Renewable energy and risk premia on electricity futures markets

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Abstract

The growing concern about climate change and the increasing adoption of intermittent renewable energies has changed the risk exposures of power generators and of retailers to electricity spot prices, that may be hedged on the electricity futures markets. Because electricity can not be stored, prices of an electricity futures contract can not be determined by arbitrage based on "cost-of-carry" strategies. Instead, futures prices encompass a risk premium which sign and magnitude depend on the market participants' hedging needs. In this paper, we study the relation between this risk premium and the share of intermittent renewables in the electricity production mix. We develop an equilibrium model that identifies market participants' costs and revenues risks, and relates them to the risk premium. Using intraday limit order book data on the German/Austrian electricity day-ahead market (2013-2018), we structurally estimate the producers' cost functions, from which we infer participants' risk exposures. This enables us to propose a counterfactual analysis in which we vary the characteristics of the distribution of intermittent power generation. Our simulations suggest that an increase in the share of intermittent renewable power generation or its volatility raises both diversifiable and non-diversifiable risks, resulting in an increase in the risk premium.

JEL classification: **G12, G23**

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1 Introduction

The growing concern about global warming has encouraged the adoption of environmental public policies that prioritize the development of clean, renewable energies to achieve net carbon neutrality. Currently, 22% of the energy consumed in Europe comes from renewable sources, and it is expected to represent 40% of the total consumption by 2030 (European Environmental Agency, 2022). A vast literature has shown that renewable generation has an impact on the spot prices of electricity – namely, that it is related to lower prices and an increased volatility (see Würzburg et al. (2013),Paraschiv et al. (2014), de Lagarde and Lantz (2018), Figueiredo and da Silva (2019), Johnson and Oliver (2019)). Yet, little is known on the impact of renewable power generation on futures market, where both producers and retailers lock in the price of most of their transactions.[1] In this paper, we investigate the implications of the intermittency of power generation due to renewables on futures prices and the sharing of risk.

Since electricity cannot be stored on a large scale, electricity futures prices can not be determined through standard arbitrage techniques, that require an arbitrageur to "cash and carry" the underlying asset. On this market, industry participants demand or supply futures contracts in an attempt to hedge their risk exposures. In a nutshell, producers have a long position and would like to sell electricity forward, while retailers have a short position and would like to buy electricity forward. Depending on the season or the time of the day, producers may be more or less exposed than retailers, thus more or less willing to trade at a price above or below the expected spot price. Bessembinder and Lemmon (2002) (hereafter B&L) formalize this intuition in an equilibrium model that studies the interactions of retailers and producers in the spot and futures electricity market. They show that at equilibrium, the clearing futures prices encompass a risk premium which sign and magnitude would depend on the participants' hedging needs and risk exposures.

We extend B&L and develop a general equilibrium model of price formation on the futures markets in the presence of different types of electricity producers. Specifically, our model analyzes the implications of intermittency in renewable power generation and demand uncertainty on hedging strategies and the risk premium. The model setup allows us to identify market participants' revenue and cost risks as a function

[1] For example according to CRE, 77% of electricity transactions were carried out in the futures market in France in 2020.

of their cost structure, and classify these risks into diversifiable and non-diversifiable. At equilibrium, the retailers' cost risk matches the producers' revenues risk so these risks cancel out in the aggregate: these risks are diversifiable, and would therefore not be priced. At equilibrium, only the non-diversifiable risks, that is, the retailers' revenue risk and the producers' cost risk, have an impact on the futures price. This distinction is relevant because although the risk premium only depends on non-diversifiable risks, diversifiable risks reveal the amount of risk shared among agents and, therefore, the usefulness of the futures market.

Having developed the theoretical model, we proceed in three steps. First, we estimate the producers' cost parameters structurally by using the sellers' price schedules from the hourly limit order book of the German/Austrian (day ahead) market (2013-2018) and the volume of intermittent power generation. This enables us to quantify the theoretical participants' revenues and cost risk exposures on the spot market. Second, we complete our estimation of the model's parameters using a regression model based on the theoretical risk premium, where the dependent variable is the futures risk premium and the explanatory variables are the various risk exposures. The panel regression enables us to identify parameters related, for instance, to risk aversion. Third, based on our complete set of parameters' estimates, we draw counterfactual scenarios that trace the consequences of the increase in intermittent renewable power production.

In our model, the electricity supply on the spot market depends on the volume of renewable power generation produced by "green" producers and on the cost structure of a group of producers that we label as "conventional". To capture the characteristics of the merit order curve, we assume that the supply curve of these producers is S-shaped, that is, first concave for low volumes (capturing the low marginal costs related to nuclear power generation) then convex for high volumes (capturing the high marginal costs related to the use of more flexible power plants). In the first estimation stage, we structurally estimate month-by-month the corresponding cost parameters by non-linear least squares using each hourly (sell-side) price schedule from the limit order book as an observation. We obtain a time series of 'montly cost parameters, that we find to be consistent with the marginal costs of the three fossil fuels that are used in flexible power generation, namely coal, gas and oil.

Using these cost estimates, we compute the revenues and cost risks of the various types of market participants, namely retailers, green producers of renewable energy, and conventional producers. We confirm that producers' revenues and retailers' costs (that are diversifiable) are indeed highly and positively correlated with the spot price, which corroborates producers' overall long position and retailers' short position. Additionally, we also find that these risks are highly seasonal. In winter, when demand is high and when there is less intermittent power generation, prices are high, and both conventional producers and retailers face the highest risk related respectively to their revenues and costs. Green producers' revenues do not correlate with the spot price. However, in summer, the revenue risk of green producers increases: because demand is low while intermittent power production is high, clearing prices are often relatively low, decreasing the marginal revenues of green producers. In turn, given the low price level and the lower volume sold by conventional producers, the cost risk of retailers and the revenues risk of conventional producers are lower than in winter.

Like diversifiable risks, producers' costs and retailers' revenue risks (that are non-diversifiable) also exhibit seasonality. In summer, the correlation between all non-diversifiable risks and the spot price is close to zero. In this season, the spot price often fall in the region of the supply curve characterized by flat marginal costs. Consequently, a positive shock in intermittent power generation has little impact on the spot price. In winter, we find that retailers' revenues are negatively correlated while conventional producers' costs are positively correlated with the spot price. These correlations suggest that these two types of participants may be induced to trade fewer futures: the fact that conventional producers' costs increase with the spot price and that the retailers' revenues decrease, in contrast to their initial long and short exposures respectively, would provide them with a natural hedge. In contrast, the correlation between the costs of green producers and the spot price is negative, which increases their initial short revenues risk exposure even further. This may be due to the fact that in winter, the spot price is more likely to fall in the convex side of the supply curve, so a positive shock of renewable production increases the production costs while simultaneously causing spot prices to fall. This shows that the contribution of conventional or green producers to the risk premium on the futures markets are not identical.

In the second step of the estimation, we perform a panel regression that finds the relationship between non-diversifiable risks and the risk premium. The results show that the risk premium is positively related to the cost risk of both producers and negatively related to the revenue risk of retailers. These results are in line with our model's expectations. From the regression, we estimate the risk aversion coefficient at a value of 0.0386 and find the time series of the marginal costs of green producers. We find that these costs decrease significantly over our study period and are approximately 7, 9, and 16 times lower than the marginal costs of the three fossil fuels: coal, gas, and oil, respectively.

Next, we use the estimates of the structural parameters to trace the effects of the increase in renewable production. We simulate two counterfactual scenarios. In the first scenario, we vary the share of renewable energy production in the production mix but keep total demand fixed. This scenario allows us to understand the role of producers' cost risk in driving the risk premium. This exercise shows that when the share of renewable production or its volatility increase, the magnitude of the cost risk of both producers increases (positively for conventional producers and negatively for green producers). Hence, the impact of the cost risk of conventional producers on the risk premium turns out to be positive, while that of green producers is negative. Since the magnitude of the cost risk of conventional producers is greater than that of green producers, the overall effect consists in an increase in the magnitude of the risk premium (that is positive). In the second scenario, we vary both the characteristics of the distribution of renewable production and that of total demand. This enables us to investigate how the retailers' revenue risk influences risk premium. Under this scenario, producers' cost risk continues to behave the same way as in the previous scenario. In turn, the magnitude of the retailers' revenue risk increases, and its magnitude is significantly higher than those of producers. Overall, although the economic mechanism is slightly different, the magnitude of the risk premium also increases with the share and volatility of intermittent renewable production.

