Does it Take Volume To Move European Electricity Spot Prices?

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Abstract By using time series of hourly spot prices and volumes of four European electricity markets, we show that the total traded volume has negligible impact in determining the volatility of electricity prices when spikes are excluded. This result is robust to the different econometric techniques adopted, namely a GARCH specification and a linear regression on price variances computed from data obtained from the European Electricity Exchange (EEX), based in Leipzig, Germany, PowerNext of France, Omel of Spain and APX of The Netherlands in Amsterdam for the period 2001-2005. Our main explanation for the absence of a positive relation between traded volume and volatility is the lack of trading in the market based on superior information. We also discuss other theoretical explanations based on models borrowed from financial economics.

Keywords Electricity, volume, volatility.

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1 Introduction

The aim of this paper is to study the link between volume and volatility in the electricity spot market. As it is well known, the relation between traded volume and price volatility is of primary importance for any asset traded in a financial market, since it can reveal basic features of the trading process, as well as shed light on how information is disseminated into the market. Moreover the economic theory provides no clue on the impact of trading volume on volatility. Economic theories on commodity prices, e.g. Chambers and Bailey (1996), are of little help given the peculiarity of electricity as a commodity.

Until early 90's the supply of electricity in Europe has been regulated by very rigid market rules. The deregulation process started in Europe with the United Kingdom in 1989 (Green (2001)), and then it was shared by all major countries, while such a process started earlier in the United States. The purpose of privatization was increasing the transparency of the market as well as the flexibility in the generation process, improving competition and, as a consequence, increasing the efficiency of production and allocation of energy, with benefits for both producers and consumers. This process led to the constitution of well established markets for trading electricity and its corresponding derivatives.

In this paper we use data on the European Electricity Exchange (EEX), based in Leipzig, Germany, PowerNext of France, Omel of Spain and APX of The Netherlands in Amsterdam for the period 2001-2005.

We focus on the relation between the volume traded on the spot market and spot price volatility. Since volatility is very high, and it is the major source of risk for participants in the electricity market (Bessembinder and Lemmon, 2002), it is natural to ask where it comes from. Many theoretical models have been studied in financial economics to explain the empirical stylized fact that volume and volatility are positively correlated in speculative markets, see e.g Karpoff (1987) and, more recently, Jones *et al.* (1994). For speculative markets, volume is usually considered a proxy for information. As the market gathers information on future prices, or asset fundamentals, the traders trade more and the prices move more. This intuition has been exploited in the seminal paper of Clark (1973), who introduces the mixture of distribution hypothesis, see also Andersen (1996), according to which the price distribution is subordinated to a given stochastic process (the information flow), which is postulated to be correlated with the trading volume. The correlation between volatility and trading volume is a consequence of this mechanism. Epps and Epps (1976) provide a trading theory which is in agreement with the mixture of distribution hypothesis, but that also introduces heterogeneity among agents as a crucial determinant of the positive link between volatility and volume. Tauchen and Pitts (1983) present a model in which three factors influence trading volume: the information flow, the dispersion of beliefs among traders, and the number of active traders. These three factors influence in a different way the volume-volatility relation, which however is still positive. The positive relation holds even if there is information asymmetry, see e.g. Wang (1994), as well as if there is a market for information, see e.g. Kim and Verrecchia (1991)[1]. Thus, a positive relation is a typical signature of speculative markets. It is also interesting to note that the economic theory, see e.g. Shalen (1993), forecasts that a positive volatility-volume relation is more driven by less informed traders, as it has been empirically confirmed by Daigler and Wiley (1999).

For electricity markets, it is not clear which should be the impact, if any, of total traded volume on price. First of all, electricity prices have distinctive features. The first feature is very well known in the literature: electricity prices display pronounced seasonality at daily, weekly and monthly levels, see e.g. Bhanot (2000); Wilkinson and Winsen (2002); Knittel and Roberts (2005); Lucia and Schwartz (2002); Escribano *et al.* (2002) and Koopman *et al.* (2005). Other simple conse-

[1] Important contributions on the impact of asymmetric information on the volume–volatility relation are given by strategic models, in which informed traders exploit their superior information by optimally timing their trades, see Kyle (1985); Admati and Pfleiderer (1988) and Foster and Viswanathan (1990).

quences of the real nature of this commodity are that prices are mean-reverting, volatility is very high when compared to other commodities or financial assets, and the price time series display frequent jumps, due to shortages in electricity generation or peaks in the electricity demand[2].

Currently, there is no clue on how the price would move depending on different levels of traded volume. First attempts in this sense have been made by Atkins and Chen (2002) and Goto and Karolyi (2004), considering the volume in the autoregressive price dynamics. The former consider simply the peak and off–peak demand months and they interestingly find that the peak demand months are not influential in both specifications[3], while the off–peak ones are. The latter use the volume series in their specification and they find a significant impact of volume on volatility only in few markets, while in most of them they find no impact. Moreover, Kanamura and Ohashi (2007) try to link transition probabilities to current level of demand. Finally Karakatsani and Bunn (2004) include demand in the variance equation, specified by a GARCH(1,1), and they conclude that, when it was not impossible to get convergence, the impact of demand is not significant because the specified volatility model does not take into account extreme values.

The problem of modelling extreme values is pervasive in electricity markets. To solve for this problem we suggest the following econometric approach. It is well known that electricity prices display pronounced spikes which are mostly due to power shortages. Modelling these spikes as random variables is difficult, since upward jumps are usually but not generally followed by downward jumps which bring back the price to the original level, see Cartea and Figueroa (2005) and Geman and Roncoroni (2006). It is economically sounder to consider prices at different levels following different regimes, see e.g. Kanamura and Ohashi (2004) and Escribano *et al.* (2002). Thus, following Huisman and Mahieu (2003); Guir-

[2] An alternative explanation is market power, see e.g. Borenstein (2000); Borenstein *et al.* (2002), Müsgens (2004) for an analysis of marginal costs of EEX, Fabra and Toro (2005) for an analysis of collusive behavior in the Spanish market.

[3] They define and implement a time–varying model and a jump diffusion model.

guis and Felder (2004) and Weron *et al.* (2004), we disentangle jumps from normal operation behavior. To exclude jumps, we use a simple threshold, as in Geman and Roncoroni (2006), and we also check if our results are robust to the choice of the threshold[4].

