Research-Thesis: Assessment of intermittent renewable energy: impact of exchange

Auteur : Lefebvre, Jean
Promoteur(s) : Gautier, Axel
Faculté : HEC-Ecole de gestion de l'Université de Liège
Diplôme : Master en sciences économiques, orientation générale, à finalité spécialisée en economic, analysis and policy
Année académique : 2025-2026
URI/URL : http://hdl.handle.net/2268.2/25855

ASSESSMENT OF INTERMITTENT RENEWABLE ENERGY: IMPACT OF EXCHANGE

Jury:
Supervisor:
Axel GAUTIER (HEC Liège - Université de Liège)
Donal PALCIC (University of Limerick)
Reader(s):
Voahary Iangotiana ANDRIAMAROMANANA (HEC Liège - Université de Liège)

Master thesis presented by
Jean LEFEBVRE
To obtain the degree of
MASTER IN ECONOMICS
with a specialization in
Economic Analysis and Policy (Double degree with the University of Limerick)
Academic year 2025/2026

EXECUTIVE SUMMARY

Intermittent renewables decrease the spot price thanks to their 'zero marginal cost'. The price depends on the marginal cost of the last energy produced, which is the most expensive ('merit-order effect'). The intermittent renewable production is volatile and therefore the price is. The second problem is that sometimes the supply is too high for the demand. This incites to sell at negative price, which represents a problem for the deployment of clean energy.

Exchanges of energy helps to reallocate a part of the domestic supply to foreign markets, which increases the domestic price. In the literature, analyses often assume 'island economy' (no exchange).

This Master thesis analyses the impact of international transmissions on the hourly day-ahead price and the place of international trades to reduce the risk of negative day-ahead price.

The method is separated in three parts: ARDL models, VAR model and descriptive statistics-based analysis of negative price. Along the analysis, the readers will notice that the problems of autocorrelation and heteroscedasticity are omni-present. The third part explains the potential origin of heteroscedasticity.

The dissertation concludes that exchanges can reduce the risk of negative price by reducing the domestic supply of energy. However, exchanges should be considered as a part of the solution among many tools.

Keywords: Intermittent renewable energy, transmissions, flexibility, merit-order effect, green transition
Word count: 15,747

Ecole de Gestion de l'Université de Liège

UNIVERSITY OF LIMERICK
OLLSCOIL LUIMNIGH

I would like to thank my supervisors for their help along the whole process. They helped me both for the administrative part and for the questions I had.

I would like to thank HEC Liège for giving me many opportunities that formed me.

I would like to thank the University of Limerick for welcoming me last year. This was an important source of learning for me.

I would like to thank my parents for their unconditional support during these study years.

Contents

1 List of abbreviations / Glossary

Day-ahead price (DHP): Lowest bid for the electricity price the day before the sale.

Duck-curve: Representation of the net load (load - intermittent renewable production) (California ISO, 2016).

Free-rider dilemma: Problem of coordination where players benefit from the other players' actions without contributing to this action.

Intermittent renewable energy: Type of energy that can be produced only when specific weather conditions are respected, which make them intermittent. Here, we will limit the discussion solar and wind energy.

Merit-order effect: The market price is the price of last unit on the market. This last unit is the most expensive. The merit-order is a concept explaining that energy used goes from the cheapest to the most expensive.

Renewable paradox: Renewable energy seems attractive to produce due to their low marginal cost. However, the competition under a market composed by a lot of renewables causes a decrease of price harming the profit.

Transmission: Transfer of an amount of energy to another substation.

Spot price: Similar meaning to Day-ahead price.

Variable Renewable Energy (VRE): Synonym of Intermittent renewable energy.

Zero-marginal cost: Hypothesis that VRE has very low marginal cost, near to zero.

2 Introduction

The CO_2 emissions, or equivalent emissions, are mainly caused by the energy industry. In 2023, the energy industry caused 77% of Greenhouse Gas (GHG)(Climate Watch, 2025a), 44% of these emissions are from electricity and heat (Climate Watch, 2025b). In Belgium, these figures are respectively 83% (Climate Watch, 2025c) and 23% (Climate Watch, 2025d). It is evident that reducing the emissions from this industry is necessary to slow down climate change. Particularly that 100% renewable economy might be achievable technically and economically despite many challenges (Al-Shetwi, Abidin, Mahafzah, & Hannan, 2024) [1].

As we will see in this introduction, the implementation of some renewable energy sources can pose problems due to their very low marginal costs and their intermittent production (Blazquez, Fuentes-Bracamontes, Bollino, & Nezamuddin, 2018). However, there are many solutions, often complementary. In this dissertation, I will discuss the solution of international exchanges to smooth the supply of renewable energy in Belgium. This can effectively be a part of the solution to decrease the price volatility and the cost of negative prices on producers. In the literature, it seems that international exchanges are often not considered in analyses. Storage took a more important place in the literature although transmissions could have similar effects. This is important to consider it because many economies are not 'island economies'; transmission between different regions/countries is an important feature to integrate (Bistline, 2017) (Guo et al., 2026).

2.1 Source of the problem

Intermittent renewable energy has two specificities that make it volatile in terms of price and quantity: the 'zero' marginal costs and the intermittency of production. The implication of these specificities can theoretically be represented as (Blazquez et al., 2018) did. When the merit-order effect happens and the energy demand and the supply of non-renewable energy are constant, the price will decrease throughout these renewable units. Given the 'zero marginal cost', the price is determined by the price of non-renewable sources. Their production is therefore attractive for producers until the price of energy is too diminished. Given the intermittent production of renewable energy, the supply of energy is unstable over time. There are two 'equilibria'[2] in a simplistic representation: when there is production of intermittent energy and when there is not. In the first equilibrium, the price is low and the quantity is high. In the second is that the price is high and the quantity is low. Because the supply varies over time, there are back and forth between these equilibria causing the volatility. The more renewable energy supplies are important, the more volatile is the energy market. One of the risks would be that non-renewable plants disappear due to profitability problems for them according to the authors (Blazquez et al., 2018). This could create a greater volatility in the exchange due to the lower supply of non-renewable energy and reinforcing the cycle.

Another risk of volatility is the 'Dunkelflaute', which happens when the weather is in bad conditions for the production (no wind and no sunbeams) for a long period. In this situation, the supply is constrained to pollutant energy and therefore leads to higher prices and lesser quantities (except if we consider a perfectly inelastic demand). In case these non-renewable energy plants are unable to produce energy to meet demand, there will be problems. Given the prediction of (Blazquez et al., 2018), the deployment will decrease these non-renewable capacities. This means the impact of Dunkelflaute will be heavier. In this work, the risk of Dunkelflaute will not be the main focus. However, it might

[1] This point is highly debatable. For example, (Blazquez, Fuentes, & Manzano, 2020) argue that the 100% is not achievable due to political issue and due to the difficulty to decarbonise some sectors.

[2] This must not be understood as a multi-equilibria.

be useful to keep in mind that the more renewables, the more Dunkelflaute risks to happen and the heavier will be the effect. Therefore, this is also an important risk of volatility, which makes crucial the transmissions with other countries for the energy security.

Many empirical works have shown that renewables decrease the price of electricity (For instance: (Mulder & Scholtens, 2013), (Dillig, Jung, & Karl, 2016) and (Macedo, Marques, & Damette, 2020)). This problem is not only theoretical; this is a current problem.

The problem is not only a problem of volatility but a problem of supply and demand match. The production of Variable Renewable Energy (VRE) can be higher than the full demand, encouraging negative price. Negative prices are predicted to be more frequent without any intervention (Biber, Felder, Wieland, & Spliethoff, 2022), which could harm producers. Another way to visualise this problem is to use the 'Duck curve' prism (first described by the CAISO (California ISO, 2016)). The graph represents the load (which can be used to estimate the demand) that must be covered by non-renewables (the net load) over the day. The net load has cyclical phases. While integration of intermittent renewable energy, the net load is highly variable over a day.

2.2 Solutions

In the literature, many solutions for these problems can be found. The most intuitive is to store the excess of energy and to sell it in other period. Although this sounds an easy solution, the practice is more complicated. For example, we can observe in theory that storage represents a decision where 'the free rider problem' happens (Zhao, Wang, Huang, & Lin, 2019). Each producer indirectly benefits from the storage of the other producer. Another observation is that the storage devices are not used at their full capacity given the level of competition and the ownership of the storage capacities (Schill & Kemfert, 2011). In other words, the optimal amount of storage capacity (social standpoint) is not incited by the free market

A possible solution is to adopt system that adapts the consumption of energy to the supply of renewable or that lowers the consumption in general. An example of this is pre-cooling houses (Calero, Cañizares, Bhattacharya, & Baldick, 2022) However, these solutions are often specific to agents (at firm-scale) or to a specific use. In my analysis, I will only treat the supply-side of the energy market. There will be some mentions of the demand but the problem of negative price and volatility should be approached from the supply-side towards the demand-side and not on the other way. This dissertation assumes the problem comes from an inadequate supply instead of inadequate demand.

However, these different studies implicitly consider that the economy is an 'island'. This is the hypothesis that the thesis will mainly discuss. As (Bistline, 2017) has shown, international exchanges matter on the paradox. First, the excess former described can be exchanged to a country in needs of energy instead of selling for a negative price within the country. It should reduce the profitability problem. The second advantage is that the energy mix could contain more renewable energy by importing some energy from countries producing in excess (relative to their domestic demand).

2.3 Question of the thesis

The objectives of the dissertation will be to assess the impact of international exchanges of energy in Belgium on the price, the limits of exchange benefits and its place in renewables-promoting policies. Exchange is potentially interesting to reduce volatility and still letting competition plays its role although it does not seem enough to promote intermittent energy. If we miss to consider the effect of these exchanges, it might be a problem to consider the effect of Variable Renewable Energy (VRE) or other solutions.

For the analysis, several ARDL models and VAR are explored. These models suffer from autocorrelation and heteroscedasticity. In order to search for an explanation, a complementary analysis of negative day-ahead price was made. Contrary to many previous works, the demand is not assumed to have a specific form.

3 Literature review

3.1 Basis of the theoretical framework

3.1.1 The paradox of renewables

As mentioned previously, (Blazquez et al., 2018) represents the theoretical framework of the problem. The framework assumes that the electricity market is a free competitive market and that intermittent energy has a constant very low marginal cost[3] for renewable sources. The nature of the market matters for the determination of the price. A non-competitive market is less affected by the 'merit-order effect' due to the optimisation of the profit (Acemoglu, Kakhbod, & Ozdaglar, 2017). Compared to many empirical studies (for instance (Zipp, 2017)), my dissertation does not assume a specific form of demand. The conclusions of (Blazquez et al., 2018) are that the deployment of VRE needs to coexist with fossil fuel technologies and that this deployment cannot be achieved within a liberalised market. Renewable investments are not profitable for private agents indefinitely. There is a point where too much renewable in the generation mix erodes price such as the profit is also eroded. This problem cannot happen in a planned economy. The competition mechanism is not efficient for the integration of VRE. The marginal profit is too low when the deployment is important and the volatility of the price is too high. The proposed solutions require interventions of the State.

(Prokhorov & Dreisbach, 2022) is an example, among many, of a study seeing the impact of renewables on spot/day-ahead prices. It is also a good example of a study using other tools than econometrics to the analysis (in this case, it is a simulation). They conclude that without any change in the regulation (auction design, bidding system, ...) the instances of negative price will increase in Germany through the deployment of intermittent renewables. As said, it is a paper among many that study the relationship between VRE and price and conclude/admit with proof the empirical existence of the 'paradox of renewables'

In the theoretical model, any variable renewables should increase the volatility of price. According to (Maciejowska, 2020), wind energy can decrease it in high demand periods and solar energy can stabilise in intermediate demand level.

3.1.2 The Duck curve

A famous way to represent the problem of volatility and the problem of mismatch supply-demand is to use the Duck Curve. This curve appeared for the first time on (California ISO, 2016). The curve represents the net load, which should be interpreted as the demand that must be served by pollutant-fuel energy. This 'Duck' represents three phases of the day. The first phase is the 'tail', where the demand is low and production of VRE is low. The second, when the mix-energy consists of a high share of VRE, shows the 'belly'. This belly is caused when the demand increases slower than the increase in VRE production. The net load therefore decreases and is the hearth of the first problem, which is to have an excess/a net load negative. The last step is the 'neck', where the demand is at its peak and the production of VRE decreases.

This curve is often used to analyse the potential solutions of balancing supply and demand. Without any intervention, the deployment of intermittent renewable energies increases the risk of oversupply in the 'belly'. The deployment also causes important change in the net load.

[3]Hence the 'zero-marginal cost' assumption in the literature.

The problem is to find an optimal way to smooth the curve. One of the potential solutions is to avoid the oversupply, for instance via the storage. An example of this study is (Pitra & Musti, 2021). Another way is to export the excess. Without these solutions, we need to rely on flexible energy sources, which currently are often pollutant-fuel.

It could be added to the discussion that, instead of studying the price, we can study the quantity. shows how storage can be used to smooth the duck curve and avoid imbalance on the market. As we will see over the dissertation, price is highly correlated with the quantities. In the approach I used, the focus is on the price given exportation is supposed to reallocate the quantity where it is needed, even if this not sufficient to smooth completely the duck curve of each country.