1.1 Literature Review

There is a growing interest in studying the impact of renewable generation on electricity spot prices. Many papers document that renewables decrease spot prices as they displace conventional production in the supply chain (a phenomenon known as the *merit order effect*) (see Baldick (2011), Woo et al. (2011), Azofra et al. (2014), Cludius et al. (2014), and Figueiredo and da Silva (2019)). Additionally, the intermittency in renewable generation introduces more volatility to an already volatile electricity price, given the lack of storage and nearly inelastic demand (see Karakatsani and Bunn (2010), Figueiredo and da Silva (2019), and Johnson and Oliver (2019)). We complement this literature by focusing on futures prices.

Because electricity cannot be stored, the theoretical price of an electricity future cannot be determined based on "cost-of-carry" strategies and no-arbitrage conditions. To establish the future price, one needs to rely on the market equilibrium theory in which the futures price can be determined via market clearing conditions. More precisely, the future price wil be equal to the expected value of the underlying commodity plus (or minus) a risk premium that compensates market participants for bearing a risk when holding a position in the futures market. Within the literature employing this approach, the seminal work of Bessembinder and Lemmon (2002) is noteworthy, as it has become a leading reference in the field. B&L identify the optimal quantity supplied or demanded by retailers and producers on the futures market. The market clearing condition yields a closed-form solution for the future price (and risk premium), that depends on producers' cost risk exposures and on retailers' revenues risk exposure. They show that these two risk exposures can be approximated by some central moments of the electricity spot price distribution (i.e., variance and skewness), which provides a simple empirical test of their model. Based on their assumptions regarding the supply level of convexity and the retailers' participation constraint, the authors find a positive relationship between the variance and a negative relationship between the skewness and the risk premium.

Based on this model, a whole empirical stream of research has emerged aiming to test B&L's theory, and more particularly the validity of the relation between the risk premium and the central moments of the spot price. The results of these empirical studies have been diverse, divided into those supporting (Longstaff and Wang (2004), Diko et al. (2006), Douglas and Popova (2008), Viehmann (2011), and Fleten et al. (2015)), partially supporting (Torró et al. (2008), Redl et al. (2009), Furió and Meneu (2010)), and opposing (Karakatsani and Bunn (2005), and Haugom and Ullrich (2012)) the theory. However, it is difficult to conclude why these studies differ from each other and from B&L conclusions. Potential differences arise from factors such as the region of study, the period of analysis, the maturity of the financial instrument, or the inclusion of additional variables to explain risk premium. Furthermore, the difference in the empirical results may also be due to the structural changes in the electricity market.We contribute to this literature by extending B&L to account for more heterogeneity in power generation, and by directly testing the relation between the risk premium and the participants' risk exposures built from cost parameters' estimations, instead on the approximated relation linking the risk premium to moments of the spot price distribution.

Undoubtedly, renewable power generation is changing the price risk exposure of market participants. Although in the electricity market, most of the transactions occur in advance via the futures market, there is scant literature studying how hedging strategies and futures prices have changed as a result of the growth of renewables. Peura and Bunn (2021) find that wind generation affects the risk premium in a direction that depends on the amount fed into the system. For moderate wind amounts, the quantity hedged via the futures market reinforces the merit order effect, reducing spot prices and causing the risk premium to be negative. In contrast, higher wind amounts lead to a less aggressive hedging strategy which increases spot prices and causes the risk premium to be positive. Using a model in which power generators produce from a mix of renewable and fossil sources, Schwenen and Neuhoff (2021) find that the effect on the futures market depends on how renewable power generation co-varies with the spot price. In periods of low covariance, the risk premium increases, while the risk premium decreases in periods of high covariance. Koolen et al. (2021) separate the effects on the risk premium of large-scale renewable production (i.e., solar and wind farms) and distributed renewable production (i.e., rooftop solar). The authors find that both types of renewable technologies affect the risk premium oppositely, and this contrast results from asymmetries in information predicting renewable production. We add to this new stream of research by developing a structural model that allows us to understand how the inclusion of different conventional production technologies and the use of renewable production impact hedging decisions, spot prices, and risk premium. Additionally, our study exploits the specificities of the hourly German/Austrian limit order book (2013-2018) to estimate the parameters of the different conventional technologies involved in the supply curve. Unlike other studies, from this detailed database, we can distinguish and compute all the risks involved in the futures market (both diversified and non-diversified risk) and the risk premium determination. The level of specification we can reach allows us to have a better picture of the hedging decisions of market participants.

2 The model

Our model is an extension of the equilibrium model initially proposed by Bessembinder and Lemmon (2002) and analyzes interactions of producers and retailers at two dates, namely on the spot electricity market and on the futures market. Our extension studies the impact of electricity generation from renewable energy and conventional sources (i.e., fossil fuels and nuclear energy).

2.1 Timing and participants

2.1.1 Model setup

There are three periods in the model. The last date corresponds to the wholesale market. On this market, producers deliver electricity to retailers, who satisfy the demand of their final consumers. Our model does not study any decision made by final consumers and assumes that the amount of electricity delivered by retailers to their end-customers is a random variable equal to the amount demanded by final consumers realized at date 3, $\widetilde{Q}_D \sim \mathcal{N}\left(\mu_D, \sigma_D^2\right)$. Furthermore, we assume that renewable power production, $\widetilde{Q}_G^w \sim \mathcal{N}\left(\mu_G, \sigma_G^2\right)$, is a random variable that depends on weather conditions and cannot be optimized, also realized at date 3. In the wholesale market, the provision of electricity follows the merit order, which means that the cheapest electricity source, i.e., renewables, satisfies total demand in the first place. Then, conventional producers provide the residual demand $\widetilde{Q}_N$ (i.e., $\widetilde{Q}_D - \widetilde{Q}_G^w$).

To satisfy this demand, N_R retailers buy a fraction of electricity (optimally chosen) on the futures market open at date 1, and the rest on the spot market open at date 2.[2] Likewise, N_G green and N_B conventional producers supply electricity via the futures and spot markets.[3] We will solve for the equilibrium backward: we first find the supply of electricity of conventional producers at date 2, and the equilibrium spot price in the spot market. Then we will identify the optimal positions of market participants on the futures market, and the futures prices that clears the market.

[2]More precisely, the spot market corresponds to the “day-ahead” market.

[3]Since we refer to physical futures contracts, there are no financial intermediaries. If they exist, they will close their positions before the contract maturity, and they will not affect the model's results.

2.1.2 The generation stack

Since the spot electricity market is competitive, each generator submits a bid showing their willingness to produce electricity for every possible market price. In other words, each generator submits an individual supply curve to the system operator. Thus, the system operator collects all the bids, arranges them in ascending order, and decides, on an hourly basis and according to the lowest marginal cost, which generators produce and which are shut down. This procedure occurs at noon for every hourly production on the following day. Thus, the aggregate supply curve is the result of adding the individual supply curves. It is also called the "generation stack," as it shows all producers' production stacked up in ascending order according to their marginal costs. The empirical evidence shows that this supply curve adopts an inverted S-shape, as displayed in the following figure.