Our findings show that, in the considered electricity markets, there is a negligible relation between volume and volatility. We study the relation with two different approaches. The first one regards volatility as a latent variable which follows a GARCH process (Bollerslev (1986)). This approach is nearly standard to model heteroskedasticity in financial asset prices, and it has already been pursued in modelling electricity prices with many refinements, but it has the drawback that the variance is not observable and it has to be filtered. We then exploit the availability of intraday prices, and in our alternative econometric specification we regard price volatility as an observable variable, which can be estimated using intraday prices. However, even when using this second approach, we observe no correlation between volume and volatility. Thus, this finding is robust with respect to the adopted technique. Both econometric models are specified taking into account the main features of electricity price dynamics, that is mean reversion, seasonality and heteroskedasticity.

We then interpret this empirical finding under the light of models on informed trading. Our main conclusions are that there is no information asymmetry in the electricity market, or, if there is, it is not exploited for speculation, that is to trade mispriced contracts[5]. We also analyze competing hypothesis, such as the possibility that informed traders trade in the market to enhance their private investment opportunities.

[4] Using a threshold to detect jumps is not only simple, but it also has a solid theoretical background, see Mancini and Renò (2006).

[5] The possibility of arbitrage in the electricity market is limited by the impossibility to store it, see Eyeland and Geman (1998).

The paper is structured as follows. In Section 2 we describe market structures and data sets. Section 3 contains the econometric specifications and model estimates. Results are discussed in Section 4 and Section 5 concludes.

2 The European electricity markets

Four European markets have been employed in this analysis: Germany, France, The Netherlands and Spain.

Among the European markets analyzed, the German electricity market, the European Energy Exchange (EEX), is the biggest by number of participants, 123 companies from 16 different countries, and volumes continuously rising in the last years moving from 539 TWh in 2002 to 554 TWh in 2004 for the total electricity demand (with traded volumes on day–ahead market being 33 and 60 TWh respectively)[6]. It is centrally located in the heart of Europe, with wires and pipes connected to the rest of the continent. EEX was created by the fusion of two preceding companies, that is LPX Leipzig Power Exchange and the European Energy Exchange. Both exchanges and their supporting associations merged within the year 2002. The spot market, with physical fulfillment on the following day, is operating since summer 2000. The auction market provides the possibility of placing purchase and sale bids for single hours and block bids. The determined equilibrium price is a market price which is defined by way of bilateral auction by suppliers as well as by consumers.

In France the power exchange, known as PowerNext, started to operate at the end of 2001. The number of members has increased and today there are more than 45 members active on French day–ahead market, where traded volume values were 2.6, 7.5 and 14.2 TWh in 2002, 2003 and 2004 respectively and being the total electricity demand increased slightly from 450 to 447 TWh from 2002 to 2004 (Cocker and Lundberg, 2005). Here there is the same mechanism of price

[6] See Cocker and Lundberg (2005).

determination, distinguishing between 3 periods. Market participants start to submit their orders on Wednesday of the previous week, this is the pre–action period. Then the buying and the selling offers are aggregated and prices and volumes are determined for each hour of the following day, which is the action period. Any imbalances are solved in the post–action period.

The Amsterdam Power Exchange (APX) started in 1999. In 2001, the trading volume on the spot market was 8.24 TWh, jumping to 14.1 TWh in 2002, decreasing to 12 TWh in 2003 and increasing again to 13.4 TWh in 2004 where the total demand remained practically constant until 2004 (Cocker and Lundberg, 2005). It must be emphasized that APX acquired APX UK (the Automated Power Exchange) in 2003 and in 2004 they merged with UKPX (the UK power exchange) into APX group[7]. The APX works in the same way with a two side auction model, offers are presented until 10:30 and prices and corresponding volumes are determined at noon.

The last market considered is Spain. The Omel, the Operador del Mercado de Electricidad, started in 1998 and the main generation capacity is provided by five companies, Endesa, Iberdrola, Unión Fenosa, Hidrocantábrico and Enel. In Spain the total electricity demand increased from 233 TWh to 260 TWh with interestingly high volumes demanded on the day–ahead market, 184 TWh in 2002, 198 TWh in 2003 and 201 TWh in 2004. Again the pool works as in the other markets, but with few differences on the frequency of adjustments, indeed there are few intra–day markets. Sellers and buyers submit their offers for each hour of the following day up to 11:00. Then by matching aggregated demand and supply curves, the equilibrium price and the amount traded are determined. However the price considered in this study is that processed at 14:00, that is the *provisional feasible daily schedule*. But by 16:00, the administrator verifies that the technical restrictions are satisfied and if not a new price is defined, which is

[7] Given the acquisition and merging, the last part of the data set may contain gas and power traded in UK.

the *final feasible daily schedule*. This process ends with all required adjustments in six sessions of the intra–day markets which produce the *final hourly schedule*.

The electricity prices series used in our study was obtained directly from the official websites. The data sets are composed by both hourly prices of the so-called *spot electricity market*, and they represent the cost to obtain a certain quantity of electricity in a specific hour of the following day, and hourly average prices per day for the hours 1-24. We also consider average daily prices, as it is common in the literature, see e.g. Lucia and Schwartz (2002). All prices are denominated in Euro per Megawatt hour. Finally, the data set includes the total quantity of electricity traded on the markets for each hour of all days with respect to the period considered. We use the total electricity traded as our volume measure. The time span for the considered market is, for Germany, from 15 June 2001 to 22 June 2005 (1,469 days), for France from 27 November 2001 to 30 July 2005 (1,342 days), for The Netherlands from 27 November 2001 to 20 May 2005 (1,272 days) and for Spain from 1 January 2001 to 13 August 2005 (1,682 days).

The price time series, shown in Figure 1, display, as it is usual for this commodity, three features which are evident just from visual inspection: pronounced volatility, seasonality and jumps.