3.2 Storage: part of the solution?

The basic theoretical framework presented in 3.1.1 implicitly assumes that energy must be exchanged in the same moment of its production. The way to avoid this is to use storage, which allows to sell for a later period. In theory, producers should store when the supply is superior to the demand, which is called excess. If this energy is not stored, it must be sold for a negative price[4]. The energy stored will be sold in a period where the price is higher, which happens when the production of intermittent renewable energy is low or absent and when the demand is especially important. This will decrease the price (increase of supply) when stored energy is sold.

However, there are many questions about their attractiveness because they are many costs related too. Storage might also create a free-rider problem. There is already a theoretical proof for a duopoly with (Zhao et al., 2019). The authors modelled the decision of storage investment and their bid in the day-ahead market. Their conclusions are that uncertainty increases the profit and therefore reduces the incentives to invest in storage, given storage reduces the uncertainty. Reducing the uncertainty increases the competition and, therefore, decreases the profit of producers. If a producer invests, all producers benefit. This situation creates a free-rider problem. The first-mover is disadvantaged of investing because it supports the cost while the others also reap the benefits.

Another conclusion is that storage has no benefits when every player invests in. This situation could lead to a profit of zero when the demand is too low. A situation where at minimum a player does not invest presents positive profits. An absence of storage maintains the uncertainty and decreases the competition, which firms leverage to increase price.

(Motalleb & Ghorbani, 2017) assumes a non-cooperative game with incomplete information. The assumption is that the competition is Stackelberg and prosumers (consumer and producer of energy in the same time) can participate. The authors concluded that limitation for transactions powers and price decreases the expected profits, compared to an unlimited and unscheduled demand resources case. The presence of the leader decreases the expected profits of the other players.

As mentioned in the introduction, storage capacity is not fully utilised (Schill & Kemfert, 2011). The authors showed that the capacity is the most used when there is perfect competition in the storage utilisation and the conventional generation. Storage capacities are under-used in less competitive market and there are less incentives to invest in. In this paper, they also showed that the storage utilisation depends on the the distribution of the storage capacity. They also conclude that there is a prisoner dilemma, where producers have incentives to use storage although they would be better off if some producers do not use. The ownership of storage matters to the distribution of economic surplus.

[4]I only consider the situation where selling at negative price is more profitable than disconnect from the grid. At my knowledge, the disconnect case/the temporally shut down of production is rare and not much sourced in the literature.

In all cases, storage helps to smooth price. The introduction of storage can create welfare but there is a redistribution: consumers and merchant storage are better off contrary to the energy producers

(Zhao et al., 2019) have the same conclusion on the incentives to invest. They put the focus on the free-rider problem. These conclusions are contrary to (Li & Hedman, 2014), which have shown that storage becomes more attractive over the renewable production. This difference might be due to their other conclusion, which is conventional generation loses in attractiveness as renewables are deployed. However, storage can be used to provide a stable supply (Z. Zhang, Makowski, Nahorski, & Granat, 2024).

In the literature, storage has been shown as a potential tool to reduce price volatility but this is not incited because producers[5] lose to use storage. Transmissions with other countries can lead to the same effect on the price but does not suffer from free rider problem.

3.3 Hypothesis of 'island economy'

As mentioned earlier with (Bistline, 2017), international exchanges matter for the paradox. In order to avoid selling at a negative price, there is the possibility to sell to other countries that need. The renewable-fuel energies could be exchanged between two (or more countries). The interest is when the countries have different demand and production profiles. A country with a high-demand but a low (VRE) production could buy to a high-producer country with a low demand, respectively, to the production of the foreign country. The period after, the seller becomes the buyer and the buyer the seller. In such a situation, the risk of negative marginal profit might be lower because companies can ensure a part of the profit by selling to other countries, which would be a higher price than periods with high supply and low demand in Belgium.

(Bistline, 2017) describes this as the temporal and spatial variability increases the value of the VRE. This might be an important factor to the deployment because the current market design might be too local to valorise VRE at an enough good value to incentive its implementation by private agents. In this perspective, it is important that countries involved in the exchange have different profiles. However, this solution is not sufficient by itself for the implementation given the price still decline in the penetration.

In his model, the storage increases the value of VRE although the merit-order effect remains the same. The storage value depends on the penetration of VRE and depends on the storage capacity, which is consistent with other studies.

Increasing flexibility, either by storage or new transmission capacity, reduces the subsidies used as renewable supports (Brown & Reichenberg, 2021). Therefore, transmissions between regions could be favoured by Governments willing to allocate a lower part of their budget for spending. It is important to ensure that exportation's drawbacks are known and studied to take them into account correctly.

3.4 Difficulty of modelling energy price

As we will see in the analysis part, modelling the energy price deeply changed these last years with the integration of variable renewable energy sources. What changed are the volatility has increased and the increase of structural changes.

[5] If we consider that storage owners are different from energy producers, the discussion is slightly different.

(Tselika, 2022) showed that using aggregate data minimise the effect of intermittent renewables. The author also showed that the impact of the different sources on price is different given the quantile of the price. Wind energy has more effect on lower tail and increases the price volatility while solar energy has more effect on higher tail. (Maciejowska, 2020) has the same conclusion.

The price volatility increases in the intermittent renewable production. One of the reasons is that the likelihood of negative prices increases in a non-linear way. There is a structural break after a certain amount produced, depending on the flexibility of the grid (Pavlík, Kurimskỳ, & Ševc, 2025).

The price volatility is sensitive to the change of the demand. As (Blazquez et al., 2020) have shown in 'their stages in the energy transition', the more renewable energy is on the market, the less supply can adapt itself to the demand. This means that demand component must be included. However, the demand is determined on the same time as price. Care must be taken.

4 Methodology

The database is composed of hourly day-ahead prices (DHP) (Elexys, 2025a), net position of the energy balance of Belgium (Elia, 2025), the net physical flow of energy between Belgian and the neighbour countries (Germany, France, The Netherlands, the United Kingdom and Luxembourg) (Elia, 2026b), the total load of Belgium (Elia, 2026a), EEX ZTP gas spot (monthly average) [6] (Elexys, 2026) and the generation mix of Belgium (including the energy from storage) (Elia, 2026c). At the exceptions of the hourly DHP and the gas price, the variables were quarter hourly data. To treat them in the analysis, I aggregated them.

I used hourly data because of the volatility of price and the number of variables. Daily average could prevent to detect or could minimise the merit-order effect. This has also the inconvenient to not see the hourly dynamics. However, it could reduce the error terms. Examples of daily average data use are (Zipp, 2017) and (Mulder & Scholtens, 2013). quarter hourly data would have been the most adapted because it provides more detailed results. I did not use the quarter hourly spot price because in Belgium, this is a new practice (since October 2025, BELPEX traded in quarterly (Elexys, 2025a). quarter hourly price measured since August 2025 (Elexys, 2025b)) and therefore month seasonality would have been potentially undetected. For the other variables, there would not have been problems because there were already in quarter hourly. The 'hourly database' solved this problem thanks to a more important number of observations but tribute the accuracy.

Given there was only one value of gas price per month, it was extended for the whole month. For example, the monthly average gas price was €11.19 in January 2020. Therefore, each observation of January 2020 considers that the gas price is €11.19. At my knowledge, there is no public available dataset with a more precise gas price. Gas price is a driver of the energy price. I did not consider oil price because oil price is a driver of the gas price (risk collinearity) (Biber et al., 2022).

Missing data for the generation and the physical flows was considered as zero. The missing data for the physical flows is due to the absence of exchange (before possibility of exchange).

The 'hourly dataset' starts at first January 2020 00:00 and ends at 31$^{\text{th}}$ July 2025 22:00 [7]. From October 2025, there is no more hourly day-ahead price but only quarter hourly day-ahead price.

The initial methodology was to use ARDL regressions to take into account the high autocorrelation of Day-Ahead Hourly Price (DHP). This method also enabled to include other factors that are important to take into account, such as the border capacities, gas price and of course the production of renewables.

However, as we will see, it is difficult to create a model that does not suffer from autocorrelation and heteroscedasticity [8]. An 'alternative' (VAR) was examined in order to find any solution. These points will be discussed later.

To complement the reflection around these issues, there is an analysis of the negative DHP. To this part, I used a method similar to (Pavlík et al., 2025). This is useful to understand the nature of the modelling problems. First, the volatility is not linear in the integration of intermittent renewables. Second, the volatility is multi-factorial and cannot simply be modelled with the data I used. The

[6] The ZTP index was used instead of the TTF to be closer to Belgium reality. The ZTP index is the price in Belgium while the TTF index is the EUropean price. It could be argued to use the TTF if we consider the spillover effects important. In this case, I considered that the electricity imported in Belgium is more likely from renewables than from fuel sources.

[7] It is 10 PM. It is possible that some parts still contain formal time format because it is commonly used in Belgium.

[8] It appears that the appropriate method requires model types I have not learnt. Unfortunately, I have noticed it too late and I was not able to study quickly enough the methods. Please see 6.3 for more information

crises as we have lived these last years impact heavily the models, more than simply via the gas price. These points will be deepen later.

5 Analysis

5.1 Stationarity

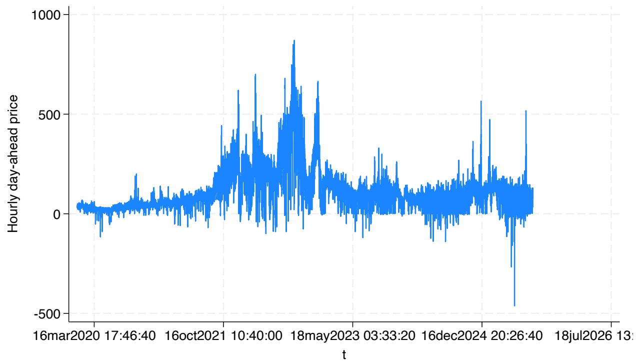

Figure 1: Hourly day-ahead price

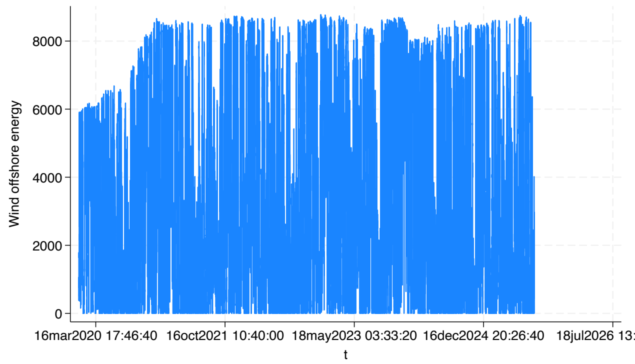

Figure 2: Wind offshore energy production

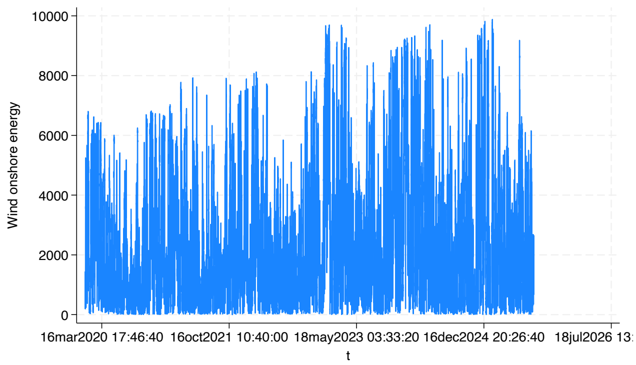

Figure 3: Wind onshore energy production

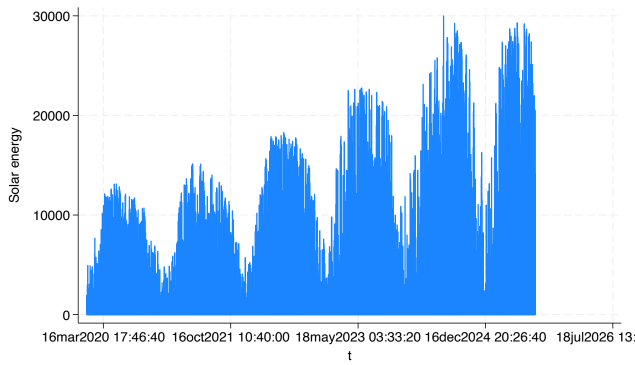

Figure 4: Solar energy production

Figure 5: Graphs based on the date from (Elexys, 2025a) and (Elia, 2026c)

The readers can see a representation of the main variables (from the 'hourly database') at the figure 1 to 4. Despite the high volatility, we can expect that these series are stationary, potentially around a trend. For solar energy generation, peaks grew over times. This is expected given the nature of solar energy. This presents a risk of being non-stationary. However, the first difference is probably non-stationary given the quadratic form of the production over time.

