fundamental variables.

4.3. Results

Maximum likelihood (ML) estimates of the fixed transition probability model are reported in Table A.7. The model appears to be well identified: parameters are significant and the standardized residuals exhibit no signs of linear or nonlinear dependence. The significance levels are high enough to dissipate fears of variance inflation due to multicollinearity.

The statistical tests identify two regimes, with the estimated mean electricity prices in Sicily being farther from 0 in the high regime ($\mu(h) = 0.0408$) than in the low regime ($\mu(l) = -0.0042$). The Sicilian electricity price is also more volatile in the high regime ($\sigma(h) = 0.1339$) than in the low regime ($\sigma(l) = 0.0648$).

The fixed transition probability model shows that changes in demand have a significant effect on prices only in the high regime ($\alpha^h = 0.7346$). Along with the lack of significance in the low regime, these results are consistent with a hockey-stick supply stack (flat in the low regime, steep in the high regime). Renewable energy exercises a downward pressure on prices in both regimes, although more strongly so in the high regime ($|\delta^h| > |\delta^l|$). The same pattern is observed for the residual supply index, for which we find positive and significant coefficients in both regimes ($\lambda^h > \lambda^l$); and similarly for congestion ($\theta^h > \theta^l$). Both regimes are very persistent: the estimated p_{ll} and p_{hh} are both in the vicinity of 97%, so that the average duration of the system in the low regime is nearly 33 days, and 38 days in the high regime.

Looking at the time-varying transition probability model, in order to assess whether changes in demand, renewable energy supply, residual supply index and congestion contribute to predict changes in the electricity prices in Sicily, we need to both (i) analyze the sign and significance of the parameters of the time-varying transition probabilities, as this will enable us to find out whether the independent variables affect the probability of staying in, or switching regime; and (ii) inquire, by looking at the temporal evolution of the time varying transition probabilities, whether changes in regime are triggered by changes in the independent variables.

The estimated coefficients for the transition probability functions, presented in Table A.8, show that an increase (decrease) in the renewable energy supply increases (decreases) the probability of remaining in the low (high) regime; an increase (decrease) in the RSI raises (decreases) the probability of remaining in the high (low) regime; whereas an increase (decrease) in congestion raises (decreases) the probability of remaining in the high (low) regime.

The impact of demand on the probability to stay in the low regime is not significant whereas it has a strong and significant effect ($\alpha^h = 24.2837$) on the probability to remain in the high regime. Again, this is consistent with a hockey-stick supply stack. In comparison, the coefficients associated to the RSI (λ^l and λ^h) are higher in magnitude than those related to congestion (θ^l and θ^h), and more unequal across regimes. Having assumed logit transition probabilities, we can interpret the coefficients as elasticities of the log-odds to stay in a certain regime. A 10% increase in congestion yields a fall in the log-odds of the low-regime probability by 13.02% and increases the log-odds of the high-regime probability by +3.73%, whereas the effects induced by a 10% increase in the RSI amount to, respectively, −35.98% and +7.41%. Market power, thus, looks like a stronger driver of regime switches than congestion.

Fig. A.4 displays the estimated smoothed regime probabilities (high regime on top, low regime in the bottom panel). The Sicilian electricity zone remained in a high-price regime more frequently during the winter and summer months. Notice, however, that the high-regime probability was on average higher in 2012 than it would be later. It never fell below 0.5 from approximately mid-January to the beginning of April, and again from the end of May to mid September. These two long spells were interrupted by a rather persistent stay in the low regime (April) and a shorter dip in mid-May. The same pattern was not replicated in 2013, when the high regime was less frequent, especially in the second quarter. The first quarter of 2014 was markedly different from the first quarter of 2012, as testified by the small probability of the high regime, while some persistence resumed in the third quarter. Apart from a short spell in the low regime in late August, the high regime probability was above 0.90 from mid-July to mid-October.

It is hard to reconcile these changing patterns with the dynamics of either demand or renewables. Congestion (bottom panel of Fig. A.2) behaved very similarly in 2012 and 2013, although persistence in the high regime in the summer of 2014 can easily be linked to the amazingly long streak of fully congested days. More insights come from the change in the qualitative behavior of the RSI time series after August 2012. The lower ability of the system to sustain the high regime in 2013 and 2014 may be due to the diminished power of the pivotal supplier. As these observations imply, both the congestion and tacit collusion stories have explanatory power to some extent.