From the time series of volume it is clear that there is a linear trend in the energy exchanged on the considered markets. This is possibly due to the almost linear increase in capacity experienced by all the four considered markets. Since this trend can have a spurious influence on the forthcoming estimates, we will not directly use volume as our regressor, but the detrended volume, defined after estimating the regression:

$$V_t = C + \alpha t + \varepsilon_t, \tag{1}$$

where V_t is the observed volume at day t and ε_t is IID noise. After obtaining the

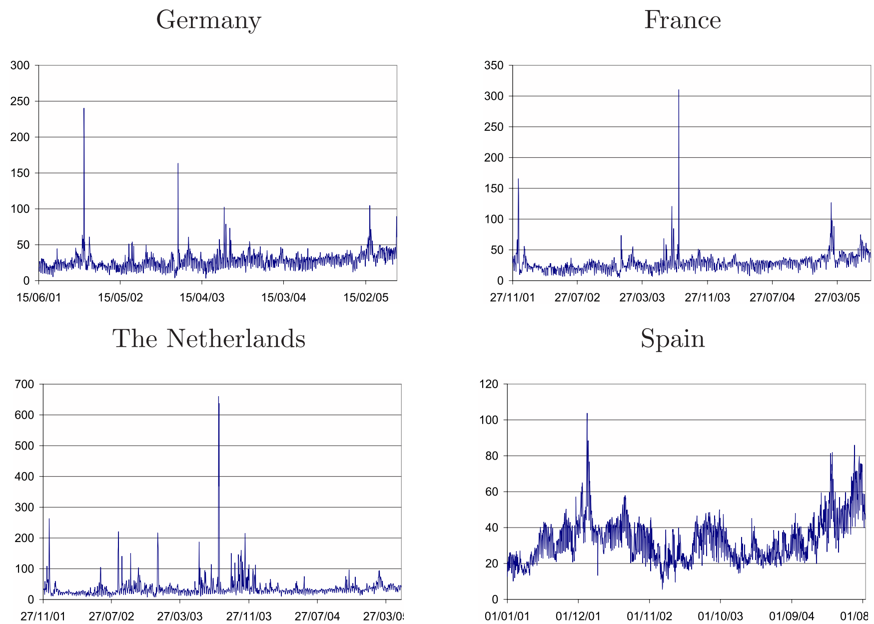

Figure 1: Time series of prices for the four considered markets.

estimates $\hat{C}, \hat{\alpha}$ by OLS, we use the detrended volume[8] $\widetilde{V}_t = V_t - \hat{\alpha}t$. Time series of detrended volumes are shown in Figure 2.

3 The relation between volatility and volume

In this section, we use two different econometric specifications to assess the impact of trading volume on electricity price volatility, the first in which volatility is regarded as a latent variable, and the second in which it is regarded as an observable quantity.

[8] We also estimate our models with volume, without detrending. We encounter much more difficulties in getting convergence when estimating GARCH models. However, for the linear models and for the GARCH models when we get convergence, results are unchanged with the exception of France, for which we find a significantly positive relation between volatility and volume. Results are available upon request.

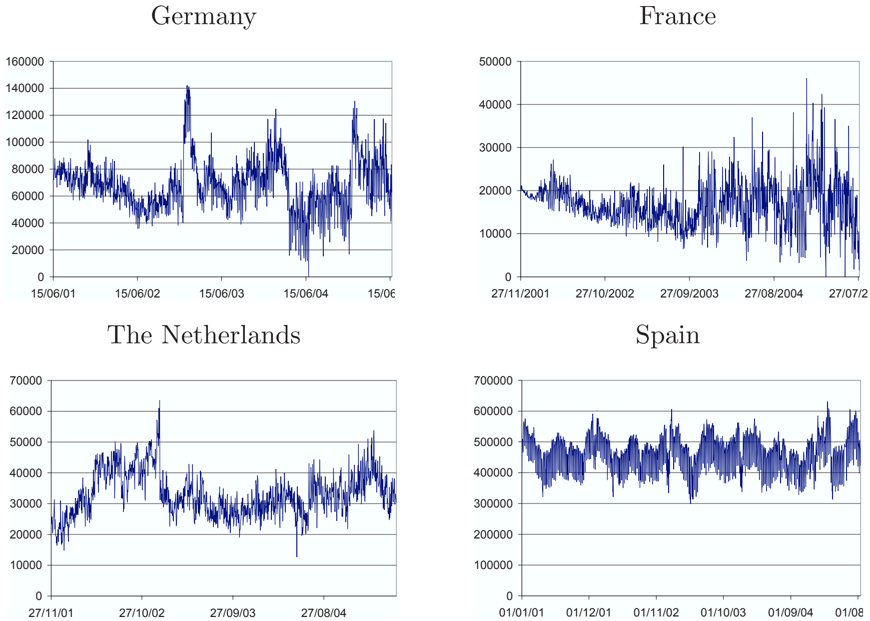

Figure 2: Time series of detrended volumes for the four considered markets.

The volatility of electricity price is mostly affected by the presence of sudden and large variations which, typically, last for one day: upward jumps in the price level are usually followed by downward jumps of almost the same size who revert the price to its "normal" levels. Following the approach of Huisman and Mahieu (2003) and Mari (2006), it is possible to distinguish between two price dynamics: a mean–reverting *normal* process and a jump *abnormal* process[9]. Therefore, we first try to understand whether volume affects the normal price dynamics and, if this is the case, then further investigations can be performed on the jump components. To separate jumps from the normal dynamics, we use a trick similar to that used by Duffie *et al.* (1998) and Weron *et al.* (2004). Whereas the former use an adapted GARCH model according to the magnitude of shocks, the latter

[9] In a similar regime-switching specification, Mount *et al.* (2006) relate the spikes to total load and reserve margin, finding that especially the latter plays an important role as spike predictor.

consider a threshold corresponding to a variation of prices greater than three times the standard deviation of all price changes and in both cases the modified GARCH performed better than the simple one. In our case we eliminate prices who are above a given threshold and we include volume as explanatory variable. Also Karakatsani and Bunn (2004) include volume as an explanatory variable, but they do not eliminate spikes and use a different model specification. We consider three values of the threshold to check the robustness of the results.

Then, in the following subsections, we discard prices which are above a given threshold T, with $T = 50, 70, 90$ Euro. We also eliminate prices below 2 Euro, since the price is sometime null or very low, especially for The Netherlands. We finally eliminate observations with null volume.