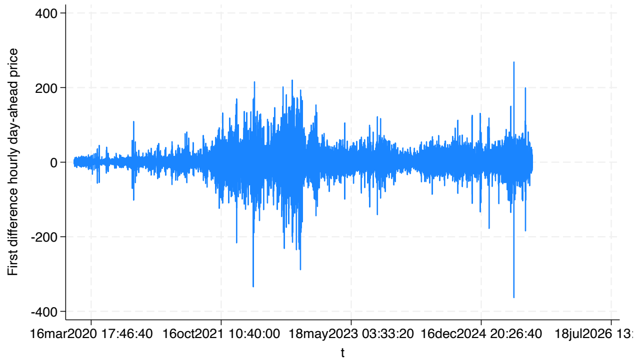

Figure 6: First difference of hourly day-ahead price

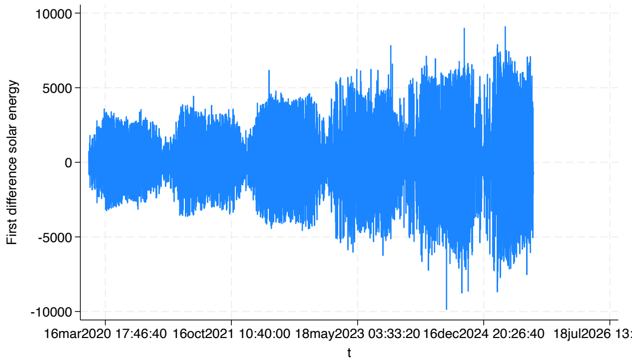

Figure 7: First difference of solar generation

Figure 8: Graphs based on the date from (Elexys, 2025a) and (Elia, 2026c)

As the readers can see, the first difference of solar generation (figure 7) cannot prevent the increasing variance. Taking the first difference of DHP (figure 6) can smoother the peaks but this does not reduce (relatively) the variance. A closer glance at the graph can help the readers to see that most of the peaks happen during energy crises. In this perspective, I preferred to take the result of the Augmented Dickey-Fuller (ADF). Including the gas price should help to take into account of the peak in 2022.

The different Augmented Dickey-Fuller (ADF) tests include the trend to compare with ADF tests associated without trend. In the different ADF tests, the different variables are stationary not around a trend. For some of the ADF tests with a trend component, we should not reject the null hypothesis (non-stationary). However, these trends are not significant. For these variables, the ADF test without the trend component leads to reject the null hypothesis.

5.2 Seasonalities

Wald test	$F(45, 48841) = 1425.36$
	$p = 0.0000$

Table 1: Wald test of hourly day-ahead price on time dummies; based on my calculation from the database

The models should include hourly periodicities and daily, monthly and yearly seasonalities. This should help to deal with some autocorrelations.

Including seasonalities help to improve the model because it will capture demand features. The demand is highly dependent on the moment of the day, of the week and/or of the year. For example, demand is lower during the night due to a non-consumption of the lighting. Habits and lifestyle drive in an important way the demand.

Some dummies are negative correlated with the DHP at unexpected hours (11AM - 3PM) . This is less paradoxical that it seems if we consider that this is the period of solar energy generation, which decreases the DHP, as we have seen in the literature review.

5.3 Outliers

	mean	sd	min	max	count
Hourly day-ahead price	107.2707	100.6782	-462.33	871	48887
DHP - outliers	377.3101	111.8513	-462.33	871	3610

Table 2: Descriptives statistics: General DHP VS outliers; based on my calculations and data (Elexys, 2025a)

There are 3,610 outliers if we use the Box-plots (Inter-quartile range 1.5), which means that more than 5% of observations are outliers. These outliers are mainly driven by the most important DHP. As we can see, the outliers are present in the low and in the high prices.

5.4 Detection of the autoregressive terms via univariate models

In order to prevent some problems of autocorrelation or problems of heteroscedasticity, I tried to create a simple ARMA model. This ARMA is the basis of my ARDL model. As we will see, there is likely a seasonal component other than the dummies detected earlier. A SARMA model was also tried.

5.4.1 ARMA

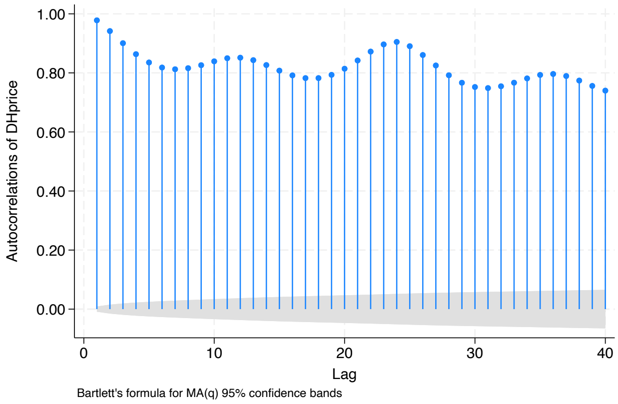

Figure 9: ACF of DHP

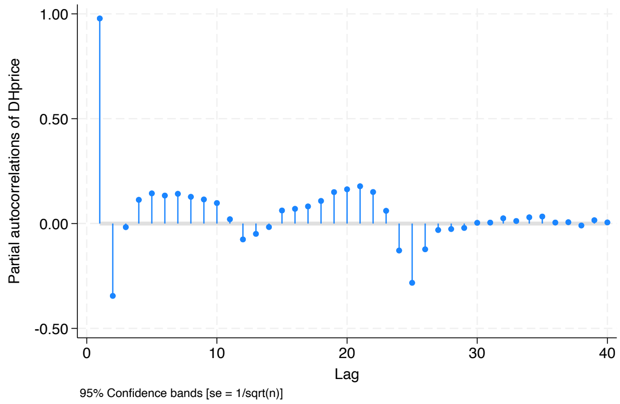

Figure 10: PACF of DHP

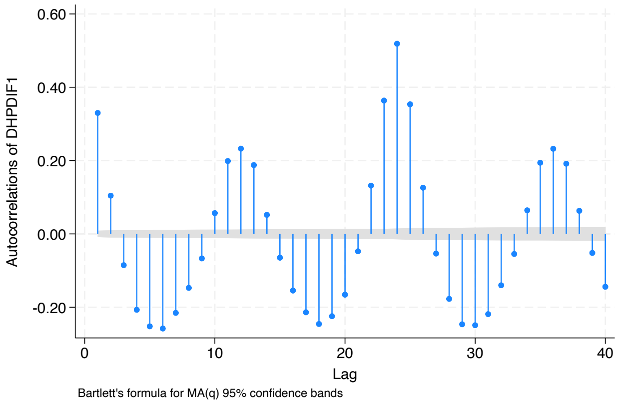

Figure 11: ACF of first difference of DHP

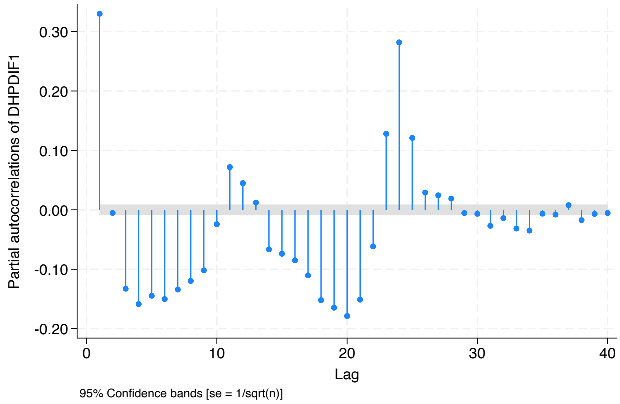

Figure 12: PACF of first difference of DHP

Figure 13: Based on calculations from the database

As the ACF of DHP is slowly decreasing and the PACF of DHP of has two peaks, I tried a model AR(2) but as expected, this model suffered from autocorrelation but also from heteroscedasticity. Later, I also test to include the 24^{th} lag to take into account of the seasonality. Unfortunately, I cannot explain why these graphs have so specific forms. I suppose that the error of the precedent periods are strongly correlated to the DHP but I do not know how much I should use such as the model is efficient and that I can compute.

Using the first difference helps to reduce the problem but reduce the interpretability. We can see there are many parts that seem seasonal. Unfortunately, I cannot find any explanation except for the 24^{th} lags, which will be likely related to the production of solar energy and to similarities of demand between consecutive days. With the first difference, I tried a ARMA(1,1) given in both graphs there are important peaks at 1. These models do not give satisfying model because the ACF and PACF of the residuals are very similar to the ACF and PACF of the first difference. However, there is a peak at 24^{th} lag for each correlograms of the residuals. In the attempt to have something coherent, I tried a SARMA.[9].

[9]It should be noted that I also tried to reduce the number of observations to see if this problem comes from structural

5.4.2 SARIMA

For the seasonal component, I considered a 24th lag. This represents the price the day before at the same moment. The SARIMA tested is a SARIMA(2, 0, 0)(1, 0, 1)[24]. Unfortunately, as the readers can see on the ACF (figure 14) and PACF (figure 15), the residuals have still a weird behaviour. At this stage, it seems that there is nothing else to do that is coherent with an interpretation. Moreover, including too much lags could impact negatively the results because these variables are likely to be correlated with the production of intermittent renewables. In Belgium, intermittent renewables have an important place in the energy mix and given their non-negligible effect on the price, it seems more cautious to avoid including too much correlation.[10]

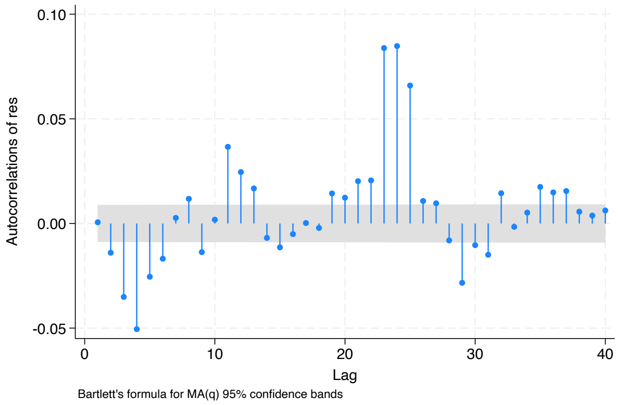

Figure 14: ACF of the residuals from the SARIMA

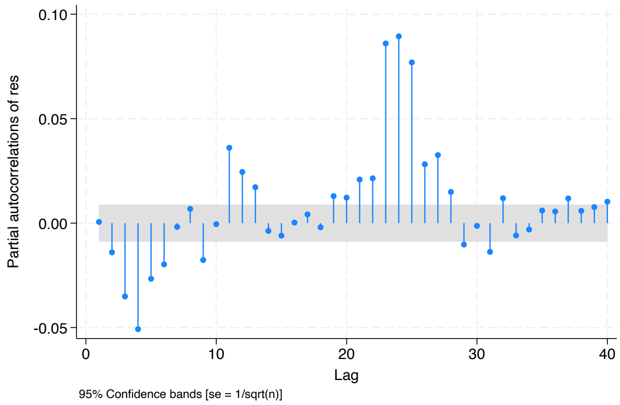

Figure 15: PACF of the residuals from the SARIMA

Figure 16: Based on calculations from the database

Even if the 24th and around lags are still significant, the scale of the graph drastically reduced. At this stage, it is difficult to deduce if this is due to a possible way to predict the production, the demand, another factor or a combination of these factors. Making heavy the univariate model risks to diminish the interpretation of the multivariate models.

Before passing to the the multivariate models, it might be worth it to check if the integration of different time dummies (hour, day, month and year) could improve the autocorrelation and moving average of the residuals, as well as gas price (a lag 1 and a lag 24 were added). Including the gas price should help to prevent the excess of influence from the outliers.

changes as discussed later. The different ACF and PACF are not different. You can see this ACF and PACF in the appendix

[10]The exploration of better univariate model was more important than what was mentioned but any important change was explained here.

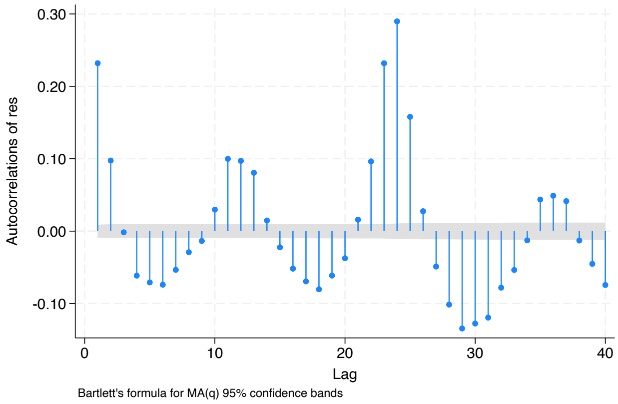

Figure 17: ACF of the residuals

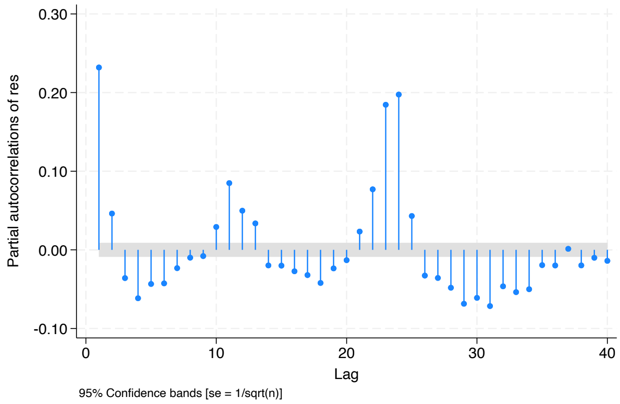

Figure 18: PACF of the residuals

Figure 19: Based on calculations from the database

We can see that it did not improve the situation. It shows 3 things. The first thing is thar AR(2) matters. The second is that without MA(1) the model loses a lot. Compared to the graphs for the DHP, the scale is better but the significant lags do not have the same signe. The problem is that MA(1) cannot be added to ARDL models.