Fig. A.5, which presents the evolution of time varying transition probabilities, is very informative. It is clear that the probabilities of remaining in the same regime vary throughout the sample. Comparing the transition probabilities with the "raw" values of the explanatory variables (Figs. A.1 and A.2), we find that the probability of remaining in the high regime (π_{hh}) is rather well in sync with the summer demand peaks, but not with the winter peaks. Interestingly, in summer months the probability of remaining in the low regime (π_{ll}) is high, too, outlining a clearer regime structure in the price process than in other seasons.

One reason for lack of synchronization between the high-regime persistence and the winter demand peak may rest with the volatile behavior of renewables during the winter season. Looking at Fig. A.2 (mid-panel), it is rather clear that the supply of renewables is often abundant during the winter, presumably because of wind power production, hence countervailing the wintertime increase in demand, while the relative scarcity of renewables during the summer reinforces the residual demand available to power producers and their market power opportunities.[20] Adding to this, congestion on the Sicily-Rossano line is on average less frequent during the winter. There is, instead, a nice visual association between the probability to persist in the high regime and the congestion indicator. The coefficient estimates, though, point to market power as a stronger determinant of regime transitions.

[20] It is worth recalling that the photovoltaic penetration rate in Sicily is about half the wind power penetration rate (see Section 4.2).

5. Discussion and conclusion

By means of regime-switching models of the day-ahead electricity price, this paper is able to compare theoretical hypotheses on the determinants of price regimes in Sicily over the 2012–2014 period, shedding light on the reasons why Sicilian prices were less responsive to the general declining trend induced by renewables in Italy.

Our statistical tests identify two regimes, both of which display a relatively high persistence, yet the price process is not absorbed in either. This would be consistent with a collusion story, in which tacit agreements between generators are sustained for rather long spells and punishment periods are similarly long. Yet, one may obtain a similar pattern from a scenario in which the line connecting Sicily with the Italian mainland is congested due to protracted supply deficits on the island. As a matter of fact, in the three sample years, summer seasons in Sicily have lasted longer than usual, keeping up the power demand and requiring massive inflows of electricity from the South zone. The serial correlation of our congestion proxy, consistently, is .468 after 1 daily lag and tapers off quite slowly (around .10 between lags 15 and 20, and .16 at the 21-days lags). By the same token, persistence in the high regime obtains if demand persistently remains above the supply kink hypothesized by Kanamura and Ohashi (2008).

Conditioning the transition probabilities is the key to discriminating among the competing hypotheses. If regimes were only due to a kinked cost profile, the RSI and congestion would not have the explanatory power they display (see the time-varying regime switching results). Indeed, Table A.2 suggests that the cost profile hypothesis is rejected if the RSI coefficients are significant in the price equations or in the transition equation. In days with more congestion, high-to-low transitions are less frequent, and conversely, congestion seems to drive transitions towards the high regime and to increase its persistence. This would support the congestion hypothesis, yet the variance in the congestion indicator within each regime is not negligible, as implied by the price equation estimates. Table A.2 in this case indicates rejection of the congestion hypothesis. What casts doubts on the arbitrary market power hypothesis, instead, is finding that price levels in the high regime are predictable by means of data on demand, supply, market power, and congestion (see Table A.2 again). Hence, while in the high regime, generators do not seem to randomize.

As a bottom line, the estimated patterns seem to only be consistent with a tacit collusion story.[21] According to our results, high-to-low transitions are more likely when the supply of renewables covers a large share of power demand, when the pivotal supplier cannot affect market clearing, and when Sicily is integrated with the rest of Italy. In all these cases, the profit share lost by deviating is relatively small, in line with theoretical insights from repeated games with multiple equilibria.

Our paper adds to the existing evidence on tacit collusion, but its key message concerns the interplay between tacit collusion and transmission constraints, responding to the challenge presented by Liu and Hobbs (2013), and in line with Bigerna et al. (2015), who estimate market power measures adjusted for congestion. While the tacit collusion story is more empirically sound than a "pure" congestion story, it must be stressed that without the bottlenecks arising in the Sicily-Rossano line, the collusive incentives would have been much weaker. An implied message is that the reinforcement of the cable connecting Sicily to the Italian peninsula will curb market power, but at least as importantly, our results point to the tacit collusion literature as a source of alternative weapons against the threat of soaring electricity prices.

