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How does market architecture affect price dynamics? A time series analysis of the Italian day-ahead electricity prices

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How does market architecture affect price dynamics? A time series analysis of the Italian day-ahead electricity prices*

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Abstract

How do changes in the market architecture affect the dynamics of deregulated electricity prices? We investigate this issue in the context of the Italian Power Exchange (IPEX), using data on the daily average day-ahead price (PUN) between April 2004 and December 2008.

Estimates of baseline time series models (ARMAX and ARMAX-EGARCH) and their forecasting performances suggest that the trend in natural gas prices, deterministic weekly patterns, the impact of perceived temperatures, persistence in conditional volatility and the inverse leverage effect are essential features of the PUN dynamics.

We then augment the best-performing models with dummies that account for changes in the market architecture, such as the introduction of contracts for differences (CfDs) to support renewables, trading of white certificates for energy efficiency, and the demand-side liberalization. The findings show that changes in the market architecture have only affected the PUN volatility. Specifically, CfDs have mitigated volatility, while white certificates and demand liberalization have increased it. Moreover, after controlling for reforms the inverse leverage effect vanishes, and the persistence in volatility is lower than in the baseline estimates.

Keywords: Electricity prices, Italian Power Exchange, Market architecture, ARMA, EGARCH.

JEL Classifications: C51, G12.

1 Introduction

The simple picture drawn by uniform price auctions - the crossing of demand and supply curves, so reminescent of Economics 101 classes - is nothing but a piece in a much broader

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and complex mosaic: the architecture of restructured wholesale power sectors. As Glachant (2009) put it,

> what we refer to as "the" wholesale electricity market in fact consists of several complementary modules that trigger a sequence of operations as required for satisfying the claims on the commodity.

Over time, the existing "modules" undergo gradual and radical transformations, and new modules are added to the overall architecture. Often this happens in response to new policy challenges - such as climate change and energy security - that are increasingly met by policy-makers by means of Coasian mechanisms, in line with the "marketization" of the public intervention in the formerly integrated infrastructure industries.

A common working hypothesis in the electricity markets literature is that changes in the details of the industry architecture will cause the dynamics of the two market curves to change, perhaps radically. The main challenge for economic researchers, however, is to understand whether those changes drive the market closer to the desired policy goals. The literature on forward trading, for instance, has underlined how electricity forwards may cause power generating companies to play more competitively in the spot market, but it may also facilitate the enforcement of collusive behaviors, discourage entry and investments in new capacity. Exposing end users to power price fluctuations may mitigate market power by increasing the short-run price-elasticity of demand, but this might be very conditional on the diffusion of metering technologies. Tradable white certificates for energy efficiency are expected to reduce the national energy consumption and the dependence on the imports of fossil fuels, thereby yielding lower power prices, but these benefits may be offset by the rebound effect. With respect to these relevant policy issues, we can take the Italian electricity industry as a testing ground, as a number of related changes in its architecture have occurred since the Italian Power Exchange (Ipex) was launched in April 2004.

In the paper, we estimate time series models of the average daily day-ahead system marginal prices quoted on the Ipex (the so-called Prezzo Unico Nazionale, or PUN) between April 1, 2004 and December 31, 2008. We use ARMAX and GARCH models to match the observed time series properties, such as seasonals and volatility clustering. We show that an ARMAX-EGARCH model featuring natural gas prices, deterministic weekly patterns, perceived temperatures, persistence in conditional volatility and the inverse leverage effect provides the most satisfactory forecasting performance.

Such a baseline model is then augmented with dummy variables that account for three main changes in the architecture of the Italian power exchange: (i) the introduction of Contracts-for-Differences (CfDs) to support renewables, (ii) the status of eligible customers extended to residential customers, and (iii) the opening of a market for white certificates. The main finding is that changes in the market architecture have only affected the PUN volatility. Specifically, CfDs have mitigated volatility, while white certificates and demand liberalization have increased it. Moreover, after controlling for reforms the inverse leverage effect vanishes, and the volatility persistence is lower than in the baseline estimates.

To our knowledge, this is the first paper addressing the effects of changes in the Italian power market architecture. Some previous works estimated market power indicators using plant-level data (Bollino and Polinori 2008b, Baselice 2007), an issue touched upon also in the papers by Floro (2009) and Perekhodtsev and Baselice (2009), wherein individual offer data are used to evaluate oligopoly models. Issues concerning the transmission system are analyzed in the paper by Bollino and Polinori (2008a), who investigate contagion effects between zonal markets, and in Gianfreda and Grossi (2009), who fit fractionally-integrated Reg-ARFIMA models to zonal prices. Boffa, Pingali and Vannoni (2009) estimate the welfare gains from increased interconnection among Italian market zones. Finally, Bosco, Parisio and Pelagatti (2007) show that a periodic ARMA-GARCH model outperforms periodic ARMA models in terms of predictive power.

The paper is organized as follows. Section 2 briefly describes the Italian power industry, the main changes in its market architecture and their expected impacts on day-ahead prices. Section 3 offers a preliminary anaysis of the data. Section 4 illustrates the baseline time series models, whose estimates are in Section 5. Section 6 reports the estimates obtained after including dummies that account for CfDs, demand-side liberalization and white certificates. Conclusions and insights for future research are outlined in Section 7.

2 The Italian wholesale electricity market

Thirty-seven years after the nationalization of the Italian electricity industry, the Legislative Decree 79/1999 (also known as Bersani decree) re-introduced market-based governance in the power generation segment of the industry, in application of the European Directive 96/92/EC on the creation of the Internal Electricity Market (Ferrari and Giulietti 2005, Floro 2009). The former State-owned vertically-integrated monopolist, Enel, was required to unbundle its generation and distribution activities, and the management of the grid was entrusted to a newly-formed, state-owned transmission system operator (GRTN until October 2005, Terna afterwards). Regulatory oversight of the liberalized electricity industry is responsibility of the Italian Electricity and Gas Authority. The restructuring process culminated with the inauguration of the Italian Power Exchange (Ipex) in April 2004. Ipex, run by Gestore del Mercato Elettrico (GME), takes care of trading in the day-ahead and adjustment markets, up to gate closure, i.e. one hour prior to delivery. The reserves and balancing markets are under the responsibility of the transmission system operator.