I tried to create a SARMA to analyse the pattern of DHP a day based on the same day the year before but my laptop was not able to compute the calculation [11].

5.5 Comparisons of the models

5.5.1 ARDL models

VARIABLES	(1) DHprice	(2) DHprice	(3) DHprice	(4) DHprice	(5) DHprice	(6) DHprice
L.DHprice	1.044***	1.023***	0.928***	0.928***	0.919***	0.942***
	(0.00454)	(0.00453)	(0.00457)	(0.00455)	(0.00456)	(0.00456)
L2.DHprice	-0.135***	-0.133***	-0.0799***	-0.0753***	-0.0710***	-0.115***
	(0.00654)	(0.00647)	(0.00621)	(0.00618)	(0.00616)	(0.00442)
L3.DHprice	-0.0691***	-0.0670***	-0.0386***	-0.0401***	-0.0315***	
	(0.00653)	(0.00647)	(0.00616)	(0.00612)	(0.00604)	
L4.DHprice	0.0547***	0.0323***	0.0284***	0.0262***	0.0395***	
	(0.00435)	(0.00431)	(0.00415)	(0.00413)	(0.00388)	
solar	-0.00310***	-0.00301***	-0.00225***	-0.00254***	-0.00341***	-0.00201***
	(0.000124)	(0.000118)	(0.000112)	(0.000113)	(0.000109)	(0.000103)
L.solar	0.00193***	0.00145***	0.00117***	0.00134***	0.00235***	0.00114***
	(0.000265)	(0.000213)	(0.000201)	(0.000201)	(0.000199)	(0.000195)
L2.solar	0.000263	0.000959***	0.000581***	0.000702***	0.000807***	0.000549***
	(0.000265)	(0.000120)	(0.000114)	(0.000114)	(0.000110)	(0.000107)
L3.solar	0.000513***					
	(0.000126)					

[11] I waited two hours with a fresh new MacBook (a MacBook Pro, Apple M5, 24Go).

onshore	-0.00132***	-0.00197***	-0.00144***	-0.00173***	-0.00292***	-0.00191***
	(0.000283)	(0.000233)	(0.000264)	(0.000265)	(0.000266)	(0.000269)
L.onshore	-0.000747	0.000837***	-0.000678	-0.000369	0.00110**	-0.000177
	(0.000483)	(0.000229)	(0.000451)	(0.000449)	(0.000453)	(0.000458)
L2.onshore	0.00132***		0.00114***	0.00127***	0.00131***	0.00145***
	(0.000278)		(0.000260)	(0.000260)	(0.000264)	(0.000264)
offshore	-0.000176***	-0.000206***	-0.000258***	-0.000903***	-0.00134***	-0.000412***
	(4.32e-05)	(4.27e-05)	(4.05e-05)	(0.000125)	(0.000127)	(4.34e-05)
L.offshore				0.000623***	0.00104***	
				(0.000127)	(0.000129)	
Gas price		0.187***	0.142***	0.143***	0.157***	0.199***
		(0.00567)	(0.00551)	(0.00552)	(0.00440)	(0.00434)
lagdhp24			0.288***	0.281***	0.284***	0.333***
			(0.00418)	(0.00417)	(0.00409)	(0.00406)
L.lagdhp24			-0.149***	-0.145***	-0.154***	-0.179***
			(0.00616)	(0.00613)	(0.00609)	(0.00616)
L2.lagdhp24			-0.0741***	-0.0721***	-0.0751***	-0.0992***
			(0.00621)	(0.00617)	(0.00612)	(0.00614)
L3.lagdhp24			-0.0195***	-0.0200***	-0.0191***	-0.0171***
			(0.00441)	(0.00439)	(0.00432)	(0.00396)
Net position			0.000144***			
			(4.73e-05)			
France				0.00108***	0.00142***	0.000690***
				(5.57e-05)	(6.54e-05)	(4.83e-05)
L.France				-0.00106***	-0.00113***	-0.00107***
				(5.40e-05)	(9.49e-05)	(6.87e-05)
L2.France					-0.000347***	0.000366***
					(6.41e-05)	(4.42e-05)
Germany				0.000464***	0.00101***	0.000127***
				(6.79e-05)	(7.74e-05)	(3.56e-05)
L.Germany				-0.000230***	-0.000429***	
				(8.46e-05)	(0.000106)	
L2.Germany				-0.000262***	-0.000598***	
				(5.93e-05)	(7.67e-05)	
Luxembourg				0.000157		-0.00189***
				(0.000232)		(0.000445)
L.Luxembourg						0.00234***
						(0.000553)
L2.Luxembourg						0.00198***
						(0.000394)
Netherlands				0.000858***	0.00145***	0.000649***
				(6.25e-05)	(7.21e-05)	(5.70e-05)
L.Netherlands				-0.000659***	-0.000891***	-0.000676***
				(8.33e-05)	(0.000106)	(5.64e-05)
L2.Netherlands				-0.000317***	-0.000662***	
				(5.31e-05)	(7.23e-05)	
UK				-0.000218***	0.000238***	-0.000610***
				(4.14e-05)	(9.11e-05)	(3.37e-05)
L.UK					-0.000106	
					(0.000126)	

L2.UK					-0.000523***	
					(9.00e-05)	
totalload					0.00315***	0.000542***
					(7.89e-05)	(1.66e-05)
L.totalload					-0.00216***	
					(0.000142)	
L2.totalload					-0.000643***	
					(8.37e-05)	
outliers	24.91***	24.90***	21.48***	21.23***	18.85***	21.25***
	(0.474)	(0.469)	(0.445)	(0.444)	(0.422)	(0.433)
Constant	5.501***	2.938***	3.581***	2.654***	-6.476***	-12.46***
	(0.590)	(0.589)	(0.557)	(0.605)	(0.599)	(0.590)
Time dummies	V	V	V	V	X	X
Observations	48,879	48,879	48,831	48,831	48,831	48,833
R-squared	0.972	0.973	0.976	0.976	0.976	0.975

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: ARDL models; based on calculations from the database

France, Germany, Luxembourg and Netherlands are the variables for the physical flows from (if positive value) or to Belgium (if negative value). Net position is the implicit net position.

On the different ARDL models, we can see that the first lag of the price has an important influence on the DHP. It might be due to 2 reasons: either a part of the demand remains between the hours or the production of other sources adapts slowly, which could lead to a lower supply. The other lags do not give hints.

On the first ARDL model, solar and wind energy contribute to decrease the price as expected by the literature. For solar energy and for onshore wind energy, the price increase in the next periods. With the lags of price and the short time production, this means that the DHP is higher after 1 or 2 hours of the production of intermittent renewables; everything else remains equal. This is consistent with the theory. What is interesting is that this situation does not seem to happen with offshore wind energy. Is this because their production is less volatile and more constant over time?

On the second ARDL model, the gas price was included. The gas price seemed to change some coefficients, which tends to show that in the previous models the lags of price captured effect that should be attributed to the gas price. The wind energy (onshore and offshore) is associated to lower coefficient.

On the third ARDL model, the 24^{th} lag of the DHP and the implicit position of Belgium were added [12]. The lags of the 24^{th} lag were added, which means that the price of 2 (and more) days before where considered. This addition is useful because it indirectly considers the current situation of the demand, potential breaks around 4 days, ... The wind energy (onshore and offshore) is associated to lower coefficient, which means that wind energy has more impact. Solar energy has higher coefficient, which is likely due to a part of its effect captured by the 24^{th} lag. The idea is that solar energy is more regularly and is similar between the days, given sunshine should be similar between 2 days. A stable consumption behaviour was captured by solar energy coefficient. A part of the effect from the gas price has been captured by the 24^{th} lags due to the way the database was constructed.

[12] The coefficient of the 24^{th} lag does not change if we exclude the implicit position.

Implicit position has a positive coefficient, which is expected because the supply is 'transferred' to another State. The supply decreases in Belgium and therefore the price is increasing. In this perspective, exchange seems to be a potential tool to deal with negative DHP. However, the impact on the price is clearly lower than the production of any type of intermittent renewable according to the model. For example, the impact of 1 MWh onshore wind energy is compensated if Belgium exports slightly less than 10 MWh.

On the fourth to the sixth ARDL model, the implicit position was replaced by the physical flow. As expected, most of the exportations have positive impact on the price. However, the coefficients are different. Exportation to United Kingdom is negatively correlated to the DHP. I imagine there is a mechanism behind that is correlated to exportation towards United Kingdom. I have no supposition about this mechanism. Exportation to Luxembourg is insignificant. It might be due to low exported quantity, which could mean that Belgium exports to Luxembourg in the last moment. For the 3 other countries, the signs are positive. Their amplitudes are different, which could mean that there might be an order of preference. In this perspective, the countries with the most important (positive) coefficient are the first countries importing. This order could be due to more important demand and to higher attractiveness (higher price). Therefore, United kingdom would be a country where Belgium exports in the last resort, namely when price is drastically low. The coefficient associated to the United Kingdom would capture some extreme conditions effect. This theory would explain why some coefficients are lower. The countries with lower coefficients would be less interesting due to a lower demand and exchanges would happen only if needed. The problem with this theory is that if there is an asymmetry in the exchange effect (import versus export), some coefficients would be biased. A second remark is that if the order of preference is France, Netherlands, Germany, Luxembourg and United Kingdom (the highest to the lowest coefficient), it would mean that since 2006 Netherlands became more interesting. According to (Lise et al., 2006), exportations of electricity will have gone first to Germany because the price of electricity was more expensive (more profitable). In this perspective, the foreign electricity market matter for the Belgian market. Energy transition in foreign countries should make them less attractive for Belgian exportation. Exchange between countries could therefore be a solution of short and medium terms and must be monitor to ensure appropriate policies.

The fifth and sixth ARDL models include the total load, which is a proxy of the demand and replace the previous time dummies. These models assume a perfectly inelastic demand, which is common in the literature (for instance (Zipp, 2017)). The fifth removes the flow to Luxembourg while the sixth includes it. The total load is correlated with higher price, which was expected. The amplitude of total load divided by 6 with the introduction of flow towards Luxembourg. A potential explanation is that Belgium exports to Luxembourg when the domestic demand is too low to absorb the supply. Such situation should happen when intermittent renewable production is important. This explains the negative coefficient. When Belgium exports to Luxembourg, the quantity exported is too low to fully manage the 'supply surplus'[13]. The coefficient for Luxembourg and United Kingdom are negative probably because they absorb a part due to very negative condition for the producers, namely too important production.

The coefficients of intermittent renewables production and the coefficients of exportation (except for the United Kingdom) were much more important when the total load is including, showing that using there are some dynamics between the demand and the exportation that are not captured with the dummies. If we include the physical flow to Luxembourg, the coefficient for solar energy became much lower than the coefficient of the first models. This might mean that most exportation to Luxembourg happen when solar energy is produced. In the negative price analysis, we will see that the production

[13]This term is technically false if we consider that if the supply is sold, even for a negative price, the market managed the situation. Here, I consider as 'supply surplus' all energy sold for a negative price. The rational is that this energy is a charge for the buyer instead of being a 'classical input'.

of intermittent energy is the highest only in moments with production of solar energy. In general, coefficients of intermittent renewables are lower when we introduce physical flow. This support the initial theory. The models are therefore sensitive to the introduction of exportation.

The introduction of exchange with Luxembourg also changes the coefficient of the other 'exchange' variables. This is likely due to an omitted variable biases.

It should be noted the total load is for Belgium. Because we include the exportation, we can partly see the effect of the Belgian demand even if this is more difficult because of the simultaneity of the market equilibrium.

All of these models suffer from heteroscedasticity and from autocorrelation. Moreover, many variables seem to be highly correlated. In order to deal with the problem of possible endogeneity, several VAR models were tested.

I could not detect structural breaks with a Bai-Perron test, even with my newest laptop (a MacBook Pro, Apple M5, 24Go). Testing specific breaks would be difficult because there might be many breaks as discussed later. These breaks could have different origins, which would have required more time to list them.