Infrastructural investments, indeed, prove less viable in austerity times. Completion of the second Sorgente-Rizziconi line, scheduled for 2015, 5 years after authorization, has been meeting opposition from environmental associations, leading the regional administration to call for a revision in the project and prompting judiciary investigations. Relaxing the transmission constraints can also yield unwelcome market power "export" effects when the excess capacity in one zone can be deployed in others after integration (Boffa and Scarpa, 2009) or when integration allows a low-cost dominant generator to access a more competitive zone (Bunn and Zachmann, 2010). The experience of lower prices in Sardinia after the inauguration of the SAPEI cable in 2011 is reassuring in this respect. Sardinia is similar to Sicily as regards climate conditions, renewable energy potential and hydropower scarcity.

Alternative anti-collusive means include reforming the day-ahead auction format, limiting multi-market contracts, and stimulating renewables. Fabra (2003) showed how collusion is harder to enforce in pay-as-bid auctions. Regulatory discussions almost led to replacing the day-ahead uniform price auction in the Italian Power Exchange in 2009 under pressure from industrial consumers, before the project was halted by the new government. Multi-market contacts across the forward curve, with companies competing in several derivative markets, need to be carefully regulated. This task is far from easy, in light of the proliferation of trading venues for forwards (MTE —Mercato a Termine per l'Energia, run by GME), futures and options (IDEX, managed by Borsa Italiana). Derivatives regulation and day-ahead auction formats are subtly linked, as pay-as-bid auctions are expected to yield lower volatility (Rassenti et al., 2003) and hence reduce the demand for hedging and the associated multi-market contacts.

Fostering further diffusion of renewable energy sources is yet another way to go. Our estimates suggest that more renewables keep the price process in the low regime and, within each regime, perform a mitigating function on price. Related work (Sapio, 2015b), moreover, highlights the beneficial role of renewables as substitutes for electricity imports from neighboring zones.

Our results should be taken into account in regulatory and policy-making circles, as in the implementation of the projects of common interest envisioned by the 2030 Climate-Energy Package. The case studies of Baltic States, Ireland and the Iberian countries all have their own peculiarities, yet the evidence on Sicily provides new and useful information on the potential benefits and risks associated to different infrastructural and institutional architectures. Behind the discussion on anti-collusive tools, outlined above, lies the tension between investments in the generation and transmission segments of the electricity industry (see also Boffa and Sapio, 2015). These entertain non-trivial complementarity and substitution relationships whose full understanding is a challenging task for future research.

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[21] NR_f, the set of hypotheses that are not rejected through the fixed transition model, only includes tacit collusion; NR_{tv}, the set of hypotheses that are not rejected by the time-varying transition model, includes arbitrary market power, tacit collusion, and congestion. Only tacit collusion belongs to the intersection of the NR_f and NR_{tv} sets.

Appendix A

Table A.1
Hypotheses on the expected effects of fundamentals (demand, RE supply, market power, congestion) on wholesale day-ahead prices within regimes and on regime probabilities. >0 (<0) indicates a positive (negative) and statistically significant effect. 0 means lack of statistical significance. ≥ 0 and ≤ 0 are used when hypotheses do not yield sharp predictions on the statistical significance of the effects.

	Effects on price		Effects on probabilities	
↓ Hypotheses	Low regime	High regime	Low regime	High regime
Arbitrary market power				
Demand	≥ 0	0	≤ 0	>0
RE supply	<0	0	>0	<0
Market power	0	0	<0	>0
Congestion	>0	0	<0	>0
Cost profile				
Demand	≥ 0	>0	≤ 0	>0
RE supply	<0	<0	>0	<0
Market power	0	0	0	0
Congestion	>0	>0	<0	>0
Tacit collusion				
Demand	≥ 0	>0	≤ 0	>0
RE supply	<0	<0	>0	<0
Market power	>0	>0	<0	>0
Congestion	>0	>0	<0	>0
Congestion				
Demand	≥ 0	>0	0	0
RE supply	<0	<0	0	0
Market power	>0	>0	0	0
Congestion	0	0	<0	>0

Table A.2
Criteria for rejecting the theoretical hypotheses using the coefficient estimates of the fixed and time-varying regime switching models.