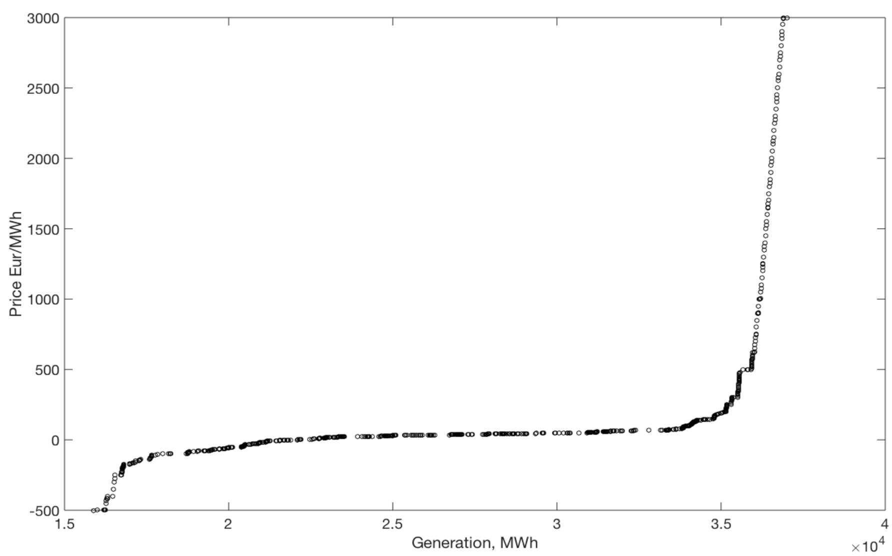


Figure 1: Snapshot of (spot market) limit order book data, January 02, 2018, at 12am
Source: Epex Spot data

In Figure 1, each dot represents a power plant sorted in ascending order according to their marginal costs. Points whose marginal costs are negative represent power plants choosing to lose production -or give electricity for free- rather than incurring the high cost of turning their plant on and off. Some inefficient nuclear, hard coal, and lignite power plants are within this type of producers. Then comes renewable energy, whose marginal cost is close to zero since the cost of producing an additional unit depends merely on weather conditions. Next comes nuclear energy with a low marginal cost since the fuel carries a large amount of energy for a small mass. Finally, these are followed by fossil fuel plants such as coal, gas, and oil. These plants incur in high marginal costs, as they must pay high fuel prices to produce electricity. Oil plants are relatively small and inefficient, producing little at a very high price. Coal is usually cheaper than gas, and gas is cheaper than oil.

The points on the aggregate supply curve prevent us from distinguishing the exact volume at which a new energy source starts supplying electricity. The maximum level of detail we can reach is to characterize the supply curve from the three regions that show an explicit change in the structure of their marginal costs. Thus, we assume that the supply curve is concave for the first production units, linear for the intermediate units, and convex for the last. Roughly speaking, each region can be linked, from left to right, with inflexible, renewable + nuclear, and fossil fuel producers. We assume that all market participants (i.e., producers and retailers) perceive this structure and optimize their choices by considering the possible region- or cost structure- where the spot price in equilibrium will fall.

2.1.3 Producers' cost structure

Since our ultimate interest is both identifying the impact of intermittent renewable energy on the risk premium and comparing intermittent renewable energies with other sources of electricity generation, we will assume the existence of two types of producers: "green" and "conventional". A different cost function characterizes both types of producers. Green producers have constant marginal costs close to zero and receive a "fed-in-tariff," θ, for each unit of electricity produced. Thus, the total cost function TC of green producer G_i who produces a quantity Q_{G_i} is defined as follows:

$$TC_{G_i}(Q_{G_i}) = F_G + a_G Q_G - \theta Q_{G_i}, \tag{1}$$

where F_G are the fixed costs, a_G a variable cost parameter, and $\tilde{Q}_G$ is the random production of renewables.

Since the marginal costs of green producers are constant and close to zero, we can attribute the inverted S-shape of the supply curve to conventional producers. We can classify conventional generators by production source: nuclear, coal, gas, or oil. Each segment of the cost function represents the producer's marginal cost fulfilling the last unit of demand. The total cost of conventional (or "brown") producer B_i who produces a quantity Q_{B_i} is given by:

$$TC_{B_i}(Q_{B_i}) = F_B + \begin{cases} \frac{a_B}{b_B}\exp(b_B Q_{B_i}) & \text{if } Q_{B_i} < \underline{Q}_{B_i} \\ \\ \frac{c_B}{2}\left(Q_{B_i}\right)^2 & \text{if } \underline{Q}_{B_i} < Q_{B_i} < \overline{Q}_{B_i} \\ \\ \frac{d_B}{g_B}\exp(g_B Q_{B_i}) & \text{if } Q_{B_i} > \overline{Q}_{B_i} \end{cases}, \tag{2}$$

where F_B are fixed costs, a_B, b_B, c_B, d_B and g_B are variable cost parameter.

The first segment, $Q_{B_i} < \underline{Q}_{B_i}$, captures producers who do not have suitable technology to turn their plants on and off quickly. Some nuclear, hard coal, and lignite power plants are within this type of producers. Total costs in this segment are increasing at decreasing rates ($a_B < 0$ and $b_B < 0$) because producers experience lower costs per unit produced. In the second segment, $\underline{Q}_{B_i} < Q_{B_i} < \overline{Q}_{B_i}$, the quantity of electricity produced increases, and the last unit demanded is provided by nuclear producers with low constant marginal costs ($c_B > 0$). The last segment, $Q_{B_i} > \overline{Q}_{B_i}$, characterizes the cost function of fossil fuel producers (i.e., gas, coal, and oil) with increasing total costs at increasing rates ($d_B > 0$ and $g_B > 0$). Since their production sources are highly dependent on the volatility of fuel prices, their cost function can explode at exponential rates.

Since in our model conventional producers are homogeneous, adopting a total cost function with exponential variable costs allows us to depict the total supply function with an inverted S-shape. We use this function as previous literature has shown that the exponential form is the one that best fits the electricity market supply curve (see He et al. (2013), and Álvaro Cartea and Villaplana (2008)). Moreover, our data regarding the electricity supply curve confirm this function as the best fit.

We assume that green producers, retailers and conventional producers are competitive and equally share the total green production, the total demand, and residual demand respectively. It follows that at date 3 on the wholesale market,

$$\begin{aligned} Q_{G_i} &= \frac{Q_G}{N_G}, \\ Q_{R_i} &= \frac{Q_D}{N_R}, \\ Q_{B_i} &= \frac{Q_N}{N_B}, \end{aligned}$$

where N_G, N_R and N_B are the number of green producers, retailers, and conventional producers respectively, and Q_{G_i}, Q_{R_i} and Q_{B_i} the quantity of electricity they produce or deliver on the wholesale market.

2.2 Second Period: The Spot Market

We will now develop the model starting with the last period. In this period, we analyze the decisions of market participants in the spot market, assuming that the hedging positions have been previously chosen.

2.2.1 Market participants' profits

We define S as the price of electricity in the spot market, F as the futures price, Q_{Bi}^{w} as the quantity sold by the conventional producer in the spot market, and Q_{Bi}^{F} as the quantity traded in the futures market (negative if market participants take a long position). The final profit of a conventional producer B_i who sells a quantity $Q_{B_i}^{w}$ on the spot market at price S and a quantity $Q_{B_i}^{F}$ on the futures market at price F writes:[4]

$$\pi_{B_i} = S \times Q_{B_i}^{w} + F \times Q_{B_i}^{F} - TC_{B_i}\left(Q_{B_i}\right). \tag{3}$$

Similarly, the final profits of green producer G_i who sells a quantity $Q_{G_i}^{w}$ on the spot market at price S and a quantity $Q_{G_i}^{F}$ on the futures market at price F writes:

$$\pi_{G_i} = S \times Q_{G_i}^{w} + F \times Q_{G_i}^{F} - TC_{G_i}\left(Q_{G_i}\right). \tag{4}$$

For both producers, the total electricity production, Q_{B_i} and Q_{G_i}, represents the sum of electricity produced and sold either on the futures or the spot market ($i.e., Q_i^w + Q_i^F$).