5.5.2 VAR model

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	DHprice	Solar	Offshore	Onshore	Net position	Storage
L.DHprice	0.944***	-1.152***	-0.790***	-0.375***	1.863***	0.000996
	(0.00527)	(0.190)	(0.164)	(0.0810)	(0.294)	(0.00690)
L2.DHprice	-0.105***	1.200***	0.217	0.0156	-0.738*	-0.00200
	(0.00713)	(0.256)	(0.222)	(0.109)	(0.397)	(0.00933)
L3.DHprice	-0.0346***	-0.188	0.151	0.0885	-0.0771	0.0125
	(0.00713)	(0.256)	(0.222)	(0.110)	(0.397)	(0.00934)
L4.DHprice	0.0348***	-0.146	0.000400	0.123	-0.244	-0.00601
	(0.00518)	(0.186)	(0.161)	(0.0796)	(0.288)	(0.00678)
L.solar	-0.00409***	1.956***	-0.00403	-0.00127	0.0278***	-0.00312***
	(0.000144)	(0.00518)	(0.00448)	(0.00221)	(0.00802)	(0.000189)
L2.solar	0.00473***	-1.490***	0.0227**	0.0320***	0.124***	0.00558***
	(0.000305)	(0.0110)	(0.00948)	(0.00468)	(0.0170)	(0.000399)
L3.solar	-0.00113***	0.605***	-0.0289***	-0.0570***	-0.250***	-0.00434***
	(0.000306)	(0.0110)	(0.00953)	(0.00471)	(0.0171)	(0.000401)
L4.solar	0.000204	-0.160***	0.0139***	0.0286***	0.112***	0.00216***
	(0.000146)	(0.00526)	(0.00455)	(0.00225)	(0.00815)	(0.000192)
L.offshore	-0.000633***	0.0275***	1.299***	0.0608***	0.0220**	-0.000832***
	(0.000166)	(0.00597)	(0.00516)	(0.00255)	(0.00924)	(0.000217)
L2.offshore	0.000111	-0.0319***	-0.384***	-0.0283***	0.173***	0.00203***
	(0.000271)	(0.00975)	(0.00843)	(0.00416)	(0.0151)	(0.000355)
L3.offshore	0.000180	-0.0115	0.0597***	-0.00172	-0.237***	-0.00141***
	(0.000272)	(0.00978)	(0.00846)	(0.00418)	(0.0151)	(0.000356)
L4.offshore	0.000115	0.00920	-0.0341***	-0.00884***	0.0457***	0.000256
	(0.000169)	(0.00607)	(0.00525)	(0.00259)	(0.00940)	(0.000221)
L.onshore	-0.00335***	0.00863	0.212***	1.566***	-0.0206	-0.00201***

	(0.000331)	(0.0119)	(0.0103)	(0.00508)	(0.0184)	(0.000433)
L2.onshore	0.00243***	-0.0776***	-0.169***	-0.746***	0.121***	0.00278***
	(0.000612)	(0.0220)	(0.0190)	(0.00939)	(0.0341)	(0.000800)
L3.onshore	0.000745	0.0758***	0.0538***	0.164***	-0.135***	-0.000407
	(0.000611)	(0.0220)	(0.0190)	(0.00939)	(0.0340)	(0.000800)
L4.onshore	-0.000861***	-0.0120	-0.0545***	-0.0315***	0.0264	-0.000232
	(0.000328)	(0.0118)	(0.0102)	(0.00504)	(0.0183)	(0.000429)
L.Net position	0.000362***	-0.0146***	-0.0131***	-0.00292**	0.766***	7.53e-05
	(9.03e-05)	(0.00325)	(0.00281)	(0.00139)	(0.00503)	(0.000118)
L2.Net position	6.53e-05	0.00520	-0.00314	0.00253	-0.0141**	3.47e-05
	(0.000114)	(0.00409)	(0.00354)	(0.00175)	(0.00633)	(0.000149)
L3.Net position	-0.000413***	0.0130***	0.00291	0.00110	0.00234	6.33e-05
	(0.000114)	(0.00408)	(0.00353)	(0.00174)	(0.00632)	(0.000149)
L4.Net position	7.26e-05	-0.000720	0.00573**	-0.00299**	0.0242***	-0.000142
	(8.91e-05)	(0.00320)	(0.00277)	(0.00137)	(0.00496)	(0.000117)
L.storage	-0.00450	1.447***	0.424***	0.0908	-0.943***	0.428***
	(0.00384)	(0.138)	(0.119)	(0.0589)	(0.214)	(0.00502)
L2.storage	-0.0106**	0.226	0.111	0.111*	-0.478**	-0.108***
	(0.00419)	(0.151)	(0.130)	(0.0644)	(0.233)	(0.00548)
L3.storage	-0.000963	0.250*	0.122	-0.0396	0.177	0.00592
	(0.00419)	(0.151)	(0.130)	(0.0643)	(0.233)	(0.00548)
L4.storage	0.00885**	-0.563***	-0.119	0.0707	-0.650***	-0.0312***
	(0.00381)	(0.137)	(0.118)	(0.0585)	(0.212)	(0.00498)
L.nuclear	0.00365***	-0.0645	0.0425	0.0163	0.224***	-0.00279*
	(0.00111)	(0.0399)	(0.0345)	(0.0171)	(0.0618)	(0.00145)
L2.nuclear	-0.00202	0.0166	-0.0935	-0.0850***	-0.142	0.00477*
	(0.00208)	(0.0749)	(0.0648)	(0.0320)	(0.116)	(0.00273)
L3.nuclear	0.000876	0.0557	0.102	0.0883***	-0.0432	-0.00372
	(0.00208)	(0.0749)	(0.0648)	(0.0320)	(0.116)	(0.00273)
L4.nuclear	-0.00247**	-0.0122	-0.0505	-0.0190	-0.0494	0.00182
	(0.00111)	(0.0400)	(0.0346)	(0.0171)	(0.0619)	(0.00145)
L.fossil gas	0.00118***	0.00510	0.0178***	0.000236	-0.00137	-0.00157***
	(0.000154)	(0.00553)	(0.00479)	(0.00236)	(0.00857)	(0.000201)
L2.fossil gas	-0.00112***	-0.0161*	-0.0265***	0.00303	-0.0690***	0.00121***
	(0.000258)	(0.00926)	(0.00801)	(0.00396)	(0.0143)	(0.000337)
L3.fossil gas	-0.000231	-0.00658	0.00339	-0.0108***	0.0529***	-6.95e-05
	(0.000257)	(0.00925)	(0.00800)	(0.00395)	(0.0143)	(0.000337)
L4.fossil gas	0.000328**	0.0186***	0.00384	0.00551**	0.0124	0.000368*
	(0.000153)	(0.00551)	(0.00477)	(0.00235)	(0.00853)	(0.000201)
L.totalload	0.00220***	-0.0905***	-0.00942**	-0.00665***	0.0385***	0.00116***
	(0.000125)	(0.00450)	(0.00389)	(0.00192)	(0.00697)	(0.000164)
L2.totalload	-0.00147***	0.132***	0.00200	0.00399	-0.0830***	-0.000814***
	(0.000200)	(0.00720)	(0.00623)	(0.00308)	(0.0112)	(0.000262)
L3.totalload	-0.000813***	-0.0326***	0.00952	-0.00639**	0.0744***	-0.000362
	(0.000199)	(0.00715)	(0.00619)	(0.00306)	(0.0111)	(0.000260)
L4.totalload	0.000477***	-0.00777*	-0.00161	0.00577***	-0.0373***	0.000137
	(0.000122)	(0.00439)	(0.00380)	(0.00188)	(0.00680)	(0.000160)
L.lagdhp24	0.135***	-0.587***	0.310**	0.257***	0.410	0.00368
	(0.00507)	(0.182)	(0.158)	(0.0778)	(0.282)	(0.00663)
L2.lagdhp24	-0.0990***	0.754***	0.0715	-0.247**	0.0508	-0.0106

	(0.00712)	(0.256)	(0.221)	(0.109)	(0.396)	(0.00931)
L3.lagdhp24	-0.0142**	-0.602**	0.117	0.152	-0.676*	0.00205
	(0.00712)	(0.256)	(0.221)	(0.109)	(0.396)	(0.00931)
L4.lagdhp24	-0.00809	0.563***	-0.309**	-0.114	0.302	0.00299
	(0.00503)	(0.181)	(0.156)	(0.0773)	(0.280)	(0.00659)
L.lag1y	0.00999**	-0.467***	0.168	-0.0378	1.453***	-0.0164**
	(0.00497)	(0.179)	(0.154)	(0.0763)	(0.276)	(0.00650)
L2.lag1y	-0.0154**	0.945***	0.0729	-0.108	-1.267***	-0.00354
	(0.00740)	(0.266)	(0.230)	(0.114)	(0.412)	(0.00968)
L3.lag1y	-0.00514	-0.438*	-0.152	0.000926	0.501	0.0145
	(0.00740)	(0.266)	(0.230)	(0.114)	(0.412)	(0.00968)
L4.lag1y	0.0140***	-0.102	-0.0758	0.121	-0.372	0.00711
	(0.00497)	(0.179)	(0.155)	(0.0764)	(0.277)	(0.00651)
Time dummies	V	V	V	V	V	V
outliers	23.80***	21.78	-3.834	31.97***	-80.06***	-0.523
	(0.521)	(18.72)	(16.19)	(7.997)	(28.99)	(0.681)
Gas price	0.198***	0.145	0.246	0.0320	-1.213***	-0.000647
	(0.00689)	(0.248)	(0.214)	(0.106)	(0.384)	(0.00902)
Constant	-17.34***	-339.5**	-59.00	63.55	336.6	-6.620
	(4.422)	(159.0)	(137.5)	(67.92)	(246.2)	(5.788)
Observations	40,095	40,095	40,095	40,095	40,095	40,095

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: VAR model part 1; based on calculations from the database

	(7)	(8)	(9)	(10)	(11)
VARIABLES	nuclear	fossil gas	Load	lagdhp24	lag1y
L.DHprice	0.0418*	0.573***	1.885***	0.140***	0.00773
	(0.0237)	(0.182)	(0.220)	(0.00546)	(0.00535)
L2.DHprice	-0.0201	-0.853***	-2.120***	-0.115***	-0.0169**
	(0.0320)	(0.246)	(0.298)	(0.00739)	(0.00723)
L3.DHprice	-0.0715**	0.339	0.277	-0.0175**	0.0115
	(0.0320)	(0.246)	(0.298)	(0.00739)	(0.00724)
L4.DHprice	0.0143	-0.0190	-0.141	0.0195***	0.00533
	(0.0232)	(0.178)	(0.216)	(0.00537)	(0.00526)
L.solar	-0.000615	-0.112***	-0.0167***	-0.00292***	-0.00218***
	(0.000647)	(0.00496)	(0.00602)	(0.000149)	(0.000146)
L2.solar	-7.63e-05	0.222***	-0.149***	0.00415***	0.00275***
	(0.00137)	(0.0105)	(0.0127)	(0.000316)	(0.000309)
L3.solar	0.000184	-0.160***	0.234***	-0.00192***	-0.000782**
	(0.00138)	(0.0106)	(0.0128)	(0.000317)	(0.000311)
L4.solar	0.000600	0.0558***	-0.101***	0.000675***	0.000265*
	(0.000657)	(0.00504)	(0.00611)	(0.000152)	(0.000148)
L.offshore	-0.000503	-0.0201***	0.0342***	0.000335*	3.36e-05
	(0.000745)	(0.00572)	(0.00693)	(0.000172)	(0.000168)
L2.offshore	0.000531	0.0802***	-0.112***	-0.000476*	0.000123
	(0.00122)	(0.00933)	(0.0113)	(0.000281)	(0.000275)

L3.offshore	-2.24e-05	-0.0851***	0.125***	0.000671**	8.72e-05
	(0.00122)	(0.00936)	(0.0114)	(0.000282)	(0.000276)
L4.offshore	-0.000411	0.0270***	-0.0436***	-0.000489***	-0.000166
	(0.000758)	(0.00582)	(0.00705)	(0.000175)	(0.000171)
L.onshore	0.00153	-0.132***	-0.111***	-0.000548	-0.00116***
	(0.00148)	(0.0114)	(0.0138)	(0.000343)	(0.000336)
L2.onshore	-0.00228	0.175***	0.0306	0.000849	0.00111*
	(0.000612)	(0.0220)	(0.0190)	(0.00939)	(0.0341)
(0.000800)	(0.00275)	(0.0211)	(0.0255)	(0.000634)	(0.000621)
L3.onshore	2.26e-05	-0.0988***	0.115***	0.00115*	0.000195
	(0.00274)	(0.0210)	(0.0255)	(0.000633)	(0.000620)
L4.onshore	0.00108	0.0310***	-0.0585***	-0.00174***	-0.000299
	(0.00147)	(0.0113)	(0.0137)	(0.000340)	(0.000333)
L.Net position	0.000312	-0.0262***	0.000138	6.74e-05	-7.62e-05
	(0.000405)	(0.00311)	(0.00377)	(9.36e-05)	(9.16e-05)
L2.Net position	-0.000564	0.0170***	0.00615	-3.69e-05	1.17e-05
	(0.000511)	(0.00392)	(0.00475)	(0.000118)	(0.000115)
L3.Net position	0.000217	0.00111	-0.0100**	-0.000107	-0.000117
	(0.000510)	(0.00391)	(0.00474)	(0.000118)	(0.000115)
L4.Net position	-0.000403	-0.000258	0.00373	0.000119	0.000183**
	(0.000400)	(0.00307)	(0.00372)	(9.23e-05)	(9.04e-05)
L.storage	-0.0183	-0.127	1.327***	-0.00526	-0.00535
	(0.0172)	(0.132)	(0.160)	(0.00397)	(0.00389)
L2.storage	0.0338*	0.138	0.534***	-0.00125	-0.000359
	(0.0188)	(0.144)	(0.175)	(0.00434)	(0.00425)
L3.storage	-0.00484	0.0760	-0.575***	-0.000363	0.00550
	(0.0188)	(0.144)	(0.175)	(0.00434)	(0.00425)
L4.storage	0.000993	0.556***	0.0659	0.0106***	0.00812**
	(0.0171)	(0.131)	(0.159)	(0.00394)	(0.00386)
L.nuclear	1.614***	-0.132***	0.0865*	0.00246**	-0.000592
	(0.00498)	(0.0382)	(0.0464)	(0.00115)	(0.00113)
L2.nuclear	-0.853***	0.236***	-0.167*	-0.00373*	0.000436
	(0.00935)	(0.0718)	(0.0870)	(0.00216)	(0.00211)
L3.nuclear	0.311***	-0.107	0.205**	0.00220	0.000679
	(0.00935)	(0.0718)	(0.0870)	(0.00216)	(0.00211)
L4.nuclear	-0.0740***	-0.00856	-0.124***	-0.000994	-0.000665
	(0.00499)	(0.0383)	(0.0464)	(0.00115)	(0.00113)
L.fossil gas	-0.000250	1.353***	0.0669***	0.00102***	0.00112***
	(0.000691)	(0.00530)	(0.00643)	(0.000159)	(0.000156)
L2.fossil gas	-0.00106	-0.402***	-0.0783***	-0.000780***	-0.000828***
	(0.00116)	(0.00887)	(0.0108)	(0.000267)	(0.000261)
L3.fossil gas	0.00292**	0.0237***	0.0213**	5.11e-05	-0.000428
	(0.00115)	(0.00886)	(0.0107)	(0.000266)	(0.000261)
L4.fossil gas	-0.00145**	-0.00804	-0.00370	-0.000129	0.000121
	(0.000688)	(0.00528)	(0.00640)	(0.000159)	(0.000156)
L.totalload	-0.000581	0.0770***	1.239***	0.000590***	0.000389***
	(0.000562)	(0.00431)	(0.00523)	(0.000130)	(0.000127)
L2.totalload	0.000198	-0.123***	-0.324***	-0.000699***	-0.000457**
	(0.000899)	(0.00690)	(0.00837)	(0.000208)	(0.000203)
L3.totalload	0.00140	0.0504***	-0.0679***	-0.000364*	-0.000260