3.1 GARCH-based approach

In our first model of electricity prices, we use the time series of daily weighted average prices, with weights proportional to hourly trading volumes. As the preliminary analysis shows, and as it is well known, electricity prices display pronounced seasonality as well heteroskedasticity. We model intraweek seasonality using dummy variables, both in the mean equation and in the variance equation[10]. Then, we insert the detrended volume (see Section 2) directly in the variance equation, in the spirit of Lamoreaux and Lastrapes (1990). We denote by p_t the averaged price at time t, and by $r_t = \log p_t - \log p_{t-1}$ the logarithmic return. The model is then:

$$
\begin{aligned}
r_t &= \mu + \delta r_{t-1} + \sum_{i=1}^{6} c_i D_i + \varepsilon_t \sqrt{h_t}, \\
h_t &= \omega + \sum_{i=1}^{6} d_i D_i + \alpha r_{t-1}^2 + \beta h_{t-1} + \gamma \widetilde{V}_t,
\end{aligned}
\tag{2}
$$

[10] A similar specification for a highly seasonal market, the overnight money market, has been adopted by Hamilton (1996).

where $D_1, \ldots, D_6$ are dummies who take the value 1 in the $i-$th day of the week and 0 in the others[11]. The random shocks ε_t are IID standard Normal variables. We estimate this model via maximum likelihood and the estimates are reported in Table 1. The term δr_{t-1} accounts for mean reversion in price returns, which is a stylized observed fact of electricity prices.

Our results can be commented as follows. First, the coefficients on intraweek dummies are generally significant, signaling the importance of including seasonality in the model specification. This is true across markets, and for both the mean and the variance equations. The dummy coefficients in the mean equation are all negative with respect to Monday, since the return from Sunday to Monday (which is the omitted one in our specification) is typically largely positive (prices are lower on weekends). The coefficients for the dummies in the variance equation are negative as well, and this is consistent with the results in the next Section. Secondly, heteroskedasticity plays a significant role in the market, since α and β are both significant, and also their sum $\alpha + \beta$ is significantly positive and close to one, indicating persistence in shocks to the conditional volatility. Only for France we could not fit the GARCH model, but we managed to fit a ARCH(1) specification (with $\beta = 0$) and also in this case the ARCH coefficient is significant. These results are true irrespective to the value of the threshold adopted. Moreover, we find that first-lag coefficient on returns is negative and significant across markets and for all the values of the threshold. This result confirms that mean reversion is a salient feature of electricity prices. Finally, and most importantly for the purposes of this paper, the impact of volume is not positive. It is generally not significant, and it turns out to be negative and significant for France, for the smallest values of the threshold, a market in which we experienced difficulties in fitting the model. Moreover, the estimation results when the volume is not

[11] The first dummy is for the return on Tuesday, the second dummy on Wednesday and so on, till Sunday which is dummy number six, the omitted day is Monday. Prices are referred to the day on which electricity is delivered.

included in model (2) are qualitatively the same, and all the coefficients are almost unchanged. This is in strong contrast, e.g., with the results of Lamoreaux and Lastrapes (1990) on foreign exchange rates, where it is shown not only that the volume is significant, but that it also captures the heteroskedasticity of the foreign exchange rates time series.

Our results are in line with those of Goto and Karolyi (2004) on the U.S. market. Their specification is quite similar to ours, with the main difference being that our specification does not include jumps in the mean equation since we cut them using the threshold. Moreover, they use monthly dummies in the mean equation (which turn out to be almost never significant) and no dummies in the conditional volatility equation, while we focus on daily dummies both in the mean and in the conditional variance, since the time scale we are interested in is daily, and we find them to be nearly all significant. Besides model specification differences, they also find that the volume has a non significant impact on volatility.

Instead on extending a model in which volatility is latent, as e.g. in Escribano *et al.* (2002); Koopman *et al.* (2005) and Hadsell *et al.* (2004), we turn to a completely different econometric approach in which volatility is an observable quantity, exploiting the availability of high-frequency data.

3.2 Regression-based approach

In the GARCH approach presented in the above Section, volatility is a latent variable. In this Section, we want to exploit the availability of hourly intraday data to measure daily volatility, and estimate an equation for it[12]. We then first

[12] We consider markets one by one, and we do not estimate cross-relations within different markets. Thus, the fact that volatility peaks are different in different markets is not a concern for us.

compute the time series of intraday price variances[13], which we denote by $\hat{\sigma}_t^2$ at day t.

We then fit by OLS the following model, which takes into account heteroskedasticity and intraweek seasonality as well:

$$\log \hat{\sigma}_t^2 = \alpha + \lambda_1 \log \hat{\sigma}_{t-1}^2 + \lambda_2 \log \hat{\sigma}_{t-2}^2 + \lambda_3 \log \hat{\sigma}_{t-3}^2 + \sum_{i=1}^{6} e_i D_i + \gamma \widetilde{V}_t + \varepsilon_t. \quad (3)$$

Estimates of model (3) are reported in Table 2. Our results confirm those of the previous analysis. There is significant evidence of serial dependence in the price variance time series, as witnessed by the significance of λ_1, λ_2 and λ_3. This is again true across markets and with different thresholds. There is small room for the doubt that heteroskedasticity plays a role in the electricity price variations. The coefficients of the dummy variables on the volatility are generally all significant. Finally, the inclusion of detrended volume has the same effect as in the GARCH specification, with the notable exception of Spain, where it becomes positive and significant for thresholds larger than 50 Euros. For France, it is negative and significant for the smallest values of the threshold, as in the GARCH case. For Germany and The Netherlands it is not significant.

As a further robustness check, we re-estimate model (3) using only prices observed in summer months (June-July-August) and winter months (December-January-February), to see whether a volume-volatility relation may arise in these periods[14]. We are interested in these periods since they are those in which demand approaches maximum available capacity, that is periods when spikes and then huge price volatilities are more likely to occur. Estimation results are re-

[13] We also used intraday realized volatility as a measure of volatility, as in Andersen *et al.* (2003). Even in this case we did not observe a significant relation between volume and volatility.