Hypotheses	Reject in fixed transition model if…	Reject in time-varying transition model if…
Arbitrary market power	Any significant in high regime $\alpha(h) \neq 0 \vee \delta(h) \neq 0 \vee \lambda(h) \neq 0 \vee \theta(h) \neq 0$	Any non-significant in transitions, except demand $\delta^i = 0 \vee \lambda^i = 0 \vee \theta^i = 0, i \in \{h, l\}$
Cost profile	Market power significant in either regime $\lambda(i) \neq 0, i \in \{h, l\}$	Market power significant in transitions $\lambda^i \neq 0, i \in \{h, l\}$
Tacit collusion	Any non-significant in either regime, except demand $\delta(i) = 0 \vee \lambda(i) = 0 \vee \theta(i) = 0, i \in \{h, l\}$	Any non-significant in transitions, except demand $\delta^i = 0 \vee \lambda^i = 0 \vee \theta^i = 0, i \in \{h, l\}$
Congestion	Congestion significant in either regime $\theta(i) \neq 0, i \in \{h, l\}$	Congestion not significant in transitions $\theta^i = 0, i \in \{h, l\}$

Note: Let NR_f and NR_{tv} denote the set of hypotheses that cannot be rejected, respectively, by means of the estimated fixed transition and time-varying transition models. The data are considered to be consistent with hypotheses H such that $H \in NR_f \cap NR_{tv}$.

Table A.3
Notation, definitions, and sources of the variables used in the econometric analysis.

Notation	Short name	Variable definition	Source
p_t	Price	Daily average of hourly electricity prices in the Sicily zone	IPEx (day-ahead)
d_t	Demand	Daily purchased quantities of electricity in the Sicily zone	”
r_t	Congestion	Daily number of hours when the prices in the Sicily and South zones differed; or: daily change in the number of congestion hours	”
m_t	RSI	Daily average of the residual supply index for the Sicily zone	”
c_t	Renewables	Daily production of intermittent renewables in the Sicily zone	Terna

Table A.4
Descriptive statistics of the sample used in the econometric analysis on the Sicilian electricity market zone: before de-seasonalization and de-spiking. Number of observations: 1096.

	Mean	Std. dev.	Skewness	Kurtosis	Min	Max
p_t	89.401	19.418	0.451	11.009	20.608	273.637
d_t	52271.08	5498.788	0.253	2.874	35570.56	71830.18
r_t	12540.05	6275.72	1.072	3.640	1366	34528
m_t	33.778	94.742	3.967	22.197	0	812.298
c_t	20.694	4.154	−1.264	3.736	5	24

Table A.5
Descriptive statistics and tests after de-seasonalization and de-spiking. Number of observations: 1096.

	Mean	Std. dev.	Skewness	Kurtosis	Jarque–Bera
p_t	0.0151	0.1378	−0.1978	3.5966	23.408
d_t	0.0028	0.0305	−0.0649	3.0534	0.9008
r_t	0.0063	0.4345	0.0898	2.7824	3.6347
m_t	−0.1816	1.0508	0.8337	4.7416	28.893
c_t	−0.0063	4.2811	−0.1489	4.8508	16.332
Markov switching state dimension: Hansen test					
Standardized LR test	Linearity vs.two-states		Two-states vs.three-states		
LR	3.7765		0.4591		
$M = 0$	(0.0012)		(0.6987)		
$M = 1$	(0.0026)		(0.6900)		
$M = 2$	(0.0054)		(0.6987)		
$M = 3$	(0.0059)		(0.7034)		
$M = 4$	(0.0131)		(0.7124)		

Note: The Hansen's standardized likelihood ratio test p-values are calculated according to the method described in Hansen [31], using 1000 random draws from the relevant limiting Gaussian processes and bandwidth parameter $M = 0,1,\ldots,4$. Test results for the presence of a third state are also reported.

Table A.6
Cross-correlations among the variables, before and after de-seasonalization and de-spiking.

	log-price	log-purch.	log-RE	log-RSI	log-cong.
Before filtering:					
Daily log-price	1.0000				
Daily log-purchases	0.4515	1.0000			
Daily log-RE sold quantities	−0.5410	0.0237	1.0000		
Daily log-median RSI	0.3109	0.3166	−0.1688	1.0000	
Daily log-n. congested hours	0.6260	0.1865	−0.5269	0.1069	1.0000
After filtering:					
Daily log-price	1.0000				
Daily log-purchases	0.0673	1.0000			
Daily log-RE sold quantities	−0.5220	0.0631	1.0000		
Daily log-median RSI	0.1952	0.1819	−0.1060	1.0000	
Daily log-n. congested hours	0.5615	−0.0208	−0.5428	0.1005	1.0000

Table A.7
Fixed transition probability model of day-ahead log-prices in Sicily, after de-seasonalizing and de-spiking the daily averages: maximum likelihood estimates.