	(0.000893)	(0.00685)	(0.00831)	(0.000206)	(0.000202)
L4.totalload	-0.000930*	-0.00968**	0.0760***	0.000679***	0.000371***
	(0.000549)	(0.00421)	(0.00510)	(0.000127)	(0.000124)
L.lagdhp24	-0.0383*	0.801***	0.329	1.019***	0.0261***
	(0.0227)	(0.174)	(0.212)	(0.00525)	(0.00514)
L2.lagdhp24	0.0587*	-0.978***	-1.493***	-0.107***	-0.0335***
	(0.0319)	(0.245)	(0.297)	(0.00737)	(0.00722)
L3.lagdhp24	-0.0130	0.0106	0.818***	-0.0472***	-0.00708
	(0.0319)	(0.245)	(0.297)	(0.00737)	(0.00722)
L4.lagdhp24	-0.00239	0.151	0.572***	0.0283***	0.00834
	(0.0226)	(0.173)	(0.210)	(0.00521)	(0.00511)
L.lag1y	-0.00919	1.286***	0.633***	0.0380***	1.111***
	(0.0223)	(0.171)	(0.207)	(0.00514)	(0.00504)
L2.lag1y	0.00885	-1.224***	-1.700***	-0.0336***	-0.112***
	(0.0332)	(0.255)	(0.309)	(0.00766)	(0.00750)
L3.lag1y	-0.00174	-0.174	0.832***	-0.0216***	-0.0932***
	(0.0332)	(0.255)	(0.309)	(0.00766)	(0.00751)
L4.lag1y	-0.00220	0.0624	0.145	0.0192***	0.0492***
	(0.0223)	(0.171)	(0.208)	(0.00515)	(0.00504)
Time dummies	V	V	V	V	V
outliers	-0.664	132.9***	68.77***	8.287***	0.538
	(2.337)	(17.93)	(21.75)	(0.539)	(0.528)
GASP	0.0801***	-0.486**	-0.103	0.135***	-0.0467***
	(0.0309)	(0.237)	(0.288)	(0.00714)	(0.00699)
Constant	37.31*	549.4***	1,343***	-12.79***	-7.326
	(19.85)	(152.3)	(184.7)	(4.581)	(4.487)
Observations	40,095	40,095	40,095	40,095	40,095

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: VAR model part 2; based on calculations from the database

In the different VAR models, some exogenous variables were added. These variables are the time dummies, as earlier, the outliers (always as one variable. Same critics as earlier), the 24th lag of the DHP and the gas price. Through the different models, there were very few changes in the coefficients. Some coefficients became insignificant.

The effects of intermittent renewables are more important than in the ARDL models. It should be noted that as they are VAR models, the explanatory variables are lagged. Given the context, this is less a problem than what could be expect. The production of energy and the demand increase or decrease gradually (it does not 'appear' suddenly), which could explain why some coefficients are higher than in the ARDL models. Moreover, VAR models could solve the problem of autocorrelation because they consider some autocorrelations for other variables.

Another reason for using the VAR is that it enables to integrate some variables that would cause problems in the ARDL models, such as the storage and other sources of productions. The main problem with these variables in ARDL models is that these are highly correlated with each other. VAR also enables to include the load as the system behaves like the demand and price are determined simultaneously.

As it would be very heavy to include every physical flows variables, the models only consider the implicit position of Belgium. There is still a positive correlation with the DHP, as discussed earlier. The intermittent renewables productions seem to increase the net position, probably because of the management of 'supply surplus' discussed earlier.

The storage variable here is considered as a production source by ELIA. Therefore, the filling is not considered by this variable; this variable only considers the use of stored energy. We see that this variable decreases the DHP. A potential explanation is that when the part of 'supply surplus' stored from previous periods is use, the marginal cost of this energy is lower that the energy from other sources. The difference in the marginal cost of stored energy (from intermittent renewables) and the intermittent energy is the cost of storing, which is the potential loss of energy [14]. Energy coming from storage has a larger effect on the price that non-stored energy. The rational is that stored energy is on the market when the price is the most attractive for the seller. This happens when there are few renewables and a lot of pollutant energy (high marginal costs). The effect of low marginal cost energy is more important when most energy from the mix for a specific moment is pollutant. This helps to reduce price fluctuation by increasing the price if it is low (less supply because a part is used to fill storage devices) and decreasing it if it is high (increase the supply of low marginal cost energy).

The storage variable seems independent of the DHP and the implicit position. It is difficult to say if this is normal or if this due to the way storage is measured. Because the variable does not include energy entering into storage devices, the variable cannot take any negative values. If the variable could, the coefficients of DHP and of the implicit position could be negative. If the price is very low, storage owners want to store the current energy to increase their profit, ie. the gap between the sale price and the buy price. If the price is high, the stored energy would be profitable. If Belgiqn position is positive, it might mean that the Belgian demand is too low and therefore there is no place for stored energy. If Belgium imports, storage owners could sell because there is a demand.

Less stored energy is used when intermittent renewable energy is produced, which confirms the hypothesis that stored energy is used as complement.

Nuclear energy production is independent of electricity production from other sources. If we consider nuclear energy as cheap, non-intermittent and 'free-carbon', it seems a source that should be used the most possible.

Electricity from fossil gas increases the price, which was expected as being marginally the most expensive in sources integrated to the model. The production of electricity from fossil gas decreases in the production of nuclear and intermittent renewables. This is consistent with the merit-order effect: the most expensive is produced 'in the last resort'.

The load increases the price, which is coherent if we assume the load is an approximation of the demand. However, the load increases with the price. This might be caused by an indirect effect. The demand is not completely independent on the demand before. A high price the period before may be due to a high demand. The second possibility is that electricity is a Giffen good. I do not know what to conclude.

The 24^{th} lag and the 1-year lag of DHP[15] have positive coefficients for the DHP equation. What is worrying is that the equations of the 24^{th} lag and the 1-year lag of DHP are correlated with future observations, which can explain why there are autocorrelation problems.

[14] I do not consider the opportunity cost because here I adopted the standpoint that storage mostly stores energy when the price is negative, which would mean a negative opportunity cost. However, the reality is more complex given storage can be used to speculate: store cheap and sell expensive.

[15] This was impossible with the SARMA. This might be due to the presence of MA(1) earlier.

Unfortunately, these models also suffer from heteroscedasticity and from autocorrelation.

It is surprising that even with very different specifications, the coefficients of common variables are similar between the ARDL models and the DHP equation from VAR models.

5.6 Analysis of the negative price and the generation of intermittent renewables

	Distribution (rounded to two decimal places)																					
	.07%	.14%	.28%	.36%	.5%	1.21%	1.49%	1.92%	2.06%	2.28%	2.78%	3.06%	3.27%	3.35%	4.63%	7.9%	9.18%	10.96%	13.24%	14.02%	15.73%	Total
Hour																						
12AM						17																17
1AM								27														27
2 AM											39											39
3 AM													46									46
4 AM														47								47
5 AM									29													29
6 AM							21															21
7 AM							21															21
8 AM										32												32
9 AM															65							65
10 AM																111						111
11 AM																		154				154
12 PM																				197		197
1 PM																					221	221
2 PM																			186			186
3 PM																	129					129
4 PM												43										43
5 PM					7																	7
6 PM	1																					1
8 PM	1																					1
9 PM		2																				2
10 PM			4																			4
11 PM				5																		5
Total	2	2	4	5	7	17	42	27	29	32	39	43	46	47	65	111	129	154	186	197	221	1,405

Table 6: Distribution of negative prices between hours; based on data from (Elexys, 2025a)

As we can see on the table 6, more than 50% (53.95%) of negative prices instants happen between 11 AM and 2PM, where the production of intermittent renewables are the most expected in Belgium (driven by solar energy). We can also observe that only 1% (1.42%) of the moments with negative price happen between 5 PM and 11 PM[16]. If we enlarge the period, only 16.01% of these instants happen between 5 PM and 5 AM. The negative prices are less driven by low demand than high supply of renewables. The principal problem seems therefore the moment of the day where supply is provided. This tends to show that there is a need of flexibility (storage, exchanges and adaptation of the demand).

	Distribution							
	6.04982%	6.33452%	7.54448%	8.82562%	10.24911%	20.49822%	40.49822%	Total
day								
Sunday							569	569
Monday					144			144
Tuesday		89						89
Wednesday	85							85
Thursday			106					106
Friday				124				124
Saturday						288		288
Total	85	89	106	124	144	288	569	1,405

Table 7: Distribution of negative prices between days; based on data from (Elexys, 2025a)

However, demand plays an important role. Sunday, a day with the reputation of having low demand in electricity, has an important number of hour with negative price; 40.5% of the observations. The whole week-end (Saturday and Sunday) has 61% of these negative price occurrences. Daily demand plays an important role. If we assume that production of intermittent renewables is independent of the day, contrary to the demand, the weekly demand drives the price. Therefore, the weekend is the most prone to negative price.

	Distribution												
	.64%	1.49%	2.42%	3.56%	4.41%	5.77%	7.33%	8.04%	13.17%	15.59%	17.15%	20.43%	Total
month													
January			34										34
February		21											21
March								113					113
April										219			219
May												287	287
June											241		241
July									185				185
August							103						103
September				50									50
October					62								62
November	9												9
December						81							81
Total	9	21	34	50	62	81	103	113	185	219	241	287	1,405

Table 8: Distribution of negative prices between months; based on data from (Elexys, 2025a)

[16] It seems that there was no negative price at 7 PM.

As we observed earlier, there are some periods that are dominant in the negative price again. Between April and July, there is 66.33% of the instances. It might be surprising to see that August represents less than 10% of the instances of negative price. However it should be noted that 'oversupply' does not only depend on the solar energy generation and the low demand (historically 'vacation periods' present a low demand). Wind energy should also be important to increase the risk of negative price. 18.29% of these instances happen between September and February (lower supply but also higher demand). This tends to show that the main cause of negative price is very important production of intermittent renewables.

	Distribution						
	7.97153%	9.67972%	11.31673%	15.80071%	26.47687%	28.75445%	Total
year							
2020		136					136
2021			159				159
2022	112						112
2023				222			222
2024						404	404
2025					372		372
Total	112	136	159	222	372	404	1,405

Table 9: Distribution of negative prices between years; based on data from (Elexys, 2025a)

The 2 last years (2024 and 2025) contain 55.23% instances of negative prices. The increase of demand did not reduce the risk of negative price. There are 2 potential causes. The first cause is an increase in production of onshore wind energy and solar energy production, which would have increased more quickly than the demand. This is consistent with the EU objective of 'greenifying' the energy mix. The readers have seen these increases at the figures 3 and 4. The second reason would be the decrease of the gas price since the beginning of Russian-Ukrainian war, where the peak was in August 2022 at €177.77/MWh. The peak in 2024 was €44.9/MWh. The gas price has an impact on the electricity price as we have seen earlier.

We have seen with these different times level that there are many moments where the share of negative price quickly increase. It tends to show that there are some structural changes.