The day-ahead market works as a periodic multi-unit uniform price auction. GME uses a merit order principle to construct the aggregate supply and demand curves. If the resulting flows on the grid violate the transmission constraints, the market is split into different zones.[1] Power generating companies in that case receive the zonal prices, whereas buyers pay the Prezzo Unico Nazionale (PUN), or single national price, that is an average of the zonal prices weighted by the zonal electricity consumption levels.

On the demand side, Italy has adopted a single-buyer system: the single buyer Acquirente Unico, a state-owned company, buys electricity from the power exchange and sell it to distribution and retail companies, for them to supply captive (non-eligible) customers and those eligible customers who have not switched to competitive suppliers.[2] The thresholds for eligibility have been lowered over time, and as explained in more detail later, residential customers have become eligible in July 2007.

The time evolution of the day-ahead market is outlined in Table 1.[3] The Ipex day-ahead market is the second largest in Europe with 233 TWh power traded in 2008 - the first being

[1]Namely: North, Centre North, Centre South, South, Calabria (merged with the South zone in 2009), Sicily and Sardinia - plus foreign virtual zones, i.e. interconnection points with neighbouring countries, and constrained production poles.

[2]Acquirente Unico cannot make more than 25% of its purchases through bilateral contracts. The selling price is determined by law as a markup on costs, and is revised periodically.

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

the Scandinavian NordPool.[4] Traded volumes peak in January and July, due to heating and cooling needs respectively. About 69% of total power trading in Italy occurs through the power exchange (including day-ahead and adjustment markets); the remaining power is traded over the counter via bilateral contracts. Average annual prices have been growing steadily from about 59 Euros/MWh in 2005 to about 87 Euros/MWh in 2008, while no clear pattern can be identified in the price volatility, proxied by the coefficient of variation (standard deviation normalized by the mean).

[**Table 1 here**]

The day-ahead Italian electricity market has witnessed increasing participation from both the demand and supply sides: the number of operators with bids has grown by one-third between 2005 and 2009, whereas the number of operators with offers has doubled. Correspondingly, Enel has been slowly losing its dominance, since its market share fell from 38% to 31% in the time window under analysis. On the demand side, it is also worth noting that the share of power acquired by the single-buyer has halved within four years, as more power customers have been awarded eligibility over time. The Italian supply stack is dominated by natural gas plants, which sold around 50% of the power traded in the Ipex day-ahead market. The weight of natural gas in the fuel mix has been growing over time, while other prominent sources, such as coal, oil and hydropower, have receded.

2.1 Changes in the Italian power market architecture

The Italian power exchange has undergone a number of changes in its architecture across time, such as the introduction of Contracts for Differences (CfDs) to support renewables and to hedge the position of the single buyer (January 1, 2005); the implementation of the Tradable White Certificates (TWC) scheme for energy efficiency, or white certificates (March 7, 2006); and the full demand-side liberalization (July 1, 2007). Assessing the impact of such reforms on the day-ahead prices is a way to obtain more general insights on how changes in market architecture affect the wholesale electricity market dynamics. Let us briefly describe the mentioned reforms and their expected impacts on the day-ahead price dynamics, drawing on the existing economics literature.

Contracts for differences. Since 1992, power produced using renewables is subsidized. During 2004, such power was bought by the transmission system operator at an administered price, and sold to eligible customers through bilateral contracts. Starting January 1, 2005, the system operator was required to sell the subsidized power on the power exchange, and the ensuing price risk was hedged by means of contracts for differences (CfDs). A similar hedging strategy was implemented by Acquirente Unico, who is obliged by law to hedge against price and volumetric risks.[5]

CfDs resemble financially-settled forwards (Deng and Oren 2006) and their effects on the PX price have been extensively studied, as they accounted for 80 to 90% of the initial portfolio of British power generating companies in the wake of industry restructuring.[6] From the theoretical point of view, early studies (Allaz and Vila 1993, Powell 1993) found that when

[4]See Fig. 3.2 in the GME 2008 Report.

[5]See Fraser and Lanza (2006) for a description of the CfDs subscribed by Acquirente Unico in 2005.

[6]While Italian CfDs are aimed to support renewables, British CfDs in the early Nineties were designed to limit redundancies in the coal industry. For a detailed account, see Green (1999).

oligopolistic firms take short forward positions, they find it optimal to play more competitively on the spot market, because forward trading shifts the spot marginal revenue curve outwards. Later theoretical works have shown that forwards may in fact enhance spot market power, as they may facilitate the enforcement of collusive agreements (Liski and Montero 2006, Green and Le Coq 2009), deter entry (Newbery 1998, Lien 2000), and discourage the investments in new capacity (Murphy and Smeers 2007a, 2007b, Adilov 2006). However, such anti-competitive effects are more likely to show up in a long-term empirical study than in our daily-frequency sample. While the econometric literature on the effects of CfDs is sparse and methodologically weak (Helm and Powell 1992, Gray et al. 1996, Lowrey 1997), laboratory experiments show that forwards help curtailing market power (Le Coq and Orzen 2006, Brandts et al. 2008, Ferreira et al. 2009).

In addition, CfDs may affect the wholesale price volatility. Sapio (2009) shows that volatility is mitigated by forward trading in an Allaz-Vila model with risk-neutral agents. To understand why, suppose demand is predicted to grow. Generating companies will find it optimal to increase their forward trading, but the ensuing increase in the spot marginal revenues leads to increasing spot sales too - offsetting the price growth which would occur without forwards. For the same reason, the spot price does not fall as much when demand is expected to decline. Overall, the support of the spot price distribution will be narrower. In a model with risk-averse customers, Robinson and Baniak (2002) show that CfDs could actually *increase* volatility, because by making the market more volatile, power generating companies can stimulate the demand for hedging and profit from increased forward premia. This perspective is particularly interesting for Italy, as hedging by Acquirente Unico is compulsory - in a sense, the single buyer is "institutionally" risk-averse.