[14] We tried the same experiment with the GARCH model (2), but given the sample reduction of one fourth we encountered convergence problems. We were able to obtain convergence only in half of the models, and in all cases the results confirm those reported in Table 1 for the full sample.

ported in Tables 3 and 4 respectively, and they confirm results obtained so far. The relation between volatility and volume is not significant, if not for Spain in summer months and higher values of the threshold, and marginally for The Netherlands (negatively!) in summer months and for Germany in winter months at a singular value of the threshold. The estimates of the other parameters are compatible with those in Table 2, indicating no substantial difference in summer and winter months for week effects and heteroskedasticity.

4 Discussion of results

In financial markets, there is a pervasive positive relation between volatility and volume.

The economic theories on financial markets focused on three main explanations for this positive relation. The first is the fact that the more the agents trade, the larger should be the price volatility. This is essentially the argument of Clark (1973), which has been confirmed by many other studies and improved in the model of Tauchen and Pitts (1983), who show that the increase in volume due to market expansion needs not to have an impact on the volatility of the market, while the total number of trades in a well established market does, see also Jones *et al.* (1994). The second reason is information asymmetry, or information dispersion. In the model of Epps and Epps (1976), there is a positive relation between the level of disagreement among traders and the price volatility. Since the more the traders disagree, the more they trade, a positive volume-volatility relation arises. The third reason is risk aversion, which implies that trading is associated with price dispersion. As an example, if I need to sell, because of portfolio rebalancing needs, I have to sell at a discount to induce other traders to buy. This mechanism has a larger impact under information asymmetry. As pointed out by Wang (1994), if there are informed and uninformed traders in the market, the uninformed traders face an adverse selection problem, and they demand an additional risk premium. As a result, the correlation between volume and volatility should increase with information asymmetry. Also in the model by Shalen (1993), one important source of volatility is the dispersion of beliefs among traders, which also generates a higher trading volume and then the observed correlation between them.

The positive volume-volatility relation is generally not observed in the electricity prices time series considered in this paper. Interpreting our results in the light of the quoted theories leaves us with different competing hypothesis for explaining the observed null correlation between volume and volatility in the electricity market. It is hard to ascribe the effect to the lack of risk aversion, since e.g. Longstaff and Wang (2004) show that in their model the spread between electricity forward and spot prices are determined by the interaction of rational, risk-averse agents. It is clear that the main motivation is the substantial symmetry of the market, that is the level of pure speculation based on superior information is low in the electricity market[15]. In these studied markets, as in other electricity markets, information does not flow at the same time of trading. Traders buy and sell electricity at different hours of the day mainly to fulfill their industrial, commercial or consumption needs. Thus, dispersion of beliefs is unlikely to play a role. The fact that traders face these restrictions also limits the possibility of strategic placing of orders, which is another source for the volume-volatility relation, see e.g. Admati and Pfleiderer (1988).

On the other hand, the number of transactions is mostly due to seasonal or business cycle components than to a random stochastic process linked to an unobserved state variable which can be interpreted as the information flow. Thus, also this is unlikely to affect the volume-volatility relation.

The model by Wang (1994) provides a different, intriguing explanation. In his model, informed investors have private investment opportunities and trade in

[15] One very peculiar exception has been pointed out by Bernard *et al.* (1997), who provide evidence of price manipulation in the Canadian electricity market for political reasons.

the stock market only if they observe bad signals about their private investment opportunities. In our context, the stock market is replaced by the electricity market, and it is quite clear that most of the traders in the electricity market have private investment opportunities, and actually they buy power to run their private investment opportunities. Wang (1994) shows that, under information asymmetry, the correlation between the total volume traded in the (electricity) market and the price volatility vanishes if the signal on investment opportunities is observed with no noise. It is clear that people buying electricity for industrial reasons know very well their business, and buy electricity only if the expected return, which they estimate very carefully, is larger than the marginal costs, electricity included. Moreover, placing strategic orders may be limited by the non-storability of electricity.

Given the above cited theories, from a preliminary analysis of production, consumption, import and export data[16] of these markets one should expect a strong volume–volatility relationship in Netherlands and Spain since consumption (and also consumption plus export) exceeds production (and also production plus import) from 2001 to 2005. However one should also *keep in mind that not all power exchanges with spot markets have the same underlying design. Some thrive on regulatory constraints (OMEL, GME, Nord Pool), others are of a more voluntary nature (APX, EEX, Powernext). Thus the volumes traded on the respective market places might vary considerably*[17]. For instance, the Spanish spot traded volume accounts for 84.02 % of the total consumption, whereas German, Dutch and French traded volumes are respectively 13.24%, 11.88% and 3.37% of the national electricity consumption (data referred to period from June 2004

[16] Data are provided by UCTE at www.ucte.org.

[17] From DG Competition Report on Energy Sector Inquiry (SEC(2006) 1724, 10 January 2007, second part) at http://ec.europa.eu/comm/competition/sectors/energy/inquiry/index.html Section II.1.4.3. point (423) p.141.

to May 2005)[18]. In other words, Omel covers practically all the electricity sold in Spain and this could explain why we observe a positive correlation between volume and volatility, when the latter is computed as price variance[19].

5 Conclusions

In speculative markets, a positive relation between absolute price changes and trading volume is observed. The literature provided three main explanations for this stylized fact. First, prices move because there is an information flow in the markets, and the volume is a proxy of information flow and as a consequence of it the more the agents trade, the larger should be the price volatility. Second, there is information asymmetry between agents, which drives a positive volume-volatility relation and finally risk aversion related to price dispersion.

For electricity markets it is still unclear whether the rate of movement of prices depends on the total volume of electricity traded in a given day.

Using data from European electricity markets, we show that there is no statistical evidence of an impact on trading volume on electricity price volatility. Our conclusion is robust to two different model specifications in which we model volatility both as a latent variable and as an observable variable, by exploiting the availability of intraday prices, following a very recent econometric technique. Both model specifications include volatility seasonality and heteroskedasticity. We only find a positive relation between volume and intraday price variance in Spain, whose spot market has different features than the other analyzed markets.

The explanation for our results looks rather straightforward: the role for speculation or information asymmetry is minor for the electricity markets, since most of the trading takes place for what we would call, using financial market termi-

[18] See p. 126 table 16 in Section I.3.4. *Traded volumes on spot markets* in DG Inquiry - Second Part.

[19] We acknowledge an anonymous referee for highlighting the difference between Spain and other markets.

nology, "liquidity reasons". That is, agents buy electricity because they need it, and demand is highly inelastic to price. This is also a consequence of the fact that, since electricity is a non-storable commodity, it would be difficult for an superiorly informed agent to place her orders strategically.