	Distribution (rounded to two decimal places)								
	.07%	.64%	3.13%	6.55%	15.66%	19.07%	23.56%	31.32%	Total
Renewables production									
0 ⩽	1								1
5,000 ⩽			44						44
10,000 ⩽					220				220
15,000 ⩽								440	440
20,000 ⩽							331		331
25,000 ⩽						268			268
30,000 ⩽				92					92
35,000 ⩽		9							9
Total	1	9	44	92	220	268	331	440	1,405

Table 10: Distribution of negative prices based on hourly renewables production; based on data from (Elexys, 2025a) and (Elia, 2026c)

Most of the negative prices (81.14%) happen when the hourly renewable production (solar + onshore wind + offshore wind) is over 15,000 MWh. As showed for different countries, there is also a structural break. The negative price is much more frequent after a threshold (own to each country), which is coherent with the observations of (Pavlík et al., 2025). The distribution of share of negative price tends to show a non-linear relationship between the renewable generation and the probability to have negative price.

	Probability (rounded to two decimal places)								
	$\leqslant$ .01%	.33%	1.91%	7.26%	17.56%	33.8%	45%	58.23%	Total
Renewables production									
0 $\leqslant$	19,767								19,767
5,000 $\leqslant$		13,394							13,394
10,000 $\leqslant$			11,494						11,494
15,000 $\leqslant$				6,057					6,057
20,000 $\leqslant$					1,885				1,885
25,000 $\leqslant$						793			793
30,000 $\leqslant$								158	158
35,000 $\leqslant$							20		20
Total	19,767	13,394	11,494	6,057	1,885	793	20	158	53,568

Table 11: Probability of negative prices, conditional to the renewable production; based on data from (Elexys, 2025a) and (Elia, 2026c)

The table 11 shows that the generation is more important, the more likely this will lead to negative price. We can see that the progress is not linear. We can also see that the likelihood[17] to be negative given the generation of renewables is not constant over time for extreme generation as we can see. In comparison with the likelihood of 2025[18], extreme values have higher probabilities to lead to negative price.

I suspect a change of distribution for highest intermittent renewables production. For production under 15,000 MWh, it seems that the distribution is constant. The hypothesis is that 'lowest' productions are such that the demand can sufficiently absorb such as the flexibility tools (in this context, storage and exportation) can deal any surplus. With the highest, this is not the case. Structural changes can partly explain why the distribution is not constant. Here are the potential changes we have experienced these last years and we risk to experience in the future:

- Wars
- Enlargement of the electricity market
- Regulations
- Change in demand consumption

The Russian-Ukrainian war led to important increase in gas price. This war indirectly caused an increase in electricity price as we assumed earlier because of increase of cost for some producers. The supply decreased and made intermittent energy more profitable, given that these sources are not

[17]Using this probabilistic term is technically a mistake because, as the readers will deduce, the distribution seems unstable over time due to structural changes. Moreover, the small number observations cannot prove that this is the right conditional probabilities.

[18]Same comment

impacted. Thanks to the decrease of the supply, price increases and therefore decreases the likelihood of negative price. This type of shock is a problem if the gas price is not included while there was a war. I do not suppose that the problem is the reason of the early problems.

Increasing capacity borders make possible new exchanges. The apparition of new exchange treaties cause an increase of demand but also an increase of flexibility. In case of negative price, it is easier to deal the supply surplus. The assumption is that the flexibility increase and therefore the threshold does too. The problem of the 'export solution' is the potential concordance of production. Solar energy is produced roughly at same moment in Europe contrary to wind energy. This means that, except by an 'extra demand' in the importer country, exporting would not help to avoid negative price given there would also an important supply in the neighbour countries. However, for the wind energy, the production is less correlated with the production of neighbours and therefore exportation could increase the flexibility. In the table 12, the maximum production (in 2025) of wind energy is the category >15,000. The category just after has clearly a higher likelihood to have a negative price. This supports the hypothesis.

	Probability (rounded to two decimal places)								
	0%	.32%	2.53%	7.21%	23.55%	44.16%	76.6%	100%	Total
Renewables production									
0 ⩽	3,043								3,043
5,000 ⩽		1,894							1,894
10,000 ⩽			1,777						1,777
15,000 ⩽				1,221					1,221
20,000 ⩽					518				518
25,000 ⩽						231			231
30,000 ⩽							47		47
35,000 ⩽								5	5
Total	3,043	1,894	1,777	1,221	518	231	47	5	8,736

Table 12: Probability of negative prices, conditional to the renewable production (sample 2025); based on data from (Elexys, 2025a) and (Elia, 2026c)

The regulation has been shown in the literature to affect the bidding system and therefore the probability of having negative price. The system of marginal cost bidding contributes to the increase of negative price (Prokhorov & Dreisbach, 2022). In a certain way, the emission trading system alters the bidding system. Here I did not consider it. In my knowledge, the paper that includes it the most clearly is (Zipp, 2017) although it is the variable including it has another component. Regulation should change frequently as the transition is policy-driven (Blazquez et al., 2020).

An increase of demand, that might be caused over time through electrification, should move the threshold. Seasons could also be a shock (Biber et al., 2022).

These structural changes do not explain why the probability does increase in a non-linear way. My hypothesis is that the volatility of price increases in the renewable generation because the management of 'surplus' becomes exponentially more difficult, specially after the threshold.

	(1)				
	mean	sd	min	max	count
wind	5722.267	5098.757	3.51	18199.98	8736
Observations	8736				

Table 13: Descriptives statistics: Wind (onshore + offshore) energy (sample 2025); based on my calculations and data from (Elia, 2026c)

The structural changes caused by exchanges, regulations and temporal crises do not explain the problem we have seen to model an ARMA model or a SARMA model. Reducing the sample cannot solve the problem. It should be the case if there was not another type of profound structural change[19]. The only explanation I can see is the intrinsic volatility of DHP and the change of threshold due to changes of border capacity over the year.

Here, we saw that there might be a break after the threshold. This might explain why the coefficients for some exportation were negative. Belgium exports to these countries when they cannot deal with the 'supply surplus'. Therefore, the extreme cases could pull down the coefficients. It would be worth it to find a method to separate extreme cases and usual cases.

A summary of what seems to increase the risk of negative price on the Belgian data:

- Low demand
- High production of wind energy and solar energy simultaneously.

These conclusions match with the conclusions with (Biber et al., 2022). They have shown that the risk of negative price is higher when the solar energy production is high. They have also shown that the higher the load, the lower the probability of negative price. They have also shown that the increase of emission allowance price could lead to decrease the probability of negative price because it favours gas power plants, which are more flexible. The objective of gas phase-out in Belgium could harm the electricity market and could make more costly the transition. ETS could be a structural break by inducing a shock in the energy mix.

[19]At the exception of unidentified source of break. However, this is unlikely given the most reduced sample is only over a year. This period does not include the current Iranian-USA war, neither new exchange treaties nor new regulations.

6 Potential discussions

6.1 The place of exportation in the solution

As quickly discussed in the analysis, storage can be a useful tool to mitigate price fluctuation.[20] However, as we have seen in the literature review, storage is not incentivised in a competitive free market. The question is: is this tool can be replaced by exports? The answer is complex. Storage also increases competition (Zhao et al., 2019). Is it possible that the increase of competition cancels the effects of storage? Or is there a cumulative effect? It seems unrealistic but it should be interesting to study the relationship between trade, storage and competition.

Exportations on paper have the same effect of stabilisation. In the low price moment, a part of the production leaves the Belgian market. When the price is high, energy is reintroduced. However, exportation includes more complex factor that matter. The first element is the situation of other countries. Do they have interest in our energy from intermittent renewable? Do they have a demand interesting enough? It seems that they are not interested in our solar energy, probably because they also produce some at the same moment. It also seems that solar cannot decrease the price when demand is on its peak (Macedo et al., 2020). This is another explanation of why solar energy could be less interesting for exportations. Is the same for wind energy? My conclusions tend to show that exportation is not enough to prevent price decrease, which was not a surprise because (Bistline, 2017) had the same conclusion, and therefore negative price. My conclusions have also shown that impact of international transmissions evolve over the foreign market changes. The situation should be monitored to create adequate policies.

Moreover, not considering these exchanges can underestimate the energy security we have from intermittent energy. The exchanges can represent a source of stability if the intermittent production of countries are complementary. Not considering them also underestimates the impact of intermittent sources can have in a closed economy.

For the demand, it would interesting to study if they have similar consumption behaviours. If this is revealed as being similar, exchange could be less interesting[21]. In this perspective, it would be worth it to exchange with countries having different consumption, and production, behaviours. Are they close? What will be the costs? However, trading with countries with different demand heterogeneous would also increase the competition and it would still increase if the capacity transmission was small with them (Küpper et al., 2009). If the demand is similar, this increases of competition could risk to reinforce the problem of negative price. However, if the other country produces more expensive energy, Belgium would have higher level of competition. Increasing capacity transmissions has more effect if the other region has higher level of competition (Küpper et al., 2009). Therefore, if Belgium produces renewables while others do not, competition in Belgium would less increase. In this case, we could imagine that competition would decrease in Belgium. Exportation would decrease the negative price phenomenon by temporally decreasing competition.

In this dissertation, I assumed that variable renewables increase the volatility but (Maciejowska, 2020) has shown that wind and solar energy can, under certain demand condition, decrease the volatility.

Adaptation of demand behaviour in Belgium, or in other countries, could help to avoid the negative price phenomenon. For solar energy, it seems possible to predict and therefore adapting easily. For wind energy, the production is less regular and consumption adaptation requires more complex

[20] On the duck curve management and the use of storage technologies, (Pitra & Musti, 2021)

[21] It should be noted that I will not discuss exchange for energy security matter.

decision-processes. An example of demand adaptation is the pre-cooling strategies (Calero et al., 2022).

To reduce emissions-related, other solutions would be to decrease our unnecessary consumption and using other 'free-carbon' sources, as nuclear or biomass[22]. These solutions have their own inconveniences. Reducing the consumption reduces the demand. Therefore, it could increase the number of negative price. Nuclear energy has problem for the treatment of residuals. Biomass has high marginal cost.

6.2 Potential research

The first evident point that would worth a deeper study is the modelling of the volatility of price and structural breaks. The volatility seems to be closely related to the flexibility. It might be (more) predictable thanks to the concept of the threshold. The task seems complicated due to many potential structural breaks. A special attention should be held on the seasonal components because this could potentially influence the interest of exportation as discussed earlier. Are there different types of structural break? How do they influence price and volatility?

Several questions can be asked when we compare the impact of export to the impact of VRE. In the third ARDL model, we have seen that the impact of 1 MWh onshore wind energy is compensated if Belgium exports slightly less than 10 MWh. Does the composition of the mix matter? If the mix at the moment of the exportation is 'greener', does it increase the importance of exchange for the price? Is there an asymmetrical effect of exchange? Does importation have the same effect size that the exportation? Whether the case, what are the causes of this difference and how do they influence optimal management? In a certain measure, it could be worth it to study the intra-national transmissions to check if these conclusions are also true in more local scope.

Older papers often consider that the electricity market is Cournot-like competition, whatever is the objective of the paper (for example, (Lise et al., 2006), (Joskow & Tirole, 2007) and (Schill & Kemfert, 2011)). This was confirmed for the Californian market (Puller, 2007) in the late 2000s. This same state will experience the Duck Curve some years later (California ISO, 2016), in 2016. However, we could argue that with a high share of renewables the competition gets closer to a Bertrand-like competition due to fixed quantity. Between 2006 and 2011, the Dutch market became more Bertrand-like (Mulder, 2015). The authors do not explain the reason but it seems that this period is also a period with more wind energy on the market. This would decrease the price on the market and could also explain the increase of volatility. A small increase of intermittent renewables would not change the competitive environment and therefore would only impact the price by the merit-order effect while a high increase will impact the competition and decrease more heavily the price. This increase of effect could explain the problems of heterogeneity and why the volatility increases in the renewables production. This will deserve a deeper study. With these perspectives, the competition level would change intra-day. How does exportation play a role?

There are questions about whether the electricity market should stay liberalised. (Lise et al., 2006) show that its liberalisation has beneficial and harmful effects for the environment. However, energy transition disrupts liberalised markets (Blazquez et al., 2020). Such type of market could be not well-equipped to the transition. In this paper, I focused on the short-term market. A market based on short-run marginal pricing fails to bring enough capacity investment and does not provide stable amount of electricity(Keppler, Quemin, & Saguan, 2022). The analysis I made tends to support this

[22]It could be disputed as 'free-carbon'. Emissions emitted, directly or indirectly, depend on the way use to produce this energy. The less pollutant is to use waste to produce the energy.

idea. The potential solutions that should help to maintain the market as it exists now and decreasing the volatility have many flaws and are costly (because they need to be incentivised). A hybrid as proposed by (Keppler et al., 2022) could help to faster the transition. In a more regulated market, would cross-border transmission be attractive for producers?

A point that was overlooked in this Master thesis is the matter of energy security. Intermittent renewables have their own risks as ’Dunkelflaute’. ’Dunkelflaute’ represents a risk for the energy security. In the management, storage devices and small modular nuclear reactors will matter. Without nuclear, Belgium would need to be a net importer of energy contrary to the case with nuclear (net exporter) (Moglianesi, Coppens, Duchêne, Das, & Marenne, 2025). Belgium should rely on other countries and this might undermines its energy security [23]. However, energy security of countries with high level of renewable should suffer less from geopolitical conflicts (Q. Zhang et al., 2024).

