A Quantitative Analysis of Weather Effects on Traded Volume in the Swiss Energy Spot Market

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Abstract—This paper quantitatively examines the effect of weather uncertainty on the traded volume of energy spot prices. Traded volume is driven by agents’ anticipation of numerous factors of limited predictability, such as renewable energy in-feed or volatile fuel prices. Such stochasticity leads to volume time-series with noise like characteristics. The goal of our study is to investigate if there are structural artifacts in the time-series attributable to weather conditions. Employing a set of simple assumptions concerning the market behavior and the financial products available, we arrive at qualitatively sensible results from a more robust theoretical perspective. Our model is trained on historical data from the Swiss market, which depends on a highly predictable renewable energy, namely hydro-electric power. A filtering process is applied to remove deterministic elements of the volume time-series such as patterns due to dates or seasons. An analysis of weather impact on this time series proves to be consistent with an intuitive analysis of the data for the months of winter. An estimation of the relative volume shift during warm and cold days in winter is provided. Results prove to be consistent with the features of heating demand, particularly for spring and autumn, when the heating status (on/off) is highly sensitive to weather conditions. Numerical evidence also leads to the conclusion that there is no clear impact of extreme temperature events on the traded volume time-series in Summer months.

I. INTRODUCTION

Maturing energy markets observe increased liquidity in long-term contracts as a larger pool of agents look to hedge their exposures. This results in a more reliable reflection in Futures prices of strong demand due to heating during Winter or weak demand during Summer months. More accurate demand anticipation, combined with an increase in the relative share of intermittent renewables in-feed, has resulted in a disappearance of the traditional yearly seasonality of spot prices from the more recent historical record, as illustrated in Fig. 1.

Exceptional weather conditions cannot be anticipated by long-term contracts and represent a key driver of the spot price behavior. A forecasted wind shortfall in Germany, for example, will have a direct impact on the production of gas-fired power plants in France. While wind is a supply-side factor, forecasted weather can influence both the forecast of demand (e.g. heating in Winter) as well as the forecast of the supply (e.g. solar in-feed). It is therefore challenging to understand the mechanism by which extreme weather influences the spot price during the dynamic bidding process. The total traded volume, on the other hand, can theoretically track, for instance, exceptionally warm or cold days in Winter. Many other factors impact the volume, from the day in the week to the in-feed capacity. This results in a noisy and difficult to predict time-series in stark contrast to the smoother spot-price data, as shown in Fig.’s 2&3.

Based on this intuition and the difficulty of analyzing hourly traded volume, we propose to focus on out-of-the-ordinary weather events and to investigate their quantitative impact on the daily traded volume of the spot price. The Swiss market is used to train the model, as it relies heavily on hydro-electric power and has a highly deterministic in-flow (an analysis of the German market, for example, would require the specific inclusion of wind-in-feed in the model to account for significant installed wind capacity). The weather indicator used in this study is limited to the daily mean temperature.

Section II examines a theoretical relationship between weather and traded volume. Section III presents a filter for traded-volume time-series as well as the construction of three weather indicators. In section IV the indicators are applied to the Swiss electricity market, with results discussed in the final section.

II. TRADED VOLUME AND WEATHER

A. From Weather-based Spot Price Models to Traded Volume

For most speculative markets, such as those for equities and commodities, there appears to be a strongly positive correlation between absolute price changes and traded volume [1], [2]. However, this does not apply to electricity spot markets, due to the fact that the impact of supply and demand fundamentals far outweighs that of speculative trading on the price setting process. The real physical demand for electricity, a non-storable good, leads to a price volatility which is unaffected by traded volume [3]. The price resulting from the bidding process is therefore easier to determine than for an equity or an oil future. As a result, many models handle spot price predictions based on weather data and daily indicators [4], [5]. Fig.’s 1.2 & 4 illustrate Swiss spot prices, their traded volume and one-day ahead temperature forecasts for the year 2011.

Although the price levels remain relatively stable from one day to the next, the traded volume appears to be highly volatile, with no clear link to the spot price. Fig. 3 superimposes spot prices and traded volumes for one Summer week and one Winter at an hourly level. Although the prices are relatively smooth, the traded volume displays high-frequency random-
Fig. 1. Hourly Swiss Spot price in 2011. Strong seasonality observable in previous years has diminished.

Fig. 2. Hourly Traded volume of the Swiss Spot price in 2011.

Fig. 3. Two weeks of Spot prices (a) and their traded volume (b). The week in Winter starts the 17th January 2011, the week in Summer starts the 20th of June 2011. Both weeks starts on a Monday.

ness and can fluctuate at any time in the day. Therefore, this paper focuses on daily data, and investigates the impact of temperature forecasts uncertainty on the daily traded volume.