	Low regime			High regime	
	Parameters	p-Value		Parameters	p-Value
$\mu(l)$	−0.0042	(0.0265)	$\mu(h)$	0.0408	(0.0000)
$\alpha(l)$	−0.0057	(0.3525)	$\alpha(h)$	0.7346	(0.0000)
$\delta(l)$	−0.0811	(0.0000)	$\delta(h)$	−0.1889	(0.0000)
$\lambda(l)$	0.0164	(0.0000)	$\lambda(h)$	0.0169	(0.0111)
$\theta(l)$	0.0035	(0.0008)	$\theta(h)$	0.0059	(0.0000)
$\sigma(l)$	0.0648	(0.0000)	$\sigma(h)$	0.1339	(0.0000)
π_{ll}	0.9697	(0.0000)	π_{hh}	0.9738	(0.0000)
Duration	32.9065			38.2463	
$LB_{(5)}$	1.4232 [0.8962]		*LogLik*	947.3662	
$LB^2_{(5)}$	3.5576 [0.5422]				

Note: Autocorrelation and heteroscedasticity-consistent standard errors, computed using the Newey and West (1987) variance covariance matrix, are reported in brackets. LB_5 and LB_5^2 are respectively the Ljung-Box test (1978) of significance of autocorrelations of five lags in the standardized and standardized squared residuals, p-values are reported in brackets. Duration indicates the expected number of days the dependent variable stays in each regime, and is equal to $\frac{1}{1-\pi_{jj}}$ for regime j.

Table A.8
Time-varying transition probability model of day-ahead log-prices in Sicily, after de-seasonalizing and de-spiking the daily averages: maximum likelihood estimates.

Mean equation			Transition equation		
	Parameters	p-Value		Parameters	p-Value
μ^l	−0.0791	(0.0000)	k^l	−5.1381	(0.0006)
μ^h	0.0993	(0.0000)	k^h	−1.8593	(0.0000)
			α^l	8.4328	(0.6418)
			α^h	24.2837	(0.0031)
σ^l	0.1014	(0.0000)	δ^l	6.0316	(0.0006)
σ^h	0.1127	(0.0000)	δ^h	−4.9401	(0.0046)
			λ^l	−3.5976	(0.0055)
			λ^h	0.7411	(0.0118)
			θ^l	−1.3016	(0.0049)
			θ^h	0.3729	(0.0000)
$LB_{(5)}$	2.8293 [0.7262]		*LogLik*	839.1521	
$LB^2_{(5)}$	5.1578 [0.3969]				

Note: See notes to Table A.7. The time varying transition probabilities evolve according to Eq. (6), where α^l and α^h measure the effects of power demand on the probability to remain in the low and high regimes, respectively; the effects of renewable energy production, RSI, and congestion are measured by (δ^l, δ^h), (λ^l, λ^h), (θ^l, θ^h), respectively.