Retailers' profits come from the difference between the revenues obtained from the sale of a quantity Q_{R_i} of electricity to final consumers at a fixed retail price P_R, minus the cost of buying a quantity $Q_{R_i}^{w}$ of electricity

[4] We assume that producers have already paid the fixed costs in the second period and, therefore, these are considered sunk costs. Because of this, the positive profit condition does not necessarily hold.

in the spot market and that of buying a quantity $-Q^F_{R_i}$ on the futures market, with $Q_{R_i} = Q^w_{R_i} - Q^F_{R_i}$. The retailers' final profits are:

$$\pi_{R_i} = Q^w_{R_i}\left(P_R - S\right) - Q^F_{R_i}\left(P_R - F\right). \tag{5}$$

2.2.2 Spot market Equilibrium

Since renewable production and demand are random variables, they do not maximize their profits on the spot market. Thus, only conventional producers optimize their production. Solving the profit maximization problem, we find the following optimal production quantities for conventional producer i:

$$Q^w_{Bi} = \begin{cases} \frac{1}{b_B}\ln\left[\frac{S}{a_B}\right] - Q^F_{Bi} & \text{if } Q_{B_i} < \underline{Q}_{B_i} \\ \\ \left[\frac{S}{C_B}\right] - Q^F_{Bi} & \text{if } \underline{Q}_{B_i} < Q_{B_i} < \overline{Q}_{B_i} \\ \\ \frac{1}{g_B}\ln\left[\frac{S}{d_B}\right] - Q^F_{Bi} & \text{if } Q_{B_i} > \overline{Q}_{B_i} \end{cases} \tag{6}$$

To determine the spot price in equilibrium, the market-clearing condition has to hold. This means supply has to be equal to demand, i.e., that conventional producers have to produce to meet the residual demand:

$$\sum_{i=1}^{N_B} Q_{B_i} + \sum_{i=1}^{N_G} Q_{G_i} = \sum_{i=1}^{N_R} Q_{R_i} \iff \sum_{i=1}^{N_B}\left(Q^w_{B_i} + Q^F_{B_i}\right) = \underbrace{\widetilde{Q}_D - \widetilde{Q}_G}_{\widetilde{Q}_N} \tag{7}$$

Note that the market clearing condition (7) involves the merit order since it discounts the production of renewables from total production in the first place. Thus, our market-clearing condition is close to that of Bessembinder and Lemmon (2002), with the difference that our spot price equilibrium will depend on the residual demand.

Substituting the quantities found in equation (6), and considering that in equilibrium conventional producers must serve the residual demand (that is, $\sum_{i=1}^{N_B}\left(Q^w_{B_i} + Q^F_{B_i}\right) = Q_N$), we get the spot price in equilibrium:

$$S^* = \begin{cases} a_B \exp(\frac{b_B}{N_B}\widetilde{Q}_N) & \text{if } \widetilde{Q}_N < \underline{Q} \\ \\ \frac{c_B}{N_B}\widetilde{Q}_N & \text{if } \underline{Q} < \widetilde{Q}_N < \overline{Q} \\ \\ d_B \exp(\frac{g_B}{N_B}\widetilde{Q}_N) & \text{if } \overline{Q} < \widetilde{Q}_N \end{cases}, \tag{8}$$

where $\underline{Q} = \sum_{i=1}^{N_B} \underline{Q}_{B_i}$ and $\overline{Q} = \sum_{i=1}^{N_B} \overline{Q}_{B_i}$. The equilibrium price resumes some characteristics of the electricity market. When the residual demand is low, the spot price is negatively skewed and can reach negative amounts.[5] Conversely, when demand is high, prices increase exponentially, and skewness is positive. Also note that, as prices depend on residual demand, the spot price is a decreasing function of renewable production, a phenomenon commonly known as the merit order effect. Note that a higher realization of renewables displaces with more force the conventional production in the provisioning order.

2.3 First Period: futures hedging positions

Having determined the equilibrium price on the spot market, we now turn to the first period. Participants $i \in \{B_i, G_i, R_i\}$ will choose the quantity to sell on the futures market, Q_i^F so as to maximize their expected utility, that we assume to be mean-variance:

$$\max_{Q_i^F} EU[\pi_i] = E[\pi_i] - \frac{A_i}{2} Var[\pi_i], \tag{9}$$

where A_i represents the coefficient of risk aversion. We split market participants' profit into two components as follows:

$$\pi_i = \underbrace{\rho_i}_{\text{But-for-hedging-profits}} + \underbrace{Q_i^F(F - S)}_{\text{futures market's profits}}, \tag{10}$$

where π_i corresponds to the profits obtained in the absence of any hedging position (also called the "but-for-hedging" profits), and the second component corresponds to the profits related to trades in the futures market.

2.3.1 Producers and retailers hedging position

Market participants' profits are a piecewise linear function that depends on the realization of the state of nature $j \in \{1, 2, 3\}$.[6] Each state of nature defines whether the residual demand falls in region 1 ($\widetilde{Q}_N < \underline{Q}$), region 2 ($\underline{Q} < \widetilde{Q}_N < \overline{Q}$), or region 3 ($\overline{Q} < \widetilde{Q}_N$). Let $\mathcal{R}_j$ define the corresponding event, and α_j their probability of occurrence. We apply the law of iterated expectations and total variance to compute the unconditional mean-variance preferences.[7] First, by applying the law of iterated expectations, we find the

[5] Negative prices occur when the production of renewables is higher than total demand.
[6] See Appendix A for the details of the computation of the participants' but-for-hedging-profits.
[7] For more details on the computations of the expectation and variance of participants' profits, see Appendix B.

unconditional expected profits:

$$E\left[\pi_i\right] = \sum_{j=1}^{3} \alpha_j E[\pi_i|\mathcal{R}_j] = \sum_{j=1}^{3} \alpha_j E\left[\rho_i|\mathcal{R}_j\right] + Q_i^F\left(F - E[S|\mathcal{R}_j]\right). \tag{11}$$

We also know that the conditional variance of profits for market participants is:

$$Var[\pi_i|\mathcal{R}_j] = Var\left[\rho_i|\mathcal{R}_j\right] + \left[Q_i^F\right]^2 Var\left[S|\mathcal{R}_j\right] - 2Q_i^F Cov\left[\rho_i, S|\mathcal{R}_j\right]. \tag{12}$$

By applying the law of total variance, we find the unconditional variance:

$$\begin{aligned} Var[\pi_i] &= E[Var[\pi_i|\mathcal{R}_j]] + Var[E[\pi_i|\mathcal{R}_j]] \\ &= \sum_{j=1}^{3} \alpha_j Var(\rho_i|\mathcal{R}_j) + \left[Q_i^F\right]^2 \sum_{j=1}^{3} \alpha_j Var(S|\mathcal{R}_j) - 2Q_i^F \sum_{j=1}^{3} \alpha_j Cov(\rho_i, S|\mathcal{R}_j) \qquad (13) \\ &+ \sum_{j=1}^{3} \alpha_j \left(E(\rho_i|\mathcal{R}_j) + Q_i^F[F - E(S|\mathcal{R}_j)]\right)^2 + \left(\sum_{j=1}^{3} \alpha_j E[\rho_i|\mathcal{R}_j] + Q_i^F[F - \sum_{j=1}^{3} \alpha_j E(S|\mathcal{R}_j)]\right)^2. \end{aligned}$$

Thus the market participants' maximization problem is:

$$\begin{aligned} \max_{Q_i^F} EU[\pi_i] \quad &= \quad \sum_{j=1}^{3} \alpha_j E[\rho_i|\mathcal{R}_j] + Q_i^F \left(F - \sum_{j=1}^{3} \alpha_j E(S|\mathcal{R}_j)\right) \\ &- \quad \frac{A}{2}\left[\sum_{j=1}^{3} \alpha_j Var(\rho_i|\mathcal{R}_j) + \left(Q_i^F\right)^2 \sum_{j=1}^{3} \alpha_j Var(S|\mathcal{R}_j)\right] \\ &- \quad \frac{A}{2}\left[-2Q_i^F \sum_{j=1}^{3} \alpha_j Cov(\rho_i, S|\mathcal{R}_j) + \sum_{j=1}^{3} \alpha_j \left(E(\rho_i|\mathcal{R}_j) + Q_i^F\left(F - E(S|\mathcal{R}_j)\right)\right)^2\right] \\ &- \quad \frac{A}{2}\left[\left(\sum_{j=1}^{3} \alpha_j E[\rho_i|\mathcal{R}_j] + Q_i^F \left(F - \sum_{j=1}^{3} \alpha_j E(S|\mathcal{R}_j)\right)\right)^2\right] \qquad (14) \end{aligned}$$

From the first-order condition, we can determine the optimal quantity that participants sell on the futures market for a given futures price F:

$$Q_i^{F*} = \frac{F - E(S)}{A\sum_{j=1}^{3} \alpha_j Var(S|\mathcal{R}_j)} + \frac{\sum_{j=1}^{3} \alpha_j Cov(\rho_i, S|\mathcal{R}_j)}{\sum_{j=1}^{3} \alpha_j Var(S|\mathcal{R}_j)} \tag{15}$$

Note that a negative quantity would correspond to a purchase.