We then conclude, on an empirical basis, that the old Wall Street adage that "it takes volume to move prices" is not correct for European electricity markets for the normal status. Whether this is true for the abnormal status as well is difficult to assess, given the low statistics. Moreover, our conclusion is true for the volume traded on the spot market, while it might be untrue for other measures of volume, as load, capacity or supply. We leave these subjects as topics for future research.

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	France			*Germany*			*Holland*			*Spain*		
Threshold	50	70	90	50	70	90	50	70	90	50	70	90
δ	-0.251*	-0.257*	-0.253*	-0.160*	-0.196*	-0.205*	-0.292*	-0.292*	-0.311*	-0.283*	-0.265*	-0.270*
	(0.049)	(0.039)	(0.037)	(0.029)	(0.028)	(0.028)	(0.027)	(0.028)	(0.028)	(0.025)	(0.027)	(0.027)
μ	0.349*	0.388*	0.405*	0.403*	0.446*	0.458*	0.276*	0.336*	0.360*	0.179*	0.237*	0.254*
	(0.024)	(0.019)	(0.018)	(0.019)	(0.016)	(0.016)	(0.016)	(0.018)	(0.016)	(0.013)	(0.013)	(0.012)
c_1	-0.195*	-0.200*	-0.213*	-0.294*	-0.308*	-0.310*	-0.107*	-0.160*	-0.176*	-0.095*	-0.153*	-0.169*
	(0.032)	(0.030)	(0.029)	(0.027)	(0.027)	(0.028)	(0.022)	(0.025)	(0.025)	(0.018)	(0.020)	(0.020)
c_2	-0.341*	-0.378*	-0.400*	-0.408*	-0.443*	-0.451*	-0.259*	-0.321*	-0.353*	-0.165*	-0.225*	-0.241*
	(0.025)	(0.022)	(0.021)	(0.021)	(0.019)	(0.019)	(0.017)	(0.020)	(0.019)	(0.015)	(0.016)	(0.015)
c_3	-0.370*	-0.419*	-0.434*	-0.401*	-0.447*	-0.461*	-0.287*	-0.352*	-0.376*	-0.174*	-0.234*	-0.252*
	(0.026)	(0.022)	(0.022)	(0.022)	(0.019)	(0.019)	(0.018)	(0.020)	(0.020)	(0.015)	(0.015)	(0.014)
c_4	-0.388*	-0.445*	-0.464*	-0.447*	-0.508*	-0.522*	-0.300*	-0.370*	-0.399*	-0.188*	-0.259*	-0.272*
	(0.025)	(0.021)	(0.020)	(0.022)	(0.020)	(0.021)	(0.019)	(0.021)	(0.019)	(0.015)	(0.016)	(0.015)
c_5	-0.541*	-0.609*	-0.638*	-0.626*	-0.695*	-0.718*	-0.459*	-0.555*	-0.589*	-0.285*	-0.369*	-0.392*
	(0.026)	(0.022)	(0.021)	(0.023)	(0.020)	(0.020)	(0.020)	(0.025)	(0.021)	(0.019)	(0.018)	(0.018)
c_6	-0.645*	-0.690*	-0.710*	-0.695*	-0.749*	-0.766*	-0.526*	-0.598*	-0.634*	-0.363*	-0.443*	-0.467*
	(0.026)	(0.024)	(0.024)	(0.021)	(0.018)	(0.018)	(0.021)	(0.023)	(0.021)	(0.016)	(0.015)	(0.014)
ω	0.062*	0.058*	0.056*	0.025*	0.026*	0.029*	0.011*	0.010*	0.016*	0.015*	0.016*	0.012*
	(0.010)	(0.010)	(0.010)	(0.006)	(0.007)	(0.008)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
α	0.313*	0.304*	0.291*	0.320*	0.277*	0.269*	0.151*	0.110*	0.105*	0.087*	0.130*	0.117*
	(0.084)	(0.061)	(0.058)	(0.070)	(0.057)	(0.062)	(0.042)	(0.031)	(0.024)	(0.029)	(0.032)	(0.034)
β	-	-	-	0.318*	0.348*	0.362*	0.715*	0.771*	0.812*	0.808*	0.761*	0.816*
	-	-	-	(0.113)	(0.123)	(0.162)	(0.080)	(0.100)	(0.053)	(0.086)	(0.088)	(0.071)
$\gamma \cdot 10^7$	-3.190*	-3.530*	-2.770	0.301	0.134	-0.025	0.038	0.494	0.337	-0.021	-0.036	-0.011
	(1.140)	(1.680)	(2.150)	(0.320)	(0.348)	(0.365)	(0.392)	(0.477)	(0.357)	(0.060)	(0.073)	(0.056)
d_1	-0.044*	-0.035*	-0.032*	-0.031*	-0.027*	-0.027*	-0.024*	-0.027*	-0.035*	-0.023*	-0.023*	-0.018*
	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)	(0.009)	(0.006)	(0.008)	(0.009)	(0.005)	(0.006)	(0.006)
d_2	-0.046*	-0.038*	-0.038*	-0.024*	-0.023*	-0.024*	-0.014*	-0.014*	-0.020*	-0.014*	-0.013*	-0.011*
	(0.010)	(0.010)	(0.010)	(0.006)	(0.006)	(0.007)	(0.004)	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)
d_3	-0.034*	-0.257*	-0.024	-0.007	-0.003	-0.003	-0.001	-0.004	-0.008	-0.014*	-0.013*	-0.010
	(0.012)	(0.013)	(0.013)	(0.009)	(0.010)	(0.011)	(0.006)	(0.007)	(0.007)	(0.004)	(0.005)	(0.005)
d_4	-0.047*	-0.040*	-0.040*	-0.025*	-0.025*	-0.026*	-0.018*	-0.016*	-0.025*	-0.013*	-0.013*	-0.011*
	(0.010)	(0.009)	(0.010)	(0.006)	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
d_5	-0.032*	-0.027*	-0.029*	-0.009	-0.009	-0.012	-0.004	-0.002	-0.003	-0.002	-0.002	0.001
	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)	(0.004)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
d_6	-0.016	-0.011	-0.011	-0.023*	-0.023*	-0.025*	0.001	-0.001	-0.014	-0.021*	-0.021*	-0.020*
	(0.011)	(0.010)	(0.011)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)

Table 1: Estimates of model (2), obtained via maximum likelihood. A star denotes significance. Standard errors are in brackets.