Demand-side liberalization. Since July 2007, the definition of eligible customers includes residential energy users; therefore households are free to choose their power seller and their supply contract. This amounts to exposing to competition, potentially, 85 TWh of consumption per year, 22 million families and 5 million of other users, namely 77% of the clients and 30% of total electricity consumption in Italy. In principle, exposing final customers to wholesale price fluctuations would enhance the short-term price-elasticity of demand, therefore eroding the mark-ups set by oligopolistic power generating companies. Demand responsiveness may however be hampered by informational opacity and switching costs. A statistical survey of the Italian residential energy users, run by Nielsen-Bip in June 2009, reveals that 31% of the responders were not informed about the liberalization, therefore unaware of the opportunities to switch.[7] Among the informed customers, only about 36% are willing to change their power supplier. Such evidence is consistent with the data on customer switching rates reported by the market operator, which are not encouraging (see GME 2007, 2008). The customers who are not willing to switch claim that collecting and processing the relevant information is too costly. Interestingly, they also perceive that switching among providers would not allow any substantial saving. Nevertheless, in his international overview of the retail market performances, Glachant (2006) underlines how market concentration and barriers to entry can be very high even several years after the liberalization of retail trading. All this given, we expect that the average prices after demand liberalization will not be lower.[8] What is more, the

[7] The survey covered a sample of 25000 individuals, corresponding to about 9000 Italian households.

[8] To the extent that forward contracts help curtailing market power, demand-side liberalization and competition among retailers might even *increase* the wholesale price, as they would reduce the incentives for retailers to enter into long-term contracts. According to Green (2003), if the retail market is liberalized, few retailers are ready to sign long-term contracts, because doing so entails the risk that rivals will undercut them as soon as a short-term fall in wholesale prices occurs.

market may turn out to be more volatile, as scarcely informed, boundedly rational customers may engage in trial-and-error learning processes which may de-stabilize the market.

White certificates. A market for white certificates ("Titoli di Efficienza Energetica" or TEE) has been launched by GME in March 2006. Obliged parties are the distributors of gas and electricity with more than 100,000 customers (decreased to 50,000 in 2007), who meet their targets by assisting their customers to take energy-efficiency measures in residential and commercial buildings. Energy distributors have to generate a given quantity of energy savings or, if they fall short of their target, to buy certificates from other suppliers. Conversely, distributors who have funded more measures than their target are allowed to sell white certificates to those who are short of their target.[9]

In principle, white certificates could significantly improve energy efficiency and decrease the dependence on imports of fossil fuels (see the MARKAL simulations by Mundaca 2008). Energy demand is expected to decrease, pushing the wholesale electricity price down - unless the rebound effect is strong enough (see Brookes 2000 and references therein on the Khazzoom-Brookes postulate). An example of a rebound effect has been studied by Giraudet and Quirion (2008), who have shown that when the energy efficiency target is set as proportional to the power distributed, the marginal costs for energy distributors increase whenever they need to generate more certificates. This would decrease the optimal electricity supply, partly or wholly offsetting the price reduction brought about by energy savings.

Which effects should we expect on average electricity prices and volatility? The evidence so far reveals that although the Italian targets were largely exceeded, during the first year about 90% of TEEs were apportioned to Enel-owned distribution companies, leading to weak competitive pressure and little incentives to reduce costs (Mundaca 2008). Moreover, distributors showed a high propensity to meet the energy efficiency requirements by buying certificates, rather than by investing in more energy-saving technologies (GME 2007, Mundaca et al. 2008). The hoped-for decrease of energy demand may not have occurred. As to possible volatility effects, it is worth noting that the TEE market has been quite active: on average, about 24% of the certificates delivered have been traded. The increased TEE market liquidity and the propensity to meet the targets by trading might suggest that speculative trading was at work. Some volatility transmission from the TEE market to the PX might have occurred. For the above reasons, we expect white certificates to have left average price levels unaffected and perhaps increased volatility.

3 Preliminary data analysis

We have collected data on the Prezzo Unico Nazionale (PUN), the day-ahead system marginal buy price quoted on the Italian power exchange. The PUN data are publicly available on the IPEX website (`www.mercatoelettrico.org`) and include 24 observations per day, as each day 24 sealed-bid uniform price auctions determine the prices for each hour of the following day. Our sample begins with the prices quoted on April 1^{st}, 2004 and ends on December 31^{st}, 2008.[10]

[Fig. 1 here]

[9] The Italian target for the 2005-2009 period was set to an aggregate energy saving of 21 TWh/year (2005-2009), corresponding to 1.5% of final energy consumption.

[10] The early days of a market are typically characterized by adjustments that could in principle lead to abnormal price behaviors. However, the results to be presented are robust to cutting the first few months out of the sample.

The whole dataset includes 41665 hourly prices. Because the prices for all 24 hours of day t are jointly set on day $t-1$, the whole sample cannot be seen as a time series. Rather, we analyze the time series of daily arithmetic average prices, yielding 1736 observations.[11] Fig. 1 displays the time evolution of IPEX prices. The series seems to be driven by an upward trend, leading the price to increase by about 50% in less than 5 years. One can also quite neatly distinguish regular patterns at a high (presumably weekly) frequency, and broader within-year fluctuations. The series is characterized by sharp and short-lived spikes - e.g. a noteworthy one in July 2006 - but these seem to occur less frequently than in other power exchanges.

[**Table 2 here**]

Table 2 reports the summary statistics for the sample data, along with the values of some test statistics. Both the D'Agostino-Pearson and the Shapiro-Wilk tests cannot reject the null hypothesis of normality at standard significance levels.[12] Normality is likely to be an outcome of taking daily averages: indeed, if we analyze the time series of the 24 hourly auctions separately, we do find asymmetries and long tails.

The autocorrelogram depicted in Fig. 2 shows that the serial correlation of Ipex prices decays rather slowly and has local maxima at lags multiples of 7 days, much alike in other power exchanges. We have run a Ljung-Box portmanteau test using 7 lags (corresponding to one week) and as expected, the null of zero serial correlation is rejected at the 99% significance level.

[**Fig. 2 here**]

Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are performed in order to assess whether the trend spotted by eye-balling of Fig. 1 is a deterministic or a stochastic one. The test specifications include a constant and a trend; in the ADF test there are 7 lags of the first-differenced prices, according to the optimal lag criterion suggested by Gordon (1995),[13] whereas the PP test considers 7 lags when computing the Newey-West-adjusted standard errors. In both cases, the null of unit roots is rejected: the ADF test statistic is -5.389, well below the 1% critical value (-3.960), and the PP test statistic equals -20.095 versus a 1% critical value of -3.43. Therefore, with a high probability the IPEX price series is covariance-stationary around a linear trend. These results are in line with most previous research on electricity prices.[14] Based on test results, estimation can be carried out using models specified in levels: log-transforms and first-differences are ruled out, respectively, by the evidence of Gaussian and covariance-stationary prices.[15]

As a matter of fact, the linear trend may be nothing but a proxy for the underlying trend in fundamentals, such as fuel prices. Fig. 3, depicting the time series of natural gas prices,

[11] Alternatively, one could study the series of hour-h prices, $h = 1, ..., 24$, separately, as in Bottazzi, Sapio and Secchi (2005) and Crespo Cuaresma et al. (2004), or apply the periodic ARMA approach (Carnero, Koopman and Ooms 2007, Bosco, Parisio and Pelagatti 2007).