B. Assumptions

A limited range of products. Fig. 5 illustrates the range of products available to cope with demand. The volatility and hence riskiness of these products is seen to be inversely proportional to the time-to-delivery. Over-the-counter markets offers other possibilities, but they are neglected in this study. The ancillary market being predominantly used to correct in-feed errors resulting from poor weather forecasts or exceptional events, is also neglected.

Risk aversion of the agents. It is assumed that energy producers and retailers are risk averse. Therefore, they will try to hedge their positions as sensibly as possible through long-term contracts, which are assumed to be less risky than the short-term positions. In particular, it means the seasonal variations of the weather and indirectly of the demand are fully accounted for in the price of the long-term contracts.

Drivers of the Demand. The supply, being demand driven, is assumed to result from the combination of the long-term contract deliveries, of the spot market output (i.e. the volume) and of the ancillary market. Power in-feeds from other sources are neglected. We assume that the total demand can be modeled using a bottom-up approach based on the weather and a set of indicators to track the day in the week and the period in the year.
C. Intuitive Understanding of the Spot/Volume Relationship

Based on the previous assumptions, we expect that long-term seasonal variations in temperature will not be reflected in spot price or traded volume seasonality. This is verified for the spot price in Fig. 6 in which traditional yearly pattern of the spot price observed at the beginning of the liberalization of the power market is now barely noticeable [6]. The remaining slight peak in November can be explained by the low level of hydro-electric reservoir at this period of the year [7]. The same analysis holds for the traded volume (Fig. 2).

Conditional weather uncertainty, defined as the difference between the realized weather and its expected seasonal variations, is the main risk driver in an agents’ hedging portfolio. This uncertainty can be described as the potential for high or low peak temperatures, extreme shifts in temperature, and high temperature volatility with regards to the seasonal variation. The spot market is assumed to be the only remaining market for the risk-averse traders to cope with this weather uncertainty. This leads to two key hypotheses:

**Extreme Events** Despite the stochasticity of the traded volume, extreme weather events should be reflected in the time-series by upward or downward shifts depending on the season.

**Uncertainty** A high demand uncertainty, and indirectly a high weather uncertainty, should lead to a higher volume traded on the spot market.

III. Weather Indicators and Volume Filtering

Our model should highlight the link, if it exists, between the traded volume and extreme weather events. For testing purposes, a set of weather indicators are built and a filtering process for the volume is proposed.

Let $V_t$ denote the volume traded at time $t$. Only the daily mean data is considered for the traded volume, as weather data is provided at daily resolution. $W_t$ is the one-day ahead weather forecast for day $t$, and $S_t$ is the spot price traded for a delivery at time $t$. A three-fold filter is applied to the volume time-series to remove what are assumed to be deterministic features.

### A. Volume Filter

The volume time-series needs to be pruned of its deterministic bottom up-effects: the long-term growth and both the weekly and yearly patterns. Fig. 7 illustrates the process.

1) The long term growth in volume due to the increasing demand $b$ is assumed to be constant and is withdrawn using a regression. The obtained volume is denoted $V^*_t$.

$$V^*_t = V_t - b.t \quad (1)$$

Regression is performed using the least absolute deviation (LAD) approach. The existence of extreme outliers within the volume time-series precludes the use of non-robust squared error techniques such as the OLS [8].

2) Demand for electricity exhibits a weekly pattern, with low demand during week-ends. Therefore, the uncertainty due to extreme weather events does not have the same impact on the market on Wednesdays as on Sundays for example. The weekly pattern can thus be observed for the volume (see Fig. 8). This weekly
profile is part of the systematic component that is not treated here. We remove it by withdrawing the mean of each day in the week from the time-series, resulting in a smooth, zero-centered profile. Furthermore, the standard deviation of the volume for each day in the week is normalized (see Fig. 9). Although the weather uncertainty is the same for every day, its impact on the volume traded is not the same on a Wednesday as on a Sunday. The obtained volume is denoted $V_{t}^{\text{dayfree}}$.

$$V_{t}^{\text{dayfree}} = \frac{V_{t}^{*} - \bar{V}}{\sigma(V_{t}^{*})_{\text{day}}}$$ (2)

$\sigma$ and $\bar{\sigma}$ denote respectively the standard deviation and the mean for each seven-day cluster.