Equation (15) consists of two parts. The first part corresponds to a speculative position: when the futures price is below the expected spot price, market participants will buy more futures to benefit from this difference. The second component corresponds to the incentive to hedge. When the covariance between the "but-for-hedging" profits and the spot price S is positive, which is more likely to be the case for producers who have a long position, participants are induced to sell futures. Conversely, when the covariance between the "but-for-hedging" profits and the spot price S is negative, which is more likely to be the case for retailers who have a short position, participants are induced to buy futures ($Q_i^F < 0$). Note that the covariance and variance are weighted averages of their conditional values, where the assigned weight is the probability of the residual demand falling in different regions.

Taking a detailed look at the covariance components in equation (15), we decompose the participants' but-for-hedging-profits into costs and revenues, which translates into components of the covariance with the spot price as follows:[8]

$$Cov(\rho_{G_i}, S) = \underbrace{\frac{1}{N_G} Cov\left(S \times \widetilde{Q}_G, S\right)}_{\text{Green producers' revenue risk}} - \underbrace{\left[\frac{a_G - \theta}{N_G}\right] Cov\left(\widetilde{Q}_G, S\right)}_{\text{Green producers' cost risk}} \tag{16}$$

$$Cov(\rho_{R_i}, S) = \underbrace{P_R \times Cov(\widetilde{Q}_{R_i}, S)}_{\text{Retailers revenue risk}} - \underbrace{Cov(S \times \widetilde{Q}_{R_i}, S)}_{\text{Retailers cost risk}} \tag{17}$$

$$\sum_{j=1}^{3} \alpha_j Cov(\rho_{B_i}, S|\mathcal{R}_j) = \underbrace{\frac{1}{N_B} Cov\left(S \times \widetilde{Q}_N, S\right)}_{\text{Conventional producers' revenue risk}} \quad \underbrace{- \alpha_1 \left[\frac{a_B}{b_B}\right] Cov\left(\exp^{b_B\left[\frac{\widetilde{Q}_N}{N_B}\right]}, S\right)}_{\text{Conventional producers' cost risk}}$$

$$\underbrace{- \alpha_2 \left[\frac{c_B}{2N_B^2}\right] Cov\left(\widetilde{Q}_N^2, S\right) - \alpha_3 \left[\frac{d_B}{g_B}\right] Cov\left(\exp^{g_B\left[\frac{\widetilde{Q}_N}{N_B}\right]}, S\right)}_{\text{Conventional producers' cost risk}} \tag{18}$$

For all market participants, these risks relate to the covariation between their production's revenue/cost and the spot price. Conventional producers must weigh their cost risk according to the probability of residual demand falling in any of the three regions under analysis. Likewise, as mentioned by Bessembinder and Lemmon (2002), despite retailers setting a fixed selling price to final consumers, they still experience revenue and cost risks related to the covariance between the volume purchased in the spot market and the spot price. However, in our case, the revenue risk of retailers is also affected by the generation of renewables, and it is not necessarily positive on average.

2.3.2 First Period: futures price equilibrium

For the futures market to clear, there should be a zero net supply for futures contracts:

$$\sum_{i=1}^{N_B} Q_{B_i}^F + \sum_{i=1}^{N_G} Q_{G_i}^F + \sum_{i=1}^{N_R} Q_{R_i}^F = 0. \tag{19}$$

[8] We show the details of the ¨but-for-hedging-profits¨ in Appendix A.

Substituting $Q_{B_i}^{F*}$, $Q_{G_i}^{F*}$ and $Q_{R_i}^{F*}$ into equation (19) we get the futures price in equilibrium:[9]

$$F^* - E(S) = \overbrace{\overline{A} N_B}^{\beta_1} \left[\underbrace{\alpha_1 Cov\left(\frac{a_B}{b_B}\exp b_B\left(\frac{\widetilde{Q}_N}{N_B}\right), S\right) + \alpha_2 Cov\left(\frac{c_B}{2}\left(\frac{\widetilde{Q}_N}{N_B}\right)^2, S\right) + \alpha_3 Cov\left(\frac{d_B}{g_B}\exp g_B\left(\frac{\widetilde{Q}_N}{N_B}\right), S\right)}_{\text{Conventional Cost Risk}} \right]$$
$$+ \overbrace{\overline{A}[a_G - \theta]}^{\beta_2} \left[\underbrace{\sum_{s=1}^{3} \alpha_s Cov\left(\widetilde{Q}_G, S|\mathcal{R}_s\right)}_{\text{Green Cost Risk}} \right] - \overbrace{\overline{A}}^{\beta_3} \left[\underbrace{P_R \sum_{s=1}^{3} \alpha_s Cov\left(\widetilde{Q}_D, S|\mathcal{R}_s\right)}_{\text{Retailers Revenue Risk}} \right], \tag{20}$$

where $\overline{A} = \frac{A}{N_B+N_G+N_R}$. Equation (20) results from the optimal hedging of market participants. According to their optimal futures positions, market participants want to hedge potential variations between the futures price vs. the spot price and the covariance between their "but-for-hedging" profits and the spot price. Two components comprise these profits: 1) the covariance between their revenue vs. the spot price and 2) the covariance between their costs and the spot price. From the zero net supply condition, since the producers' revenues ($S \times Q$) correspond to the retailers costs, the corresponding risks cancel each other out: we call these risks "diversifiable".The risk premium end up being a function of the producers' cost risk and the retailers' revenue risk, that we call non-diversifiable risks.

The sign of the risk premium $F - S$ depends on that of the various covariances. First, conventional producers' production costs increase with the residual demand, which should have a positive relation with spot price. We therefore expect the covariance between their production cost and the spot price to be positive. An increase in the magnitude of conventional producers' cost risk would thus increase the futures price. Conventional producers have a long position that exposes them to losses when prices are low, which induces them to sell futures. However, since it is more likely that prices would be low when demand is low, they would also incur lower costs, which reduces their incentives to hedge, and thus their selling pressure on futures markets.

Second, unlike the baseline model of Bessembinder and Lemmon, our risk premium formula incorporates the non-diversifiable risks arising from renewable generation. Green producers' cost risk depends on the covariance between the volume of renewable power genetationand spot prices, that we expect to be negative (since a higher level of production at a very low marginal cost should decrease prices). By contrast to

[9] Shown in Appendix C

conventional producers, an increase in the magnitude of green producers' cost risk would thus decrease the futures price. When intermittent power generation is high, green producers face simultaneously higher production cost and lower marginal revenues. Since both exposures are in the same direction, this may reinforce their willigness to sell futures, which lowers the futures price.

Third, retailers's revenue risk can be decomposed as follows:

$$P_R \sum_{s=1}^{3} \alpha_s Cov\left(\widetilde{Q}_D, S\right) \quad = \quad P_R \sum_{s=1}^{3} \alpha_s Cov\left(\widetilde{Q}_N, S\right) + P_R \sum_{s=1}^{3} \alpha_s Cov\left(\widetilde{Q}_G, S\right). \tag{21}$$

Since the residual demand now depends on the volume of renewable power generation, the covariance between demand and the spot price that captures the retailers' revenue risk may not necessarily be positive, unlike the Bessembinder and Lemmon model. Indeed, we expect the equilibrium spot price to be an increasing function of residual production but a decreasing function of renewable generation.

3 Data

In this section, we describe the data used to estimate the conventional producers' costs based on the aggregate supply curve given in equation (8), and the other parameters of the model based on the futures prices given in equation (20).