	France			*Germany*			*Holland*			*Spain*		
Threshold	50	70	90	50	70	90	50	70	90	50	70	90
α	1.260*	0.988*	0.790*	1.660*	1.400*	1.290*	1.720*	1.500*	1.330*	0.490*	-0.194	-0.476*
	(0.137)	(0.139)	(0.137)	(0.144)	(0.144)	(0.145)	(0.159)	(0.164)	(0.171)	(0.165)	(0.145)	(0.145)
λ_1	0.406*	0.405*	0.428*	0.312*	0.325*	0.324*	0.341*	0.377*	0.386*	0.555*	0.527*	0.493*
	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)	(0.026)	(0.028)	(0.028)	(0.028)	(0.024)	(0.024)	(0.024)
λ_2	0.111*	0.110*	0.132*	0.015	0.057*	0.097*	0.067*	0.078*	0.110*	0.059*	0.091*	0.124*
	(0.029)	(0.029)	(0.030)	(0.027)	(0.027)	(0.027)	(0.029)	(0.030)	(0.030)	(0.027)	(0.027)	(0.027)
λ_3	0.090*	0.132*	0.123*	0.171*	0.158*	0.143*	0.157*	0.145*	0.138*	0.198*	0.202*	0.210*
	(0.028)	(0.027)	(0.027)	(0.026)	(0.026)	(0.026)	(0.028)	(0.028)	(0.028)	(0.024)	(0.024)	(0.024)
$\gamma \cdot 10^5$	-0.855*	-0.493	-0.103	-0.040	0.035	0.013	-0.089	0.110	0.268	0.017	0.164*	0.221*
	(0.372)	(0.378)	(0.392)	(0.076)	(0.084)	(0.093)	(0.198)	(0.228)	(0.270)	(0.039)	(0.038)	(0.040)
e_1	1.130*	1.310*	1.380*	0.856*	1.000*	1.080*	0.752*	1.000*	1.130*	0.640*	0.752*	0.763*
	(0.078)	(0.080)	(0.083)	(0.054)	(0.060)	(0.066)	(0.056)	(0.065)	(0.075)	(0.070)	(0.065)	(0.066)
e_2	0.651*	0.978*	1.010*	0.654*	0.887*	0.997*	0.333*	0.489*	0.573*	0.111	0.160*	0.186*
	(0.092)	(0.097)	(0.101)	(0.063)	(0.070)	(0.077)	(0.065)	(0.076)	(0.087)	(0.076)	(0.072)	(0.073)
e_3	0.545*	0.798*	0.791*	0.578*	0.776*	0.831*	0.246*	0.437*	0.392*	0.095	0.182*	0.169*
	(0.083)	(0.090)	(0.095)	(0.060)	(0.069)	(0.075)	(0.060)	(0.071)	(0.082)	(0.075)	(0.071)	(0.072)
e_4	0.411*	0.581*	0.599*	0.421*	0.579*	0.635*	0.178*	0.367*	0.374*	0.062	0.074	0.044
	(0.077)	(0.081)	(0.084)	(0.056)	(0.062)	(0.069)	(0.056)	(0.065)	(0.075)	(0.073)	(0.067)	(0.068)
e_5	0.361*	0.375*	0.372*	0.294*	0.385*	0.439*	0.117*	0.206*	0.206*	-0.037	-0.026	-0.036
	(0.076)	(0.080)	(0.083)	(0.056)	(0.062)	(0.068)	(0.056)	(0.065)	(0.075)	(0.072)	(0.066)	(0.067)
e_6	-0.717*	-0.694*	-0.731*	-0.267*	-0.247*	-0.268*	-0.394*	-0.405*	-0.375*	-0.198*	-0.222*	-0.230*
	(0.075)	(0.076)	(0.079)	(0.053)	(0.059)	(0.065)	(0.055)	(0.064)	(0.074)	(0.064)	(0.058)	(0.058)
R^2	0.280	0.246	0.232	0.434	0.376	0.351	0.481	0.534	0.504	0.540	0.550	0.531
$LB(5)$	1.28	1.43	1.54	9.20	8.08	10.08	21.97*	22.11*	22.57*	51.28*	51.94*	48.15*

Table 2: Estimates of model (3) obtained via OLS. A star denotes significance. Standard errors are in brackets.