3) There is indeed a yearly seasonality within the Volume time-series which must be removed, see Fig. 10. We extract the seasonality using a 30 day moving average. The obtained time-series illustrates the weather changes relative to the seasonality, resulting in a detrended signal $V_0$ fully independent of the day in the week and of the period in the year. Only the weather forecasts and spurious effects remain.

$$V_0 = V_{t}^{\text{dayfree}}$$ (3)

B. Weather Indicators

The weather time-series also needs to be stripped of its seasonal variations. In this respect, a thirty day moving average is again deployed for detrending. The relative weather $W_{t}^{*}$ is defined as the difference between the weather forecast time-series and the seasonal pattern. Extreme weather events are measured using three complementary methodologies:

1) Absolute peak events, defined as an absolute difference to the normal, seasonal weather greater than 4 degrees.

2) Relative peak events, defined as a difference in weather from one day to the other greater than 4 degrees.

3) A Weather uncertainty indicator, derived using a GARCH(1,1) model [9]. It is derived based on the daily difference in temperature. Weather time-series and wind chill factors do indeed exhibit a volatility clustering effect and the squared residuals of the filtered weather time-series are autocorrelated\(^1\) [10], [11] and [12].

\(^1\)The observed one-lag auto-correlation coefficient is 0.2 and significant. Due to the inertia in heating, the impact of the weather on the demand is expected to exhibit a stronger GARCH effect.

C. Dependency Measurements

The impact of weather on traded volume is variable over the year. An extremely cold day in Winter should lead to a higher volume traded to cope with the extra heating demand. In summer, the expected relation is less obvious as indoor cooling is not ubiquitous in Switzerland. Spring and Autumn, which rarely lead to extreme heating demand, are expected to be sensitive to the weather uncertainty which influences whether heating is turned on or not\(^2\). For this reason, three clusters are built:

- Winter cluster (November to February)
- Summer cluster (May to August)
- Equinox cluster (March, April, September and October)

Our methodology consists in scanning for extreme events according to the weather indicators, and then checking whether the volume is consistently reacting to this weather event. As pointed out in Section II, these indicators do not capture daily volume trends and as such the study is limited to the extreme events. Although the full filtered volume time-series has been detrended, the seasonal clusters have not, despite the removal of the moving-window variations. In order to fairly compare volume dynamics per cluster each subseries (cluster) is also detrended.

IV. APPLICATION TO THE SWISS MARKET

All time-series used in this study are from Bloomberg. The data ranges from March 2009 to January 2012. The daily volume is taken as the mean of hourly volume data for each day. The temperature data has native daily resolution. Fig. 11 represents the derived weather indicators and the volume time-series after filtering for the year 2011. The p-values of the GARCH fit parameters are all under 4% corresponding to a meaningful fit. The GARCH model results in obvious clustering, usually triggered by large temperature deviations relative to previous day ("relative event"). The results for the various seasons, weather indicators and measurement type are reported in Table I. Note that the "volume shifts" show the mean-shift as a percentage of the mean volume traded on a week-day for each cluster.

\(^2\)This difference in behavior is not necessarily seen on the mean traded volume over the season (see Fig. 10). On average, the volume traded in winter, spring and fall is constant (December is biased due to the holidays), while summer is significantly lower due to the slow-down of the economy.
Fig. 11. The cleaned time-series for 2011: (a) the absolute and relative extreme weather events, (b) the weather uncertainty measured with a GARCH(1,1) model and (c) the volume-time-series after filtering.

<table>
<thead>
<tr>
<th></th>
<th>Winter</th>
<th>Equinox</th>
<th>Summer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Sample Points</td>
<td>306</td>
<td>305</td>
<td>256</td>
</tr>
<tr>
<td>Share of Absolute Peak Events</td>
<td>24.8%</td>
<td>20.6%</td>
<td>20.7%</td>
</tr>
<tr>
<td>Share of Relative Peak Events</td>
<td>9.5%</td>
<td>1.6%</td>
<td>5.9%</td>
</tr>
<tr>
<td>Mean Volume Shift During Positive Absolute Peak Events</td>
<td>-18%</td>
<td>-28%</td>
<td>-45%</td>
</tr>
<tr>
<td>Mean Volume Shift During Negative Absolute Peak Events</td>
<td>7%</td>
<td>4%</td>
<td>-4%</td>
</tr>
<tr>
<td>Mean Volume Shift During Positive Relative Peak Events</td>
<td>-16%</td>
<td>none</td>
<td>-6%</td>
</tr>
<tr>
<td>Mean Volume Shift During Negative Relative Peak Events</td>
<td>5%</td>
<td>-6%</td>
<td>-16%</td>
</tr>
<tr>
<td>Mean Volatility During the period [kMWh]</td>
<td>2.01</td>
<td>1.92</td>
<td>1.98</td>
</tr>
<tr>
<td>Mean Volume traded during the period [kMWh]</td>
<td>1.195</td>
<td>1.200</td>
<td>1.148</td>
</tr>
<tr>
<td>Mean Traded Volume for uncertainty index above 2</td>
<td>1%</td>
<td>28%</td>
<td>-18%</td>
</tr>
<tr>
<td>Mean Traded Volume for uncertainty index under 2</td>
<td>-27%</td>
<td>6%</td>
<td>-3%</td>
</tr>
</tbody>
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TABLE I
MEASUREMENT RESULTS. THE HIGHER SHARE OF ABSOLUTE EVENTS RATHER THAN RELATIVE EVENTS REFLECT THE HIGH AUTO-CORRELATION IN THE WEATHER TIME-SERIES.