3.1 Electricity spot demand and supply curves

We collect from Epex Spot the hourly aggregated supply and demand curves of the German/Austrian day-ahead electricity market from 01.03.2013-31.08.2018. There are 24 aggregated curves for each day, each representing the sum of bids from producers/retailers to sell/buy electricity at a specific hour on the following day. Each curve contains a set of pairs (price, volume) that define the curve. Volume is expressed in MWh, and price in Eur/MWh. Bids range between Pmin=-500 and Pmax=3000, and the minimum order size is 0.1MW for each block of an hour.

3.2 Electricity futures prices

We obtain from Epex Spot the daily price of the monthly base futures (also called Phelix futures), whose delivery period is between March 2013 and August 2018. We collect 66 contracts with daily prices (in Euro/MWh) from six months before the maturity date.[10]

3.3 Data used to estimate the model parameters

Renewable generation We obtain hourly solar and wind generation day-ahead forecasts from the German Transmission System Operators (TSOs): 50Hertz, Amprion, Transnet, and Tennet. The total solar and wind generation results from the sum of generation from the four operators.[11]

Total demand and day-ahead prices We compute the hourly total demand and day-ahead price from the intersection between the aggregate supply and demand curves. [12]

Residual demand Residual demand results from the subtraction between total demand and renewable electricity generation.

Short Run Marginal Costs We construct the marginal costs of the three main fossil fuels (gas, coal, and oil) from the formulas reported by Refinitiv. We also obtain the fossil fuel prices from the same source to build these costs. For gas, we use the price of the Dutch day-ahead gas contract (TRNLTTFD1 in EU/MWh). For coal, we use the price of coal delivered to the Amsterdam, Rotterdam, and Antwerp regions (Coal ICE API2 CIF ARA in Euros/MT). For oil, we use the price of Brent crude oil (BRT in EU/Bbl). The gas and coal price series are the same used by Refinitiv to calculate its SRMCs. Section 4.3 provides more details on constructing these marginal costs.

Feed-in-tariffs We get the tariffs from the OECD database.[13] These tariffs are in USD/KWh and cover seven types of renewable energy generation: wind, solar, geothermal, small hydro, marine, biomass, and waste. However, we only use solar and wind tariffs to maintain consistency with the renewable energy generation data. In addition, we convert the tariffs to euros per MWh.

[10] The volume of these contracts results from the number of delivery days times the electricity delivered daily (normally 24MWh). Therefore, for a monthly contract with 30 delivery days, the contract volume is 720 MWh.

[11] 50Hertz,Amprion, Transnet and Tennet data, last accessed on 27.08.2022.

[12] We verified that the equilibrium prices were in line with the hourly prices provided directly by Epex Spot.

[13] OECD database on feed-in-tariffs,last accessed on 27.08.2022.

Retail Prices We obtain the electricity prices for household consumers in Germany from Eurostat.[14] Data are bi-annual, in euros per kilowatt-hour, excluding taxes and levies, and describe the consumption data over a band DC between 2500 KWh and 5 000 KWh. To keep consistency with the rest of the data expressed in MWh, we convert the units to euros per MWh.

CO2 prices We obtain from Refinitiv the daily prices of the EU emission allowances from 01.03.2013 to 31.08.2018. These prices are expressed in Eur/TCO2.

4 First stage estimation

We estimate the model in two stages. In the first stage, we obtain the parameters involved in the market supply curve (i.e., $a_B, b_B, c_B, d_B, g_B, \underline{Q}$ and $\overline{Q}$), which we get from the horizontal sum of the individual supply curves. The market supply curve is given in equation (8) recalled below:

$$S^* = \begin{cases} a_B \exp(\frac{b_B}{N_B}\widetilde{Q}_N) & \widetilde{Q}_N < \underline{Q} \\ \\ \frac{c_B}{N_B}\widetilde{Q}_N & \underline{Q} < \widetilde{Q}_N < \overline{Q} \\ \\ d_B \exp(\frac{g_B}{N_B}\widetilde{Q}_N) & \overline{Q} < \widetilde{Q}_N \end{cases}$$

In this estimation stage, first, we perform linear interpolation to create new data points. Then we approximate the points using a third-degree polynomial and consider the kinks ($\underline{Q}$ and $\overline{Q}$) as those points on the curve where the first derivative of the polynomial is equal to zero. Once we calculate the left and right kinks, we fit the first and the last segment of the piecewise function (8) using nonlinear least squares. For each hourly fitted curve, we obtain the parameter values, their 95% confidence interval, the R-Squared, the Adjusted R-Squared, the root-mean-squared error (RMSE), and the degrees of freedom. To adjust the middle segment of the piecewise function, we find the line that passes through the two kinks points. We estimate a total of $64,909$ curves. However, we removed those hours where the parameter's confidence intervals go to infinity or give NaN (we eliminate 368 curves or 0.5% of the total sample). As an example, Figure 2 shows the estimation for the market supply curve on June 5, 2017, at 4 pm. The blue, pink, and green curves show the interpolated data for each segment. The yellow curve represents the third-degree polynomial, and the

[14] Eurostat database on retail prices, last accessed on 27.08.2022.

red curve shows the piecewise function fitting curve.

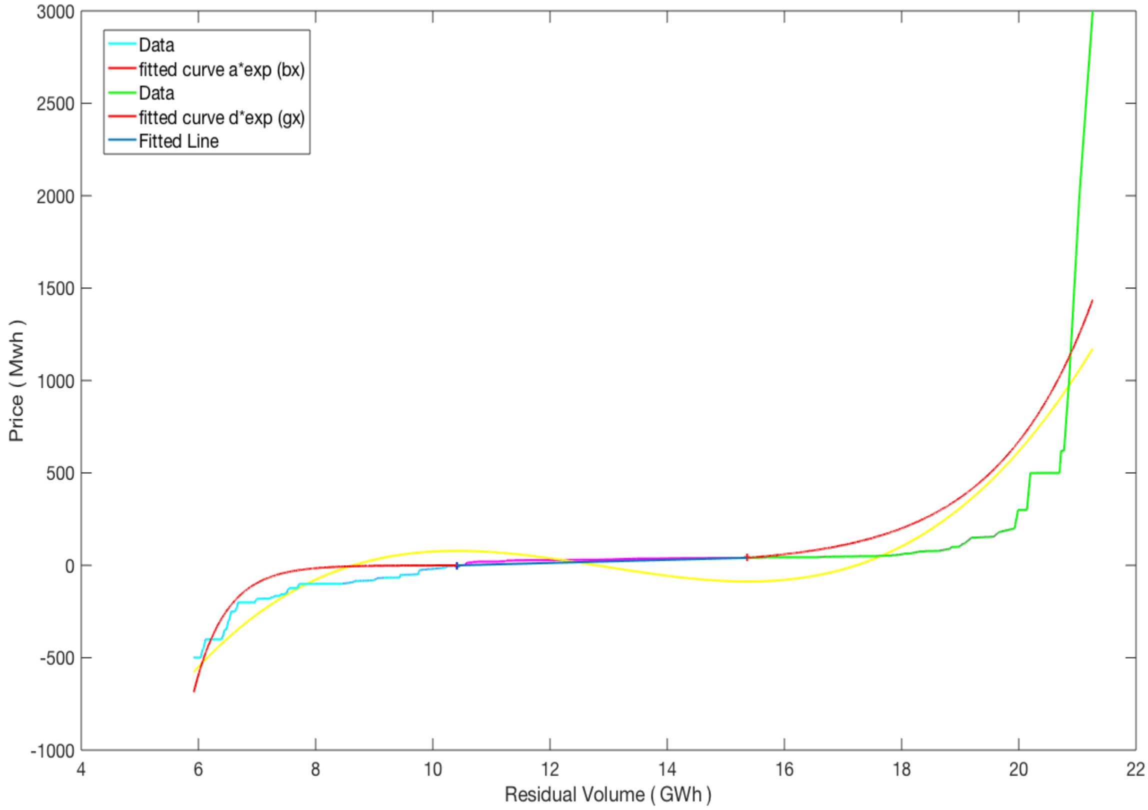


Figure 2: Curve fit on June 5, 2017, at 4 pm.
Source: Epex Spot and German Transmission System Operators (TSOs).