[12] The D'Agostino-Pearson and Shapiro-Wilk tests are considered the most powerful among normality tests (see D'Agostino et al. 1990).

[13] The criterion requires to pick the lag that maximizes the autocorrelation function for the first differenced price series.

[14] Unit roots have been found only by Helm and Powell (1992) on England & Wales pool prices, and by DeVany and Walls (1999) and Serletis and Herbert (1999) on US data.

[15] Because of the evidence of a Gaussian price distribution, there is no need to treat outliers, as often required in the time series modelling of electricity prices (see Clewlow and Strickland 2000; Truĉk, Weron and Wolff 2007).

seems to confirm this intuition. Nevertheless, the correlation between gas prices and a linear trend is as high as 0.911. One may therefore envisage the PUN series as covariance-stationary around an upward-trending natural gas price.

[**Fig. 3 here**]

4 The baseline models

In this section we sketch the baseline time series models estimated in the paper. Our goal here is to uncover the basic features of the Italian power exchange, concerning the structure of demand and supply and the efficiency of the market mechanism, and we do so in the context of autoregressive-moving average models with and without conditional heteroskedasticity (see Knittel and Roberts 2005 for a similar approach; Bunn 2004, Weron 2006 and references therein for further applications). In Section 6 we will assess the impact of market design reforms by augmenting the baseline models presented here.

We begin with a simple mean-reverting process in discrete time, or ARX(1) (*Model 1*):

$$(1-\beta L)p_t = \alpha + \rho g_t + \sigma \epsilon_t \tag{1}$$

where p_t denotes the market-clearing price at time t, g_t is the natural gas price, $\epsilon_t \sim iidN(0,1)$, L is the lag operator, β, ρ and σ are constant coefficients. $\beta = 1$ would suggest random walk dynamics in the Italian power prices, showing that changes in the price are essentially random, whereas $\beta < 1$ would be evidence of mean-reversion.

Because weekly patterns in electricity consumption appear to be important, *Model 2* adds stochastic weekly effects as 7-day lags in the AR and MA components, yielding an ARMAX(7,7) process:

$$(1-\beta_1 L - \beta_7 L^7)p_t = \alpha + \rho g_t + (1-\delta_1 L - \delta_7 L^7)\sigma \epsilon_t \tag{2}$$

We expect to find statistically significant estimates of β_7, which is the coefficient tuning the serial correlation in prices over a 7-days horizon. However, the weekly patterns in power prices may be of a deterministic nature, and so for seasonal patterns. We control for this in *Model 3*, including daily and monthly dummies. The specification is

$$(1-\beta_1 L - \beta_7 L^7)p_t = \alpha_t + \rho g_t + (1-\delta_1 L - \delta_7 L^7)\sigma \epsilon_t \tag{3}$$

with the time-varying intercept

$$\alpha_t = \alpha + \sum_{i \in I} \alpha_i d_{it} \tag{4}$$

d_{it} is a dummy variable with value 1 if day t belongs to the set $I = \{$ mon, tue, wed, thu, fri, sat, feb, mar, apr, may, jun, jul, aug, sep, oct, nov, dec $\}$, and 0 otherwise. Accordingly, the default value for the intercept (α) delivers the conditional average power price for a Sunday in January.[16] If the weekly pattern is deterministic, adding daily dummies will cause the point estimate of β_7 to decrease.

[16] Alternatively, we could have used sinusoidal functions as proxies for the seasonal and weekly effects, but because power demand varies in quite an asymmetric fashion across the week and the year, dummies are more precise proxies.

More insights on the structure of demand can be obtained by acknowledging that in a highly liquid market such as the Ipex, household consumption for heating and cooling needs accounts for a significant share of power demand. *Model 4* augments Model 3 by including the Heat Index (HI) defined in the meteorological literature by Steadman (1979):[17]

$$(1 - \beta_1 L - \beta_7 L^7)p_t = \alpha_t + \rho g_t + \alpha_{hi} HI_t + \alpha_{hi2} HI_t^2 + \alpha_{hi3} HI_t^3 + (1 - \delta_1 L - \delta_7 L^7)\sigma\epsilon_t \qquad (5)$$

The HI is calculated using temperature and humidity data, and as such it takes account of the impact of humidity on perceived temperatures. What we call here HI is actually the median of the heat indexes computed using weather data for the largest Italian cities (Rome, Milan, Naples, Turin, Palermo, Genoa; data source: http://www.wunderground.com). The PX price-weather relationship is likely to be non-linear: power demand is typically high both during the summer and during the winter, respectively because of cooling and heating needs, but lower in the milder seasons. Accordingly, we also include the second and third powers of HI, as in Knittel and Roberts (2005).

Finally, there are convincing reasons to expect time-varying and clustered volatility in power exchanges. It is a largely shared proposition that volatility and jumps in power exhanges are mainly due to convexity of the supply stack coupled with random fluctuations of an inelastic demand (e.g. Barlow 2002, Simonsen 2005, Lucheroni 2009). It has been shown that in a uniform price auction environment, companies owning several generating units may have incentives to ask competitive prices on their most efficient units - making sure that they run - and prices well above marginal costs on their most expensive units - so as to increase the chances that the system marginal price will be very high (see Ausubel and Cramton 1996). Such a positive externality across units may justify the use of "hockey-stick" supply functions. Interestingly, a recent paper by Kanamura (2009) shows that if demand is driven by a random walk and if supply is non-linear (convex or concave), one observes an asymmetric volatility response to market shocks. An appropriate tool to test for persistent and asymmetric heteroskedasticity is given by *Model 5*, an ARMAX-EGARCH model (Nelson 1991):

$$(1 - \beta_1 L - \beta_7 L^7)p_t = \alpha_t + \rho g_t + \alpha_{hi} HI_t + \alpha_{hi2} HI_t^2 + \alpha_{hi3} HI_t^3 + (1 - \delta_1 L - \delta_7 L^7)\sigma_t\epsilon_t \qquad (6)$$

where volatility is driven by the following process:

$$\log(\sigma_t^2) = \theta + \gamma \log(\sigma_{t-1}) + \kappa_1 h(z_{t-1}) + \kappa_7 h(z_{t-7}) \qquad (7)$$

$$z_s = \frac{\epsilon_s}{\sigma_s} \qquad h(z_s) = \psi z_s + |z_s| - E[|z_s|] \qquad (8)$$