These types of energy also create new relationship dynamics. The increase of a seemingly independence can be source of conflicts as argued. What is searched in electricity exchanges is different that was searched before. In this perspective, some policies to favour storage could enter in conflicts with the interest of the other countries. This also sets several questions on the sovereignty.

6.3 If I had to restart

If I had to restart from scratch, I would take a smaller sample in the hope it prevents autocorrelation problems and it makes possible the detection of structural breaks. The selection of sample would be such as I minimise the risks of structural breaks. Optimally, I would separate the sample into different meteorological seasons. Given the high number of observations, this should not be a problem. This should reduce the problem of heteroscedasticity and this would enable comparisons between different seasons.

In some papers, quantile regressions are used (for instance (Tselika, 2022) and (Maciejowska, 2020)). I have also seen the use of a GARCH model and conditional variance equation with (Macedo et al., 2020). It might have been worth it to study these types of regressions in order to see if they can deal with the heteroscedasticity and the autocorrelations. The GARCH model seems to be the most appropriate because this can deal with the volatility explicitly.

Another improvement would be to quickly study the physical flows (from Belgian) and see how they are influenced by the DHP of other countries. As we have seen in the ARDL models part, the order of preference could evolve over time. It would be interesting to determine what matters for this order. The results could be used to improve exchanges with other countries.

Another limitation of my work is that it does not treat efficiently regulatory structural breaks and the outliers. A better treatment would have improved the work.

With more time and more suited model, I would also include a short analysis using quarter hourly data to compare the results.

[23](Q. Zhang, Chen, Ma, & Liang, 2024) have also shown that countries with higher worsen their energy security if they are affected by geopolitical conflicts

7 Conclusions

As we have seen in this dissertation, international transmissions can be useful to reduce the volatility and the risk of negative price. Increasing border transmission capacity improves the flexibility and enables larger VRE production without creating a structural break. Contrary to the 'storage' solution, there is no risk of free rider.

However, this solution as many drawbacks. The first drawback is that high amount of energy must be exported to compensate the effect of one MWh from VRE. The second issue is that the effect of cross-border transmission depends on the foreign market situation. A country highly advanced in the transition with low price would not be a useful partner to manage the domestic 'supply surplus'. Moreover, it depends on how their demand is met. Exchange with countries having similarities in the consumption behaviour would not help. The last problem concerns the energy security.

Increasing cross-border transmission capacity is a means to improve the flexibility. However, it should be adapted to the currently implemented policies and should be regularly studied to check if there is any important change.

References

Acemoglu, D., Kakhbod, A., & Ozdaglar, A. (2017, June). Competition in Electricity Markets with Renewable Energy Sources. The Energy Journal, 38(1_suppl), 137–156. doi: 10.5547/01956574.38.SI1.dace

Al-Shetwi, A. Q., Abidin, I. Z., Mahafzah, K. A., & Hannan, M. A. (2024). Feasibility of future transition to 100% renewable energy: Recent progress, policies, challenges, and perspectives. Journal of Cleaner Production, 478, 143942. doi: https://doi.org/10.1016/j.jclepro.2024.143942

Biber, A., Felder, M., Wieland, C., & Spliethoff, H. (2022). Negative price spiral caused by renewables? Electricity price prediction on the German market for 2030. The Electricity Journal, 35(8), 107188. doi: https://doi.org/10.1016/j.tej.2022.107188

Bistline, J. E. (2017). Economic and technical challenges of flexible operations under large-scale variable renewable deployment. Energy Economics, 64, 363–372. doi: https://doi.org/10.1016/j.eneco.2017.04.012

Blazquez, J., Fuentes, R., & Manzano, B. (2020). On some economic principles of the energy transition. Energy Policy, 147, 111807. doi: https://doi.org/10.1016/j.enpol.2020.111807

Blazquez, J., Fuentes-Bracamontes, R., Bollino, C. A., & Nezamuddin, N. (2018). The renewable energy policy Paradox. Renewable and Sustainable Energy Reviews, 82, 1–5. doi: https://doi.org/10.1016/j.rser.2017.09.002

Brown, T., & Reichenberg, L. (2021). Decreasing market value of variable renewables can be avoided by policy action. Energy Economics, 100, 105354. doi: https://doi.org/10.1016/j.eneco.2021.105354

Calero, I., Cañizares, C. A., Bhattacharya, K., & Baldick, R. (2022, January). Duck-Curve Mitigation in Power Grids With High Penetration of PV Generation. IEEE Transactions on Smart Grid, 13(1), 314–329. doi: 10.1109/TSG.2021.3122398

California ISO. (2016). What the Duck curve tells us about managing a green grid. Retrieved 2025-10-21, from https://www.caiso.com/library/renewables-fast-facts

Climate Watch. (2025a, September). Historical GHG Emissions. Retrieved 2026-02-21, from https://www.climatewatchdata.org/ghg-emissions?apcid=000000000000000000000000&breakBy=sector&chartType=line&end_year=2023&start_year=1990

Climate Watch. (2025b, September). Historical GHG Emissions. Retrieved 2026-02-21, from https://www.climatewatchdata.org/ghg-emissions?apcid=000000000000000000000000&breakBy=sector&chartType=percentage&end_year=2023&start_year=1990

Climate Watch. (2025c, September). Historical GHG Emissions. Retrieved 2026-02-21, from https://www.climatewatchdata.org/ghg-emissions?apcid=000000000000000000000000&breakBy=sector&chartType=percentage&end_year=2023&start_year=1990

Climate Watch. (2025d, September). Historical GHG Emissions. Retrieved 2026-02-21, from https://www.climatewatchdata.org/ghg-emissions?apcid=000000000000000000000000&breakBy=sector&chartType=percentage&end_year=2023&start_year=1990

Dillig, M., Jung, M., & Karl, J. (2016). The impact of renewables on electricity prices in Germany–An estimation based on historic spot prices in the years 2011–2013. Renewable and Sustainable Energy Reviews, 57, 7–15. doi: https://doi.org/10.1016/j.rser.2015.12.003

Elexys. (2025a, October). Epex Spot. Retrieved 2026-02-22, from https://www.elexys.be/en/insights/epex-spot

Elexys. (2025b). Quarter hourly Belpex (day-ahead spot BE). Retrieved 2026-02-22, from https://www.elexys.be/en/insights/quarter-hourly-belpex-day-ahead-spot-be

Elexys. (2026, May). Spot de gaz EEX ZTP. Retrieved 2026-05-12, from https://www.elexys.be/insights/eex-ztp-gas-spot

Elia. (2025). Intraday implicit net position (Belgium's balance). Retrieved 2026-02-22, from https://opendata.elia.be/explore/dataset/ods022/export/?sort=datetime&dataChart=eyJxdWVyaWVzIjpbeyJjaGFydHMiOlt7InR5cGUiOiJsaW5lIiwiZnVuYyI6IkFWRyIsInlBeGlzIjoiaW1wbGljaXRuZX3D

Elia. (2026a, May). Measured and forecasted total load on the Belgian grid (Historical data). Retrieved 2026-05-12, from `https://opendata.elia.be/explore/dataset/ods001/`

Elia. (2026b, May). Physical flow - by border. Retrieved 2026-05-12, from `https://opendata.elia.be/explore/dataset/ods026/`

Elia. (2026c, May). Total generation - aggregated by fuel type. Retrieved 2026-05-12, from `https://opendata.elia.be/explore/dataset/ods201/`

Guo, Y., Hou, Z., Wang, Q., Huang, L., Shi, T., Wu, L., & Mao, J. (2026). Electricity Market Modeling at the European Energy Exchange: Methods, Market Dynamics, and Renewable Impacts. , 64. Retrieved from `https://www.energy-proceedings.org/wp-content/uploads/icae2025/1769701961.pdf`

Joskow, P., & Tirole, J. (2007, March). Reliability and competitive electricity markets. The RAND Journal of Economics, 38(1), 60–84. doi: 10.1111/j.1756-2171.2007.tb00044.x

Keppler, J. H., Quemin, S., & Saguan, M. (2022). Why the sustainable provision of low-carbon electricity needs hybrid markets. Energy Policy, 171, 113273. doi: https://doi.org/10.1016/j.enpol.2022.113273

Küpper, G., Delarue, E., Delvaux, B., Meeus, L., Bekaert, D., Willems, B., … Belmans, R. (2009). Does more international transmission capacity increase competition in the Belgian electricity market? The Electricity Journal, 22(1), 21–36. doi: https://doi.org/10.1016/j.tej.2008.12.006

Li, N., & Hedman, K. W. (2014). Economic assessment of energy storage in systems with high levels of renewable resources. IEEE Transactions on Sustainable Energy, 6(3), 1103–1111. doi: https://doi.org/10.1109/TSTE.2014.2329881

Lise, W., Linderhof, V., Kuik, O., Kemfert, C., Östling, R., & Heinzow, T. (2006). A game theoretic model of the Northwestern European electricity market—market power and the environment. Energy Policy, 34(15), 2123–2136. doi: https://doi.org/10.1016/j.enpol.2005.03.003

Macedo, D. P., Marques, A. C., & Damette, O. (2020). The impact of the integration of renewable energy sources in the electricity price formation: is the Merit-Order Effect occurring in Portugal? Utilities Policy, 66, 101080. doi: https://doi.org/10.1016/j.jup.2020.101080

Maciejowska, K. (2020). Assessing the impact of renewable energy sources on the electricity price level and variability–A quantile regression approach. Energy Economics, 85, 104532. doi: https://doi.org/10.1016/j.eneco.2019.104532

Moglianesi, A., Coppens, L., Duchêne, F., Das, P., & Marenne, Y. (2025). The impact of a Dunkelflaute event on the planning of a decarbonized energy system. Journal of Cleaner Production, 536, 147180. doi: https://doi.org/10.1016/j.jclepro.2025.147180

Motalleb, M., & Ghorbani, R. (2017). Non-cooperative game-theoretic model of demand response aggregator competition for selling stored energy in storage devices. Applied Energy, 202, 581–596. doi: https://doi.org/10.1016/j.apenergy.2017.05.186

Mulder, M. (2015, April). Competition in the Dutch Electricity Market: An Empirical Analysis over 2006-2011. The Energy Journal, 36(2), 1–28. doi: 10.5547/01956574.36.2.1

Mulder, M., & Scholtens, B. (2013). The impact of renewable energy on electricity prices in the Netherlands. Renewable energy, 57, 94–100. doi: https://doi.org/10.1016/j.renene.2013.01.025

Pavlík, M., Kurimskỳ, F., & Ševc, K. (2025). Renewable energy and price stability: An analysis of volatility and market shifts in the European electricity sector (2015–2025). Applied Sciences, 15(12), 6397. doi: https://doi.org/10.3390/app15126397

Pitra, G. M., & Musti, K. S. (2021). Duck curve with renewable energies and storage technologies. In 2021 13th International conference on computational intelligence and communication networks (CICN) (pp. 66–71). IEEE. doi: https://doi.org/10.1109/CICN51697.2021.9574671

Prokhorov, O., & Dreisbach, D. (2022). The impact of renewables on the incidents of negative prices in the energy spot markets. Energy Policy, 167, 113073. doi: https://doi.org/10.1016/j.enpol.2022.113073

Puller, S. L. (2007). Pricing and firm conduct in California's deregulated electricity market. The

Review of Economics and Statistics, 89(1), 75–87. doi: https://doi.org/10.1162/rest.89.1.75
Schill, W.-P., & Kemfert, C. (2011). Modeling Strategic Electricity Storage: The Case of Pumped Hydro Storage in Germany. The Energy Journal, 32(3), 59–87. Retrieved from https://www.jstor.org/stable/41323408
Tselika, K. (2022). The impact of variable renewables on the distribution of hourly electricity prices and their variability: A panel approach. Energy Economics, 113, 106194. doi: https://doi.org/10.1016/j.eneco.2022.106194
Zhang, Q., Chen, R., Ma, S., & Liang, A. (2024). Nord stream 2, geopolitical conflicts and energy security: Evidence from EU regions. Energy, 313, 133836. doi: https://doi.org/10.1016/j.energy.2024.133836
Zhang, Z., Makowski, M., Nahorski, Z., & Granat, J. (2024). Harmonizing decisions in wind farm management to provide a stable energy supply. In 2024 9th International Conference on Mathematics and Computers in Sciences and Industry (MCSI) (pp. 10–15). IEEE. doi: https://doi.org/10.1109/MCSI63438.2024.00010
Zhao, D., Wang, H., Huang, J., & Lin, X. (2019). Storage or no storage: Duopoly competition between renewable energy suppliers in a local energy market. IEEE Journal on Selected Areas in Communications, 38(1), 31–47. Retrieved 2025-10-21, from https://ieeexplore.ieee.org/abstract/document/8901978/?casa_token=BmIW0nXREJwAAAAA:rpsx6Gmsl4Wj2M3KUi0BnnxUOf2yx8zv1XVCB7ZfPYIDkPQzQ75uSt6S6p7UAEoXEl5ZVCB5rX9M
Zipp, A. (2017). The marketability of variable renewable energy in liberalized electricity markets–an empirical analysis. Renewable Energy, 113, 1111–1121. doi: https://doi.org/10.1016/j.renene.2017.06.072