Once we obtain the hourly estimates, we use these estimates to build monthly parameters, which should be interpreted as the hourly average for each month of the period analyzed. We have two main reasons to focus on monthly parameters. The first is because those are "deep" parameters related to the producers' cost production that do not change over a short time horizon. The second is that, since we use monthly electricity futures to get the risk premium, it is in our interest to construct monthly spot prices that allow us to compare both instruments. Additionally, we smooth the monthly estimates by adjusted R2 weighted averages. Thus, the closer the adjusted R2 is to 1, the more weight the hourly estimate has in the monthly parameter.[15]

Before discussing the results of the monthly estimates, let us recall the meaning of each parameter for an

[15]These results are qualitatively similar using equally weighted averages.

exponential model with the form: $Y = a * exp(kX)$. The parameter "a" defines the y-axis intersection point when "X" is zero, while parameter "k" is the rate of growth (if positive) or the rate of decay (if negative). The larger the parameter "k," the faster the function grows or decays. Thus, in our case, parameters b_B and g_B describe the speed of price increase. Higher levels of g_B show that prices will rise faster, while higher levels of b_B show that prices will decay more quickly. On the concave side of the curve, as b_B increases (or gets closer to zero), producers will be willing to give away their output at a higher negative price, which means a higher level of impatience to give away their production. On the convex side of the curve, as g_B increases, the selling price of electricity grows faster. As we observe, the b_B and g_B parameters are of main importance for our model, as they indicate the degree of convexity and concavity of the supply curve. Additionally, the parameter c_B depicts the behavior of conventional producers when residual demand is between kinks, i.e., not extremely low or extremely high. In this region, the parameter c_B should be positive but close to zero since producers anticipated the residual demand well, causing their marginal costs to remain constant and without volatile changes.

4.1 Kinks Estimation

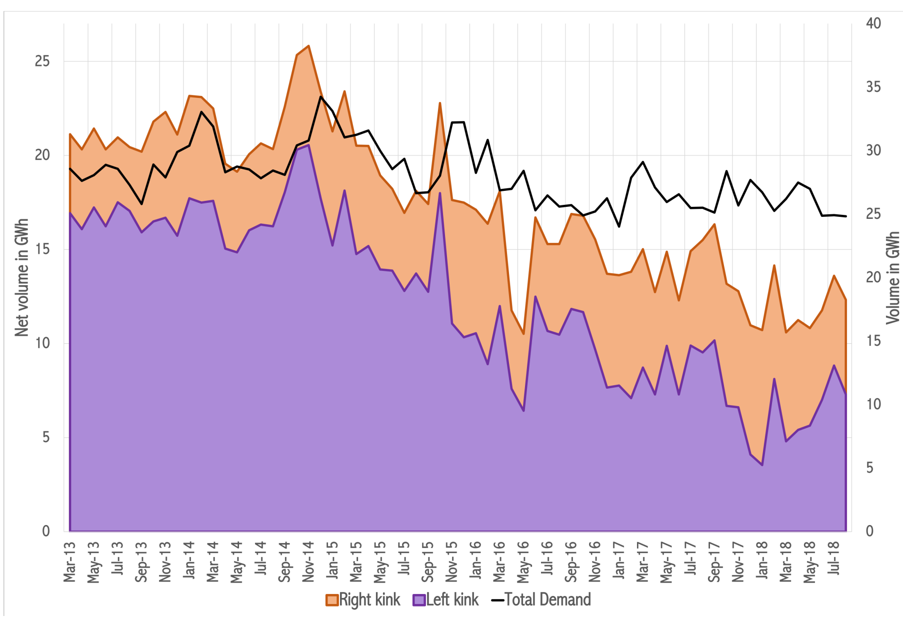


Figure 3: Parameter estimation: $\underline{Q}$ and $\overline{Q}$

Figure 3 shows the results of the estimates for the right and left kinks. Take, for example, the residual production of 15GWh. By the end of 2014, this quantity was in the concave area, but as of 2016 it was already in the convex region. This result suggests that, throughout the analysis period, there was a generalized decrease in residual production and a decline within each respective segment. The figure also displays total demand, which remains relatively constant, ruling out the possibility that such a reduction results from a drop in total demand. Figure 4 shows the net installed electricity capacity in Germany. From this figure, we can conclude that this decrease comes from an increase in renewable, a slight growth in gas, and a reduction in nuclear and hard coal installed capacity. The rest of the sources maintain their installed capacity constant over time. Therefore, the gradual decrease in nuclear and hard coal production reduced the number of producers with low levels of flexibility, which were substituted by other more flexible sources.

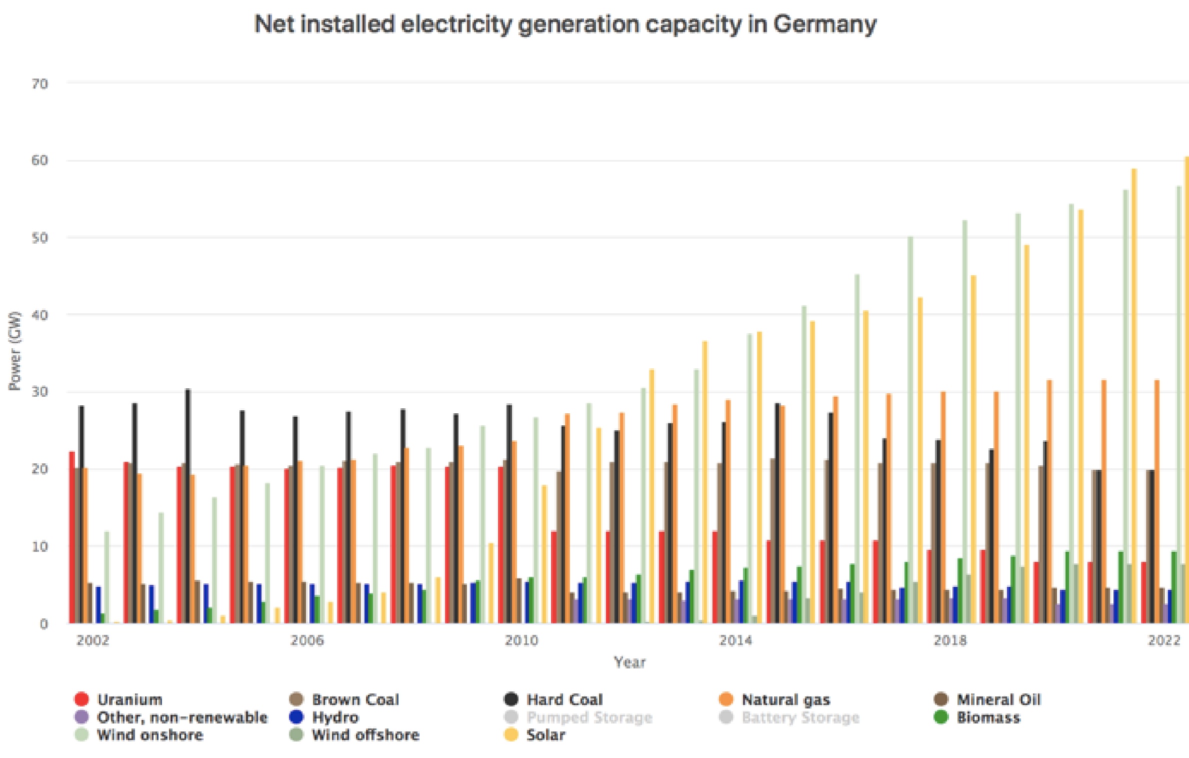


Figure 4: Net installed electricity generation capacity in Germany. Source: Fraunhofer ISE.