A. Peak Events (Large Deviation from Seasonal Norm)

The results of Table I are particularly easy to interpret for the winter cluster, which exhibits the highest share of extreme weather events. In winter, a cold day event leads on average to a 7% increase of the traded volume, while a warm day event results in a mean decrease of 18%. This leads to the conclusion that either the heating capacity has a physical limitation which is tuned for seasonal expectations rather than extremely cold days or that the electricity retailers prefer to bet on a cold winter and to hedge this position on the long-term market, rather than facing the risk of strong demand to be met at a high price on the spot market.

For the Equinox cluster (Autumn and Spring), the trend is the same as for the Winter cluster. Cold days lead to a slight increase in the volume traded (4%). Of more interest, extremely warm days lead to a significant decrease in volume traded (-28%). This can be interpreted as consumers having the heat turned off on these days.

B. Relative Events (Large Deviation from Previous Day)

The differences between the absolute and relative indicators provide information on how the volume traded is adjusted with regards to series of cold or warm days. Focus is no longer on the extreme temperature events but on extreme shifts of temperature. A set of cold days in a row are therefore removed - only the first point may be counted as an event. The results for the winter cluster are consistent with the absolute value cluster, but result in volume jumps of smaller magnitude (a decrease of -16% in traded volume is observed for an upward shift in temperature, while a downward shift will lead to an increase of 5%). This observation is consistent with assumptions made with regards to the products available: the one-week ahead weather forecast can be taken into account.
only on the Spot market. The auto-correlation in weather — for example a set of cold days in a row — is therefore also observable in the volume: the absolute weather indicator proves to impact more the volume than a relative weather shift, although the numerical evidence is weak.

For the Equinox and Summer clusters, the small number of relative weather events (1.6% and 5.9%, respectively) does not allow us make a statistically significant interpretation.

C. Periods of High Weather Volatility

The uncertainty indicator, provided by the GARCH model fitted on the filtered weather time-series, provides information about the reaction of the market agents to periods of instability. As a reference, a temperature volatility of 2°C (approximately the mean for the three clusters) is taken as threshold to distinguish a low volatility period from a high volatility period. The theoretical expectation is that a period of high weather uncertainty should result in fewer positions taken on the forward market and therefore a higher volume traded on the spot price market. The winter cluster proves to be again consistent with physical expectations - predictable temperatures lead to a significant decrease in the traded volume. The effect is the most relevant for periods of high volatility in the Equinox cluster. The sensitivity of demand to the weather in this cluster is amplified by the heating being turned on or off, which results in an asymmetric impact on demand.

V. DISCUSSION AND CONCLUSION

From reasonable assumptions, an intuition is formed linking unusual weather events to relative moves in volume traded on the Swiss energy spot market. Despite the inherent stochasticity of the traded-volume time-series, extreme weather events should lead to significant increases or decreases depending on the season. Three empirical weather indicators are built to check this intuition.

The results validate the intuition for the winter cluster. The numerical estimation of the volume suggest that warm days in winter will have a higher (negative) impact on the volume than will extremely cold days. This result is consistent with a physical understanding of heating needs and our assumption that electricity retailers are risk averse. Moreover, periods of high heating uncertainty due to weather in Autumn and Spring see a significant increase in volume traded. For the Summer cluster, weak numerical evidence does not provide a clear picture of a Spot/Volume correlation, particularly due to the economic slow-down and the correspondingly smaller volumes traded.

The weaknesses of our model include the omission of renewables in-feed impact, as well as that of German and Italian spot prices, and our assumption that there is perfect coverage of deterministic elements through long-term contracts. In particular, the transition from base to peak hours implies a smoothing of the supply curve through the Spot market. The underlying assumption that these effects would be negligible during extreme weather conditions is not checked.

A better understanding of the volume’s drivers during extreme weather events can result in a better management of energy market tail risk, leading to more consistent hedging and pricing of exposures by energy retailers as well as more opportunistic scheduling of the energy supply.

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REFERENCES