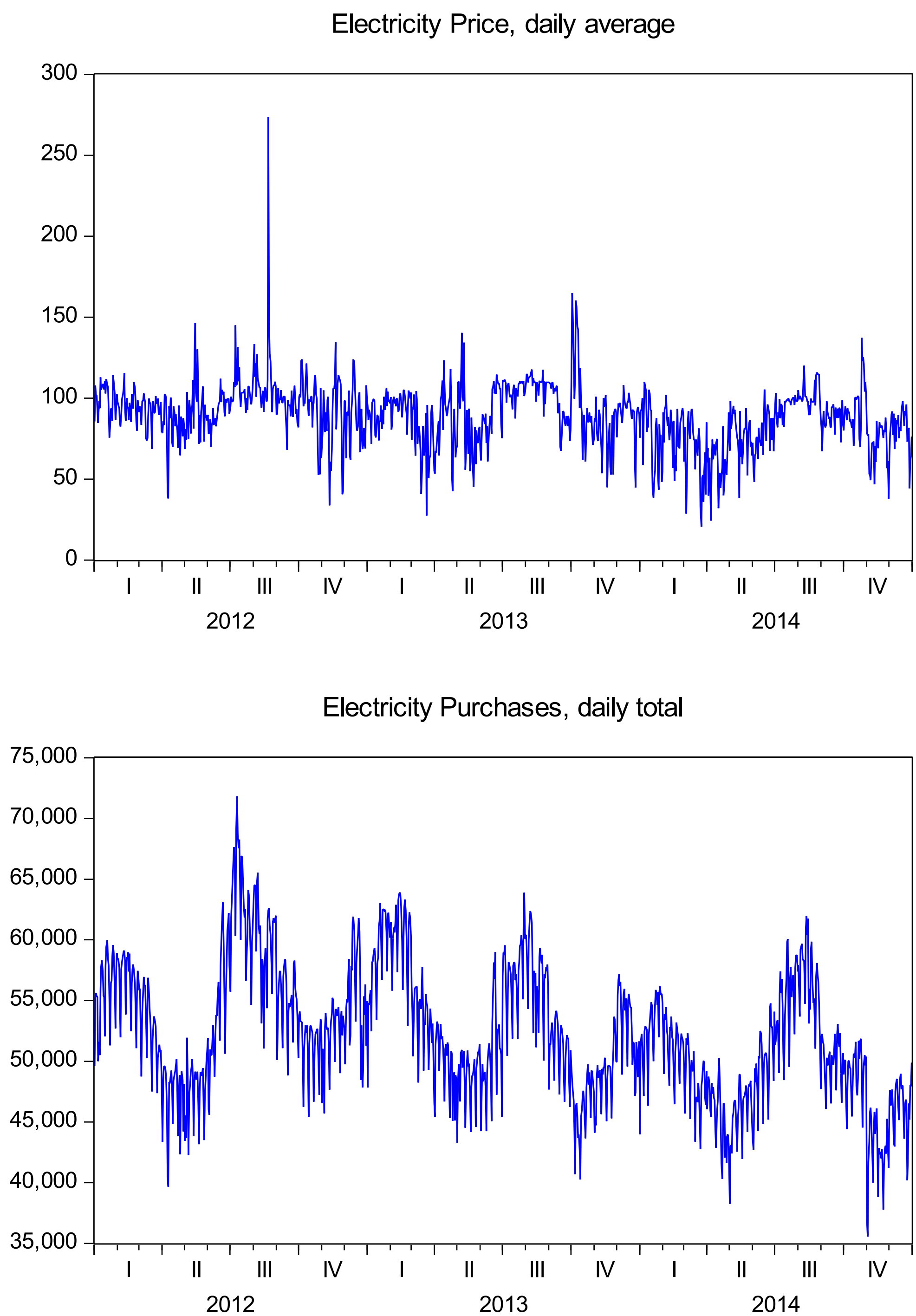

Fig. A.1. Daily average electricity price (top) and daily purchases (bottom) in Sicily, 2012–2014.