In the variance equation, θ is the unconditional volatility, κ_1 and κ_7 are the ARCH(1) and ARCH(7) coefficients, γ is the GARCH(1) coefficient, and ψ tunes the degree of asymmetry in the variance response to innovations. Previous research on PX prices found $\psi > 0$ (see Knittel and Roberts 2005, Bowden and Payne 2008), meaning that positive innovations increase volatility more than the negative ones - the so-called *inverse leverage effect*, as opposed to the leverage effect detected in financial markets. Similar evidence was found by Hadsell, Marathe and Shawky (2004) by means of a Threshold ARCH model.[18]

[17] We actually rely on the HI formulation derived by Rothfusz (1990), whose coefficients were estimated by means of a multiple regression analysis using the data from Steadman's paper.

[18] We have also attempted to estimate a jump-diffusion model, using the Ball and Torous (1983) approximation. However, the estimated jump probability is too large for the approximation to be valid.

5 Baseline results

The foregoing models have been estimated via conditional maximum likelihood on the whole sample (Apr 1, 2004 - Dec 31, 2008). The estimates are displayed in Table 3.

[Table 3 here]

The coefficients of the mean-reverting process (Model 1) are all significant at the 99% level. The first-order autoregressive coefficient is equal to 0.355, below the unit-root value of 1, confirming the covariance-stationarity previously assessed by means of unit root tests - albeit around upward-trending gas prices. A unit increase in the gas price yields a 0.574 increase in the power price, all else being given.

The time-varying mean process estimates (Model 2) show that part of the first-order autocorrelation detected in the simple mean-reverting process can be accounted for by a stochastic weekly pattern. Indeed, the first-order autoregressive coefficient is now 0.042, as compared with an AR(7) coefficient as high as 0.808. Moreover, the gas price coefficient is now much lower (0.13), and the standard deviation of the error term falls from 10.829 to 7.75. All these coefficients are strongly statistically significant (99% level).

Including daily and monthly dummies (Model 3) shows that the 7-days autocorrelation is mainly due to a deterministic pattern of economic activity across the week. Indeed, the AR(7) coefficient drops from 0.808 to 0.094, whereas daily dummies are all positive and significant, with the only exception of the Saturday dummy. The coefficients to the monthly dummies suggest that prices in February, June and July are as high as in January, the default month (the corresponding estimates are not statistically significant); lower prices are observed in spring and fall months (negative and significant coefficients). The estimated standard deviation of the error terms falls again to 6.854.

Model 4 includes the Heat Index (HI) and its second and third powers. The HI coefficients are all positive and significant. This confirms the intuition that the price-weather relationship is a non-linear one, and its increasing shape reveals that the electricity demand for cooling prevails on the use of electrical heating facilities. As it could be expected, the monthly dummies coefficients are now smaller in magnitude, and some of them lose significance (specifically, May, September, October and November). The remaining coefficient estimates are roughly unaffected.

Finally, the ARMAX-EGARCH process (Model 5) provides a more detailed description of the time dependencies in the conditional volatility, while broadly confirming the estimates of the mean equation. More precisely, one detects positive and strongly significant ARCH and GARCH effects, suggesting that volatility is highly persistent (γ, the GARCH coefficient, is equal to 0.749). In line with the previous literature cited in Section 4, we detect an inverse leverage effect, with ψ equal to 0.151 and 99% significant: positive shocks seem to increase volatility more than negative shocks.

The forecasting performances of the above models have been evaluated over 1 week, 1 month, 3 months and 6 months horizons using the Root Mean Square Error (RMSE) and Median Absolute Deviation (MAE) criteria. For the sake of robustness, we have generated forecasts based on rolling samples of 1370 observations each (first sample: Apr 1, 2004 - Dec 31, 2007; last sample: Sep 30, 2004 - Jun 30, 2008), using a 7-days step rule, totalling 27 samples. Average RMSE and MAE values and their variances across rolling samples are reported in Table 4 for each model and for each time horizon.

[Table 4 here]

Comparing the models from the forecasting viewpoint reveals that the EGARCH (model 5) outperforms all other models: its average RMSE and MAE is lower on all forecasting horizons. The ARMAX model with the heat index (model 4) is the second best model, followed by the ARMAX with daily dummies (model 3), the ARMAX without daily dummies (model 2) and the simple ARX(1) (model 1). This ranking finds an exception on the weekly forecasting horizon, when model 2 outperforms model 4. The variances of the RMSE and MAE indicators across rolling samples are quite high for the 7-days and monthly horizons, suggesting that the EGARCH may not have been the best-forecasting model along the whole history of the market. The outlined ranking seems to be more robust on the 3- and 6-months forecasting horizons, where variances are considerably smaller. The bottom line is that models including deterministic weekly patterns and non-linear weather and volatility effects are able to capture some of the essential drivers of the IPEX price dynamics, which purely stochastic and homoskedastic models are unable to reproduce.

6 The effects of a changing market architecture

The econometric analysis performed thus far implicitly assumes that all PUN observations are outcomes of the same data generating process. This amounts to assume that the market has been functioning within a rather stable market architecture, a patently false assumption in light of the reforms occurred between 2005 and 2007. We therefore amend the baseline models by including information on the changes in the market architecture in a simple way: we append some dummies to both the mean and variance equations of the models estimated in Section 5 and we re-estimate them. We focus in particular on models 3, 4, 5 (ARMAX with and without weather, and the ARMAX-EGARCH model), which provided the best forecasting performances, and rename them Models 3', 4', 5'. The dummies are $d_{cfd} = 1$ from 1 January 2005 on; $d_{twc} = 1$ from 7 March 2006 on; $d_{lib} = 1$ from 1 July 2007 on. In the case of white certificates, we could have used the time series of their prices and volumes, which are available on the GME website. However, white certificate trading sessions occur at the frequency of three sessions per week, yielding a time series which is not easy to reconcile with daily PUN data. Moreover, the effects of incentives for energy efficiency will not show up on a daily time-scale, as they require gradual adjustments that take time. By using dummies we manage to perform a comparison between the PX price distributions, conditional on all other covariates, before and after the institutional changes. In a sense, we are interested in detecting average effects over a rather long time-span, and dummies are enough for this purpose.