	France			*Germany*			*Holland*			*Spain*		
Threshold	50	70	90	50	70	90	50	70	90	50	70	90
α	1.860*	1.220*	0.884*	2.190*	1.700*	1.850*	3.120*	1.970*	1.410*	0.609	-0.715*	-1.770*
	(0.290)	(0.294)	(0.293)	(0.302)	(0.290)	(0.323)	(0.475)	(0.448)	(0.423)	(0.410)	(0.308)	(0.307)
λ_1	0.382*	0.360*	0.382*	0.324*	0.347*	0.279*	0.094	0.256*	0.382*	0.541*	0.460*	0.415*
	(0.056)	(0.055)	(0.055)	(0.053)	(0.053)	(0.053)	(0.062)	(0.060)	(0.060)	(0.047)	(0.049)	(0.050)
λ_2	0.071	0.252*	0.284*	0.059	0.138*	0.189*	0.027	0.010	-0.003	0.073	0.106*	0.144*
	(0.060)	(0.057)	(0.057)	(0.055)	(0.055)	(0.054)	(0.062)	(0.062)	(0.064)	(0.054)	(0.054)	(0.053)
λ_3	-0.042	-0.015	0.000	-0.008	-0.007	-0.033	0.069	0.212*	0.228*	0.219*	0.156*	0.128*
	(0.056)	(0.055)	(0.055)	(0.052)	(0.052)	(0.053)	(0.062)	(0.060)	(0.060)	(0.046)	(0.048)	(0.047)
$\gamma \cdot 10^5$	0.644	-1.040	-0.903	-0.134	-0.051	-0.130	-0.957*	-1.370*	-1.330*	-0.111	0.278*	0.566*
	(0.878)	(0.753)	(0.802)	(0.170)	(0.196)	(0.233)	(0.403)	(0.475)	(0.532)	(0.092)	(0.087)	(0.101)
e_1	1.030*	1.900*	2.070*	1.340*	1.710*	1.870*	1.200*	1.620*	1.870*	1.170*	1.280*	1.180*
	(0.169)	(0.154)	(0.164)	(0.106)	(0.121)	(0.140)	(0.120)	(0.137)	(0.154)	(0.150)	(0.137)	(0.147)
e_2	0.446*	1.120*	1.280*	0.592*	0.765*	1.040*	1.160*	1.420*	1.520*	0.633*	0.677*	0.497*
	(0.189)	(0.206)	(0.220)	(0.143)	(0.171)	(0.191)	(0.151)	(0.185)	(0.211)	(0.166)	(0.158)	(0.168)
e_3	0.540*	0.932*	1.010*	0.585*	0.806*	0.998*	1.000*	1.390*	1.320*	0.739*	0.695*	0.483*
	(0.176)	(0.188)	(0.202)	(0.122)	(0.148)	(0.170)	(0.141)	(0.175)	(0.201)	(0.165)	(0.152)	(0.159)
e_4	0.588*	0.889*	0.870*	0.625*	0.728*	0.886*	0.926*	1.150*	1.120*	0.586*	0.505*	0.346*
	(0.167)	(0.161)	(0.172)	(0.108)	(0.127)	(0.149)	(0.120)	(0.142)	(0.156)	(0.160)	(0.135)	(0.139)
e_5	0.367*	0.534*	0.539*	0.531*	0.529*	0.667*	0.929*	0.921*	0.834*	0.497*	0.481*	0.336*
	(0.166)	(0.158)	(0.166)	(0.106)	(0.124)	(0.144)	(0.120)	(0.143)	(0.160)	(0.159)	(0.134)	(0.139)
e_6	-0.542*	-0.624*	-0.698*	-0.468*	-0.560*	-0.514*	0.099	0.009	-0.138	0.163	0.158	0.065
	(0.160)	(0.147)	(0.156)	(0.101)	(0.116)	(0.135)	(0.120)	(0.138)	(0.154)	(0.133)	(0.110)	(0.107)

Table 3: Estimates of model (3) obtained via OLS on **summer** months. A star denotes significance. Standard errors are in brackets.

	France			*Germany*			*Holland*			*Spain*		
Threshold	50	70	90	50	70	90	50	70	90	50	70	90
α	1.320*	1.240*	1.220*	1.950*	1.360*	1.270*	1.910*	2.030*	1.950*	1.920*	0.633*	0.294
	(0.246)	(0.257)	(0.260)	(0.264)	(0.255)	(0.264)	(0.310)	(0.320)	(0.350)	(0.401)	(0.307)	(0.287)
λ_1	0.446*	0.508*	0.515*	0.415*	0.438*	0.435*	0.303*	0.381*	0.313*	0.599*	0.566*	0.550*
	(0.055)	(0.054)	(0.054)	(0.054)	(0.054)	(0.055)	(0.054)	(0.054)	(0.054)	(0.050)	(0.050)	(0.049)
λ_2	0.046	0.024	0.107	-0.007	0.165*	0.183*	0.063	0.051	0.090	-0.058	0.106	0.082
	(0.060)	(0.061)	(0.061)	(0.059)	(0.058)	(0.059)	(0.056)	(0.058)	(0.056)	(0.058)	(0.057)	(0.056)
λ_3	0.114*	0.069	-0.012	0.052	0.032	0.038	0.205*	0.115*	0.123*	0.160*	0.169*	0.246*
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.055)	(0.054)	(0.054)	(0.054)	(0.049)	(0.049)	(0.048)
$\gamma \cdot 10^5$	-0.107	0.778	0.839	0.262*	0.136	0.104	-0.274	0.060	0.434	-0.132	0.045	0.077
	(0.695)	(0.766)	(0.807)	(0.126)	(0.137)	(0.153)	(0.324)	(0.362)	(0.446)	(0.080)	(0.067)	(0.066)
e_1	0.830*	1.030*	1.170*	0.423*	0.640*	0.731*	0.445*	0.539*	0.787*	0.170	0.203	0.267*
	(0.154)	(0.166)	(0.176)	(0.108)	(0.120)	(0.134)	(0.106)	(0.117)	(0.140)	(0.141)	(0.116)	(0.111)
e_2	0.168	0.193	0.162	-0.313*	-0.030	0.083	0.031	-0.001	0.118	-0.262	-0.329*	-0.270*
	(0.177)	(0.197)	(0.211)	(0.119)	(0.137)	(0.152)	(0.115)	(0.129)	(0.151)	(0.148)	(0.124)	(0.118)
e_3	0.244	0.295	0.190	0.050	0.765*	0.139	-0.045	0.034	0.173	-0.241	-0.282*	-0.182
	(0.154)	(0.176)	(0.188)	(0.111)	(0.126)	(0.142)	(0.106)	(0.120)	(0.145)	(0.147)	(0.121)	(0.117)
e_4	0.165	0.264	0.344*	-0.061	0.099	0.221	-0.074	0.073	0.169	-0.085	-0.120	-0.167
	(0.146)	(0.161)	(0.170)	(0.109)	(0.119)	(0.133)	(0.104)	(0.115)	(0.140)	(0.146)	(0.119)	(0.114)
e_5	0.126	-0.002	0.027	-0.200	-0.162	-0.146	-0.047	-0.050	0.116	-0.371*	-0.429*	-0.405*
	(0.146)	(0.162)	(0.173)	(0.108)	(0.121)	(0.137)	(0.103)	(0.116)	(0.140)	(0.144)	(0.119)	(0.114)
e_6	-0.958*	-1.040*	-1.140*	-0.459*	-0.568*	-0.590*	-0.425*	-0.460*	-0.255	-0.315*	-0.415*	-0.368*
	(0.142)	(0.154)	(0.164)	(0.104)	(0.115)	(0.129)	(0.103)	(0.114)	(0.139)	(0.129)	(0.107)	(0.102)

Table 4: Estimates of model (3) obtained via OLS on **winter** months. A star denotes significance. Standard errors are in brackets.

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