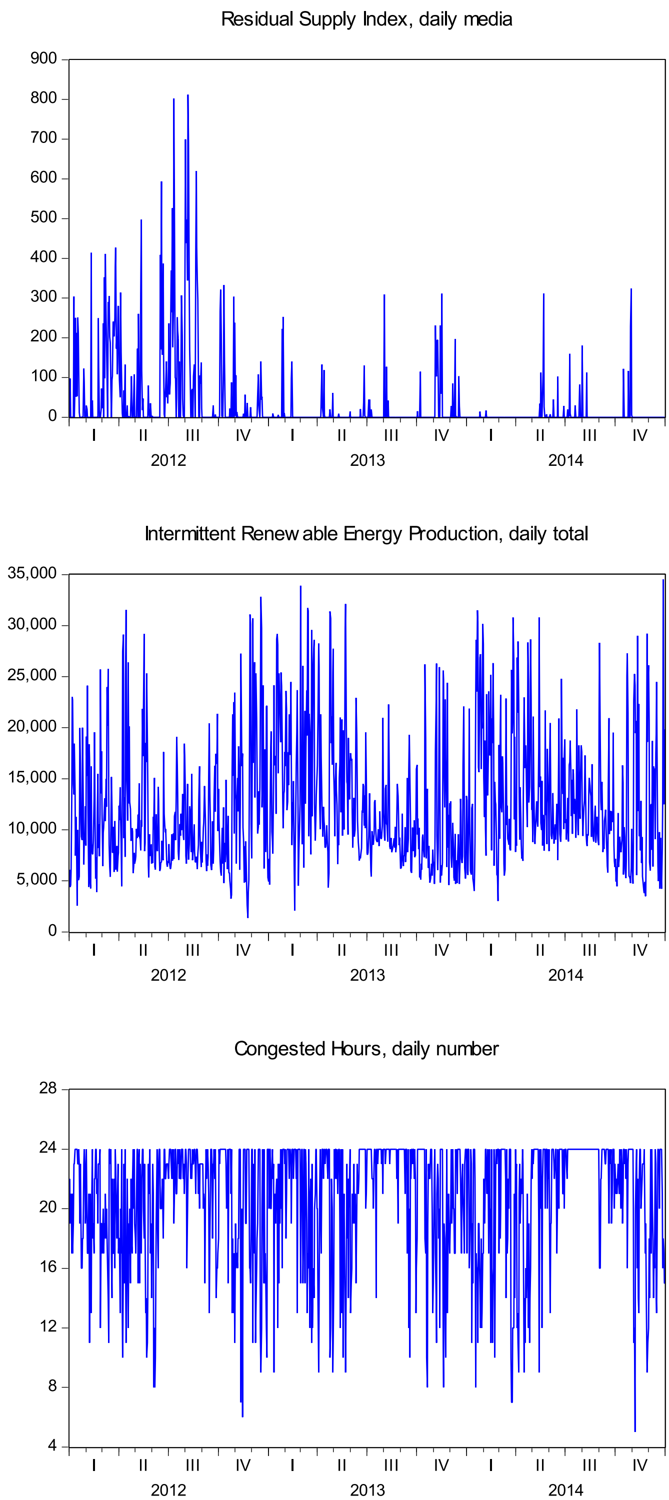

Fig. A.2. Daily median residual supply index (top), daily total production of intermittent renewable energy (middle), and number of congested hours (bottom) in Sicily, 2012–2014.

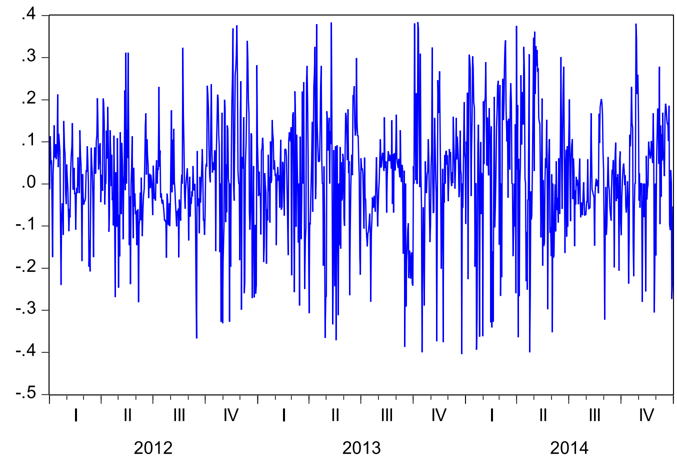

Fig. A.3. Deseasonalized and despiked daily average electricity prices in Sicily, 2012–2014.