The new estimates are reported in Table 5. The main message is that changes in market architecture have significantly affected the conditional volatility of the Ipex day-ahead prices, but not its conditional mean. A few more detailed remarks are in order.

[Table 5 here]

Concerning the mean equation estimates, the dummies for white certificates and demand-side liberalization enter the time series models with positive signs, but the coefficients are never statistically significant, except for white certificates, significant in the ARMAX model with HI (Model 4'). The coefficients for CfDs are not significant, and their signs, which are negative in Models 3' and 4', turns to positive in Model 5'. At the same time, the autoregressive and moving average structure, the deterministic weekly pattern and the influence of gas prices and weather are robust to controlling for changes in market architecture; only the seasonal pattern is partly modified. Therefore the average behavior of the PUN is broadly unaffected by changes in market architecture.

When it comes to the conditional volatility, the outlook is different. CfDs seem to have mitigated the PUN variance both in the ARMAX and in the ARMAX-EGARCH models, as testified by the corresponding dummy coefficients - negative and significant. On the contrary, the signs of white certificates and liberalization dummies are positive and significant, suggesting that the beneficial effects of CfDs may have been at least partly offset by those reforms. Indeed, in all models the sum of the TWC and liberalization coefficients attached to the conditional variance is higher than the CfD coefficient in absolute terms (3.157 vs. -2.47 in Model 3', 3.073 vs. -2.606 in Model 4', 0.585 vs. -0.52 in Model 5').

An interesting effect of changes in the market architecture relates to the dynamic structure of conditional volatility. As compared to the estimates of the basic models discussed in Section 5, in the new ARMAX-EGARCH estimates the GARCH coefficient drops from 0.749 to 0.423, while the ARCH coefficients slightly increase (ARCH(1) from 0.397 to 0.437, and ARCH(7) from 0.154 to 0.199). Also, the asymmetry coefficient ψ turns negative and loses its significance. We can therefore conclude that changes in the market architecture are partly responsible for the persistence and asymmetry in the dynamics of the PUN conditional volatility observed in the baseline estimates.

The forecasting performances of the models including the dummies for CfDs, white certificates and demand-side liberalization are compared in Table 6. Average MAE and RMSE suggest that the EGARCH model is the best on the short term forecasting horizons, but it is slightly outperformed by the ARMA model with heat index on longer horizons. Overall, the average forecasting performances are worse than in the baseline model; but the average values hide the fact that MAE and RMSE experience a decreasing trend in MAE and RMSE across rolling samples - higher than in the baseline model in the early samples, lower in the later samples.[19] This is not surprising: in early samples (i.e. Apr 2004-Dec 2007, May 2004-Jan 2008 and so on) the number of pre-reform observations is relatively higher, so that parameter estimates reflect decisions made by agents during the spring and summer of 2004, when the effects of the reforms were hard to predict.

[Table 6 here]

7 Conclusion

How do changes in the architecture of restructured electricity markets affect the dynamics of electricity prices? This paper is an attempt to answer to this relevant question. Upon estimating time series models of the average daily day-ahead system marginal prices quoted on the Ipex, we have shown that changes in the market architecture have only affected the price volatility. Specifically, CfDs have stabilized the market, while white certificates and demand liberalization have increased its turbulence, perhaps offsetting the beneficial effects of CfDs. Moreover, controlling for institutional changes suggests that phenomena often detected in the empirical literature, such as the inverse leverage effect and volatility persistence, may be partly due to the very evolution of the market architecture. By appealing to the received theoretical literature, we may identify a number of policy issues worthy of further investigation.

[19]Further details on this issue can be provided by the authors upon request.

First, while policy-makers introduced CfDs with the goal of encouraging electricity production from renewables sources, the detected volatility mitigation effect appears as a sort of positive externality for all market participants who are not hedged. The relationship between electricity derivatives and spot market volatility is surely an under-studied issue, with only a couple of exceptions (Robinson and Baniak 2002, Sapio 2009). As a matter of fact, Robinson and Baniak's (2002) analysis predicts that CfDs would *increase* volatility, because with risk-averse customers, power generating companies may increase their forward premia by making the market more volatile. But when it comes to the Italian PX, this argument fails despite the fact that the single buyer is obliged to hedge against price risk (see Fraser and Lanza 2006). Nevertheless, it would be interesting to devote more efforts on the theoretical mechanism behind this result. Also, more evidence is bound to be available in the coming years, as two Italian forward markets have been inaugurated in November 2008: a physical forward market, MTE (Mercato a Termine Elettrico) and a market for financial futures (IDEX).

Second, with respect to the demand-side liberalization of the market, the results are not encouraging. One may subscribe to the view that no institutional arrangement will overcome the intrinsic limitations in demand responsiveness. A more positive take on this issue would be to encourage policy-makers to adopt more incisive measures towards the diffusion of metering technologies and of information on the switching opportunities. Relatedly, the weak competitive pressure that characterizes the Italian power market may be behind the poor effects of white certificates; perhaps the incentives for distributions companies to implement energy efficiency projects are not properly designed.

Let us conclude with a few thoughts on future research. As revealed by volatility estimates, our results casts doubts on the robustness and on the economic interpretation of the inverse leverage effect. Our results suggest that the inverse leverage effect only shows up if we fail to take care of the changing architecture. We wonder whether the effect detected in previous papers (Hadsell, Marathe and Shawhy 2004, Knittel and Roberts 2005, Bowden and Payne 2008) would survive to controlling for institutional change. Perhaps market clearing tends to occur in a roughly linear branch of the market supply curve, but the slope of the curve itself has evolved after the reforms.

Finally, the robustness of the results may be assessed by means of more sophisticated methodologies, such as endogenous break tests and rolling window estimation (see Chevallier, Le Pen and Sevi 2009 for an application of these techniques to study the effects of options on EU ETS futures).

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Appendix

		2008	2007	2006	2005
volumes (TWh)		233	221	197	203
liquidity (%)		69	67	60	63
avg. price (Eur/MWh)		86.99	70.99	74.75	58.59
std.dev./avg.price		0.15	0.22	0.17	0.22
operators with offers		85	71	54	42
operators with bids		91	74	68	61
Enel share (%)		31	31	34	38
single-buyer share (%)		34	48	40	68
sales by source (%)	natural gas	n.a.	53.3	49.5	46.2
	coal	n.a.	8.2	8.4	9.0
	oil	n.a.	14.4	17.3	19.0
	self-generation	n.a.	10.1	9.7	8.8
	hydropower	n.a.	10.4	11.9	13.7
	other renew.	n.a.	3.5	3.3	3.2

Table 1: Time evolution of the Italian day-ahead market, 2005-2008 (source: GME Annual Reports, various years).

statistics	value	p-values	outcomes
mean	69.4758		
minimum	1.2108		
maximum	142.5955		
standard deviation	18.1568		
skewness	0.0383		
kurtosis	2.9800		
D'Agostino-Pearson		0.8031	do not reject N
Shapiro-Wilk	0.9980	0.0273	do not reject N
Ljung-Box	5214.18	0.0000	reject white noise
Augmented Dickey-Fuller	-5.389	0.0000	reject I(1)
Phillips-Perron	-20.095	0.0000	reject I(1)

Table 2: Summary statistics and tests.

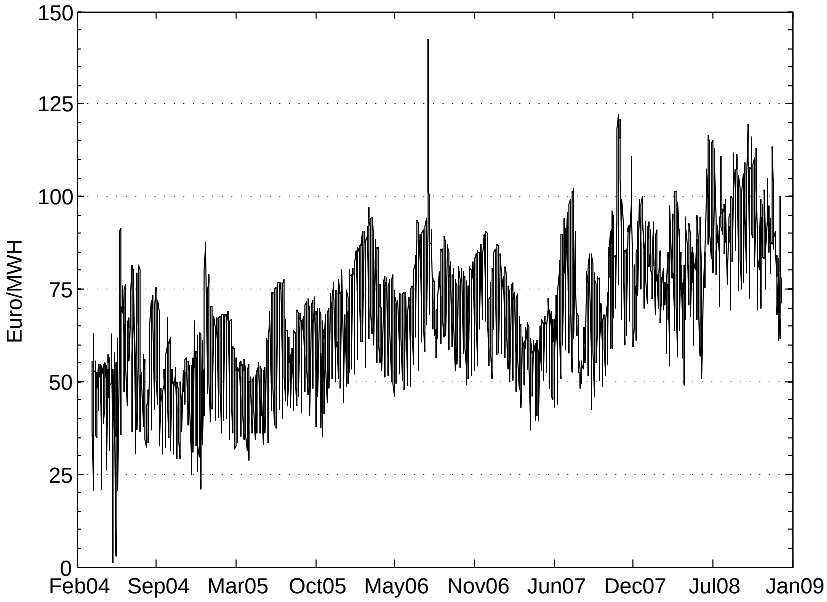

Figure 1: Plot of the IPEX average daily day-ahead price series, from April 1, 2004 to December 31, 2008.

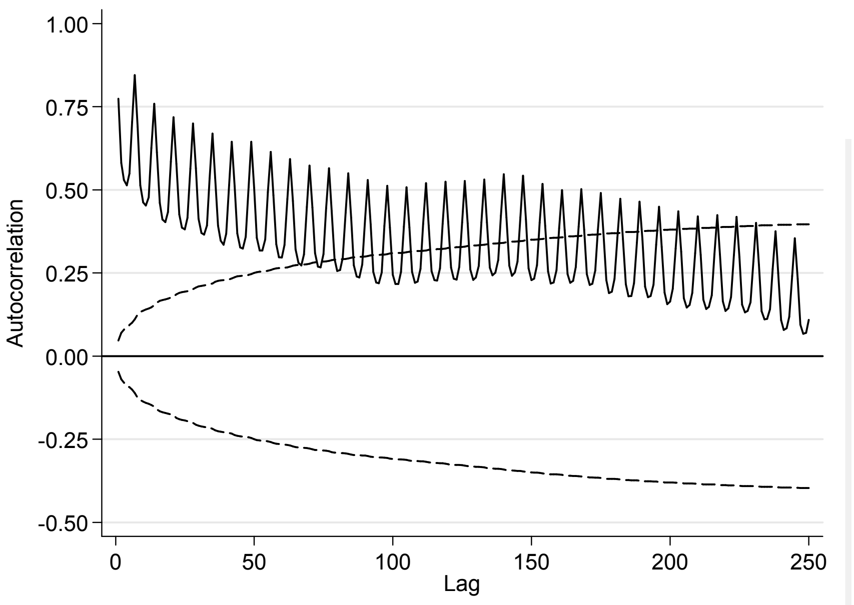

Figure 2: Autocorrelogram of the IPEX average daily day-ahead price.

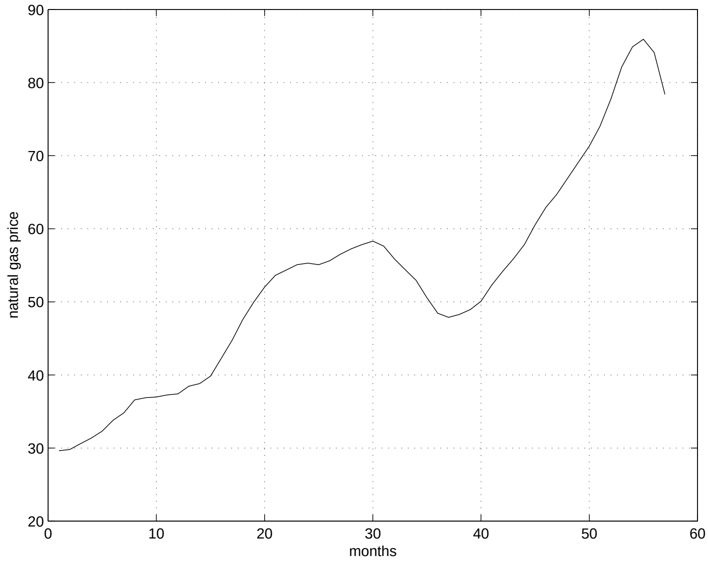

Figure 3: Plot of the monthly time series of natural gas prices. Source: Ref.