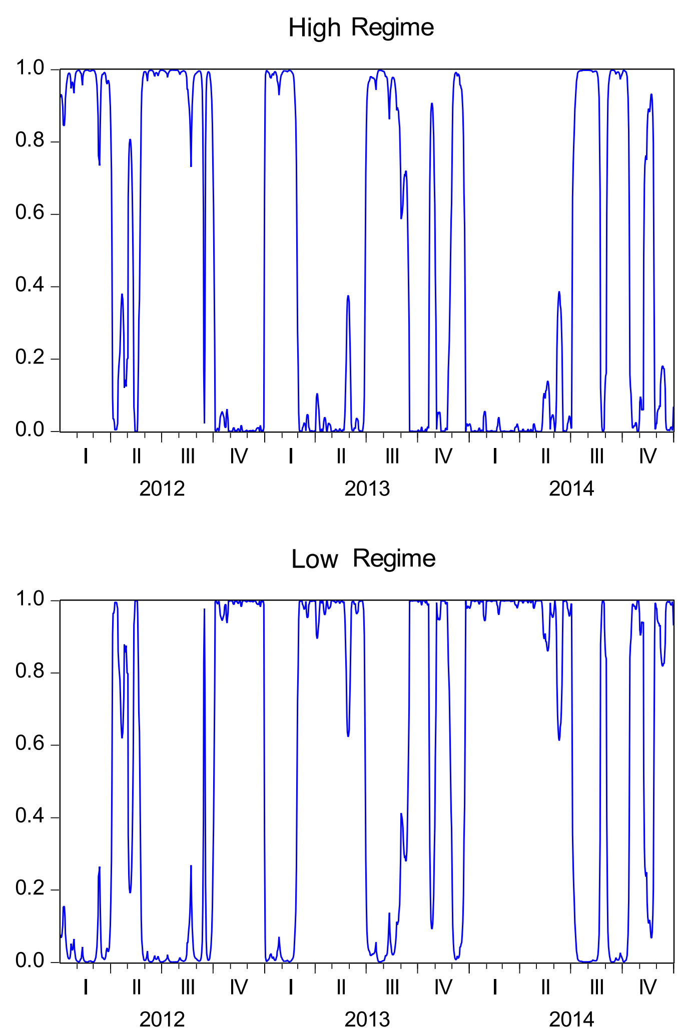

Fig. A.4. Smoothed probabilities that the price process be in the low ($Pr(s_t = l)$) and high ($Pr(s_t = h)$) regimes.

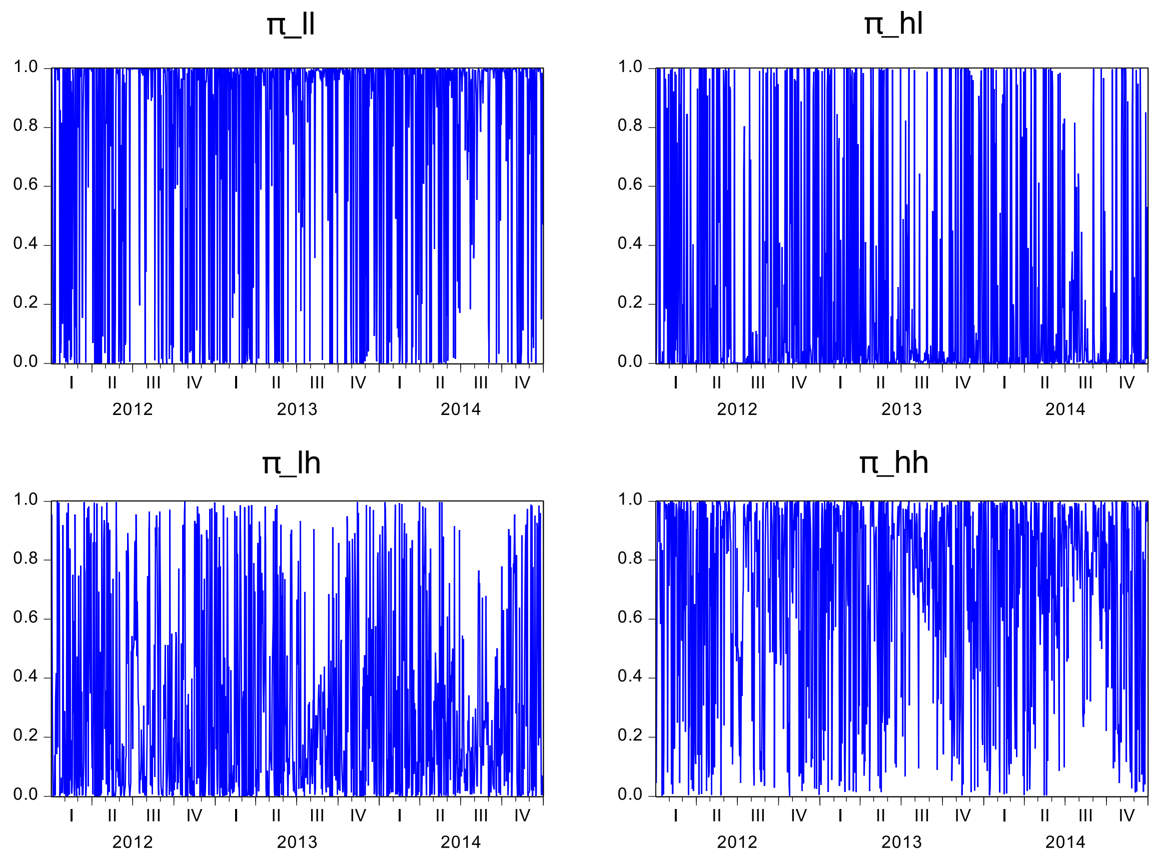

Fig. A.5. Transition probabilities in the time-varying transition probability model (Eqs. 4, 5 and 6). π_{hh} and π_{ll} denote the probability of staying in the high regime (state h) and the probability of staying in the low regime (state l) respectively, whereas π_{lh} and π_{hl} denote, respectively, the probability of low-to-high and high-to-low transitions.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2016.01.008.

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