Models	(1)	(2)	(3)	(4)	(5)
			Mean		
const	10.818**	3.560**	-2.298*	-3.654**	-6.297**
gas	0.574**	0.130**	0.189**	0.199**	0.179**
β_1	0.355**	0.042**	0.684**	0.659**	0.698**
β_7	-	0.808**	0.094**	0.107**	0.107**
δ_1	-	0.442**	-0.186**	-0.171**	-0.178**
δ_7	-	-0.291**	0.172**	0.157**	0.150**
feb	-	-	-1.111	-1.087	-0.418
mar	-	-	-2.471**	-1.945*	-0.775
apr	-	-	-3.501**	-2.220**	-2.332**
may	-	-	-2.896**	-1.303	-0.101
jun	-	-	-0.917	0.052	0.784
jul	-	-	0.174	0.445	0.225
aug	-	-	-2.972**	-2.490*	-0.740
sep	-	-	-2.281*	-0.973	0.137
oct	-	-	-2.438**	-0.781	0.514
nov	-	-	-1.997**	-1.237	-0.789
dec	-	-	-2.932**	-2.937**	-4.441**
mon	-	-	22.858**	22.424**	24.712**
tue	-	-	13.602**	13.500**	13.554**
wed	-	-	11.404**	11.391**	11.462**
thu	-	-	10.753**	10.767**	10.696**
fri	-	-	9.908**	9.969**	10.180**
sat	-	-	-0.477	-0.295	-0.812
HI	-	-	-	0.116*	0.062
HI^2	-	-	-	0.016**	0.013**
HI^3	-	-	-	0.0003*	0.0003**
			Variance		
σ	10.829**	7.750**	6.854**	6.811**	-
ψ	-	-	-	-	0.151**
θ	-	-	-	-	0.545**
γ	-	-	-	-	0.749**
κ_1	-	-	-	-	0.397**
κ_7	-	-	-	-	0.154**

** significant at the 99% level.

* significant at the 95% level.

Table 3: Estimates of the time series models of Italian day-ahead power prices.

Statistic	Model	RMSE7	MAE7	RMSE31	MAE31
Mean	(1)	11.37	9.28	12.16	9.82
	(2)	9.30	7.29	11.44	9.14
	(3)	10.60	9.09	11.20	9.09
	(4)	10.00	8.56	10.40	8.41
	(5)	8.50	7.03	9.93	8.02
Variance	(1)	11.78	8.07	7.27	5.47
	(2)	15.35	9.35	12.89	10.62
	(3)	30.35	26.77	7.02	6.09
	(4)	19.47	16.29	3.84	3.39
	(5)	12.90	11.09	3.37	3.63

Statistic	Model	RMSE92	MAE92	RMSE184	MAE184
Mean	(1)	12.73	10.08	12.90	10.26
	(2)	12.22	9.58	12.68	10.00
	(3)	11.41	9.12	11.83	9.37
	(4)	10.87	8.70	11.45	9.09
	(5)	10.52	8.43	10.79	8.58
Variance	(1)	1.26	0.76	0.09	0.08
	(2)	1.05	0.78	0.43	0.45
	(3)	1.37	0.96	0.36	0.28
	(4)	0.75	0.60	0.32	0.27
	(5)	1.13	0.58	1.57	0.69

Table 4: Forecasting performances of the baseline time series models.

Models	(3')	(4')	(5')	Models	(3')	(4')	(5')
		Mean				Variance	
const	-2.076	-2.775*	-4.505**	σ	7.618**	7.720**	-
feb	-0.744	-0.706	-0.947	σ_{cfd}	-2.470**	-2.606**	-
mar	-2.443**	-2.007**	-1.413	σ_{twc}	0.684**	0.667**	-
apr	-3.592**	-2.557**	-3.127**	σ_{lib}	2.473**	2.406**	-
may	-3.049**	-1.762*	-1.616	ψ	-	-	-0.008
jun	-1.208*	-0.612	0.215	θ	-	-	1.883**
jul	0.044	0.028	-0.095	θ_{cfd}	-	-	-0.520**
aug	-3.003**	-2.727**	-1.762	θ_{twc}	-	-	0.202**
sep	-2.221*	-1.137	-0.607	θ_{lib}	-	-	0.383**
oct	-2.622**	-1.146	0.017	γ	-	-	0.423**
nov	-2.008**	-1.327*	-1.500	κ_1	-	-	0.437**
dec	-2.750**	-2.775**	-4.763**	κ_7	-	-	0.199**
mon	23.619**	23.021**	23.807**				
tue	13.785**	13.775**	13.219**				
wed	11.617**	11.736**	11.548**				
thu	11.001**	11.132**	10.987**				
fri	10.243**	10.421**	10.066**				
sat	-1.048	-0.699	-0.846				
d_{cfd}	-0.287	-0.461	0.334				
d_{twc}	0.721	1.047*	0.375				
d_{lib}	0.068	0.024	0.197				
gas	0.177**	0.191**	0.179**				
HI	-	0.124*	0.071				
HI^2	-	0.015**	0.014**				
HI^3	-	0.0003*	0.0003**				
β_1	0.690**	0.654**	0.655**				
β_7	0.089**	0.104**	0.126**				
δ_1	-0.206**	-0.179**	-0.104*				
δ_7	0.165**	0.147**	0.157**				

** significant at the 99% level.

* significant at the 95% level.

Table 5: Model estimates under changes in the market architecture.

Statistic	Model	RMSE7	MAE7	RMSE31	MAE31
	(3')	11.15	9.64	12.24	10.20
Mean	(4')	10.06	8.55	11.07	9.16
	(5')	8.59	7.11	10.98	9.10
	(3')	32.03	28.14	6.35	6.72
Variance	(4')	19.86	17.30	4.09	4.53
	(5')	11.42	9.02	4.98	5.20
Statistic	Model	RMSE92	MAE92	RMSE184	MAE184
	(3')	12.13	9.87	12.20	9.84
Mean	(4')	11.16	9.09	11.36	9.17
	(5')	11.38	9.31	11.42	9.28
	(3')	2.41	2.35	3.25	2.54
Variance	(4')	2.49	2.11	2.86	2.04
	(5')	7.65	5.83	8.84	6.08

Table 6: Forecasting performances of the time series models controlling for changes in the market architecture.