4.2 Cost Parameters Estimation

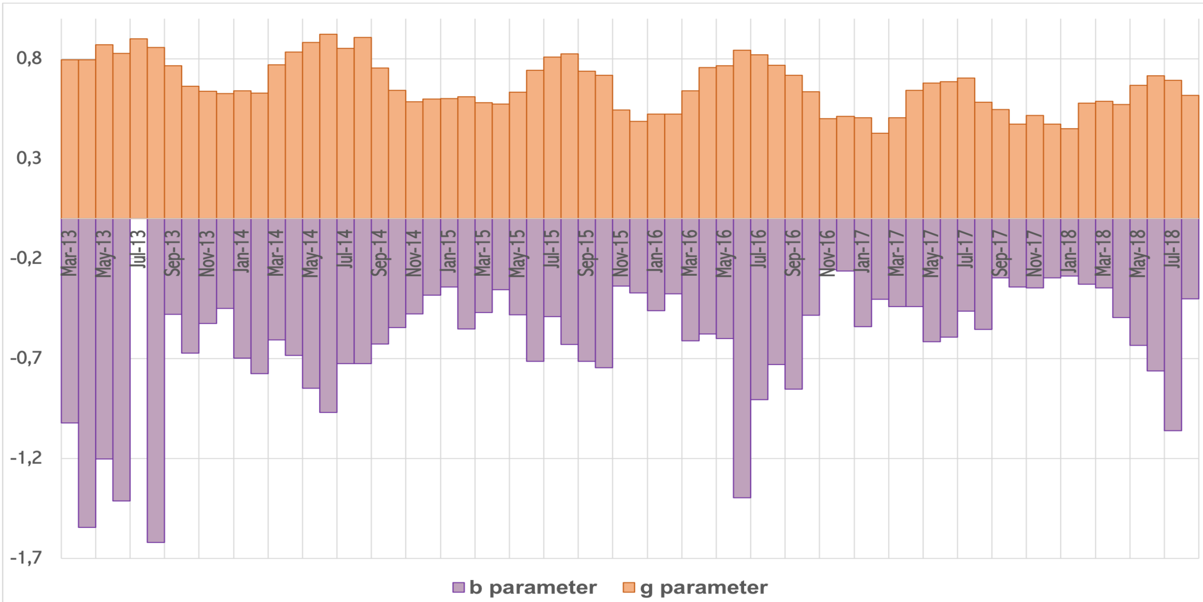


Figure 5: Parameter estimation: b_B and g_B (curvatures)

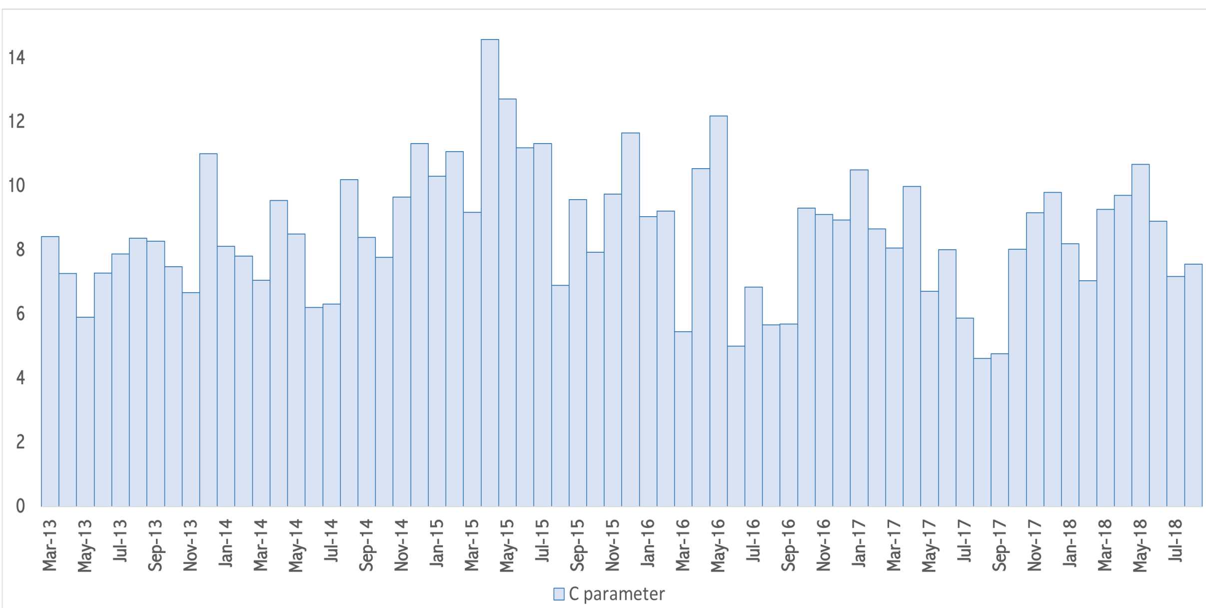


Figure 6: Parameter estimation: c_B

Figure 5 and 6 show the estimates for parameters b_B, g_B, and c_B. All parameters are aligned with our model expectations (i.e., $b_B < 0$, $g_B > 0$, and $c_B > 0$). Furthermore, they show seasonality, where parameters reach maximum values (minimum for $b_B < 0$) during summer. The b_B parameter shows values between -3 and 0, averaging -0.68, while the g_B parameter ranges between 0.4 and 1 and averages 0.75. To interpret the results of these parameters, we perform the following linear regressions:

$$g_{Bt} = \beta_1 \times GSRMC_t + \beta_2 \times CSRMC_t + \beta_3 \times OSRMC_t + \beta_4 \times RL_t + F_t + \varepsilon_t \tag{22}$$

$$b_{Bt} = \beta_1 \times GSRMC_t + \beta_2 \times CSRMC_t + \beta_3 \times OSRMC_t + \beta_4 \times RL_t + F_t + \varepsilon_t, \tag{23}$$

where the dependent variables are b_{Bt}, the left parameter, and g_{Bt}, the right parameter. GSRMC, CSRMC, and OSRMC are the monthly electricity short-run marginal gas, carbon, and oil costs in Eur/MWh, respectively. RL is the residual load in GWh, and F_t are yearly dummy variables to control for seasonality.

4.3 Goodness of fit: Short Run Marginal Costs (SRMC)

We construct the marginal costs of the three main fossil fuels used as independent variables in regressions (23) and (22). We base our computations on the formula provided by Refinitiv. Since SRMC are only available for gas and coal from 2014 onwards, we calculate those for 2013 and create the SRMC of oil for all years.[16] The SRMC formula of Refinitiv is:

$$\begin{aligned} \text{SRMC[eur/MWh]} &= \frac{\text{Fuel price[eur/ton or eur/therm]}}{\text{heat value[GJ/t or GJ/therm]} * \text{efficiency}} * 3.6\text{[GJ/MWh]}+ \\ &+ \frac{\text{emission intensity[tCO2/GJ]} * \text{carbon emission price[eur/tCO2]}}{\text{efficiency}} * 3.6\text{[GJ/MWh]}+ \\ &+ \text{O\&M costs[eur/MWh]} \end{aligned} \tag{24}$$

The first part is the marginal cost of the fuel needed to produce one MWh of electricity. This cost considers the efficiency of the plant used, expressed as the percentage of energy, out of the total, converted into electricity. The second part of the formula depicts the marginal cost of carbon emissions, where the emission intensity factor approximates the amount of CO2 released per fuel type. Again, Refinitiv considers the plant's efficiency in this calculation. The third part of the formula accounts for the operation and maintenance costs. Table 1 shows the values used by Refinitiv in the SRMC over the period from 2014 onwards:

[16] In Refinitiv, prices are found with the quote: SRMCTTFMc1 (for gas) and SRMCAPI2Mc1 (for coal).

	Coal	**Gas**
Heat value [Gj/MWh]	10	7.2
Efficiency [%]	36	50
Emission intensity [tCO2/Gj]	0.094	0.056
O&M costs	4.4 [eur/MWh]	3.2631 [GBP/MWh]

Table 1: Refinitiv-Eikon reported values to compute the SRMC.
Source: Refinitiv-Power composite methodology and specification guide.

We use this formula to complete coal and gas and to create oil time series. However, since coal is expressed in metric tons and oil in barrels, we first convert the original units into MWh. For this, we rely on the information provided by the US Energy Information Administration (EIA), which uses the British thermal units (Btu) as a reference unit to compare the energy produced by different units (barrels of oil, metric tons of coal, terajoules, etc.).[17] Once we convert prices to MWh, we apply the formula (24) using the following values for all the analysis period:

	Coal	**Gas**	**Oil**
Efficiency [%]	44	48.5	38
Emission intensity [t CO2/Gj]	0.0946	0.0561	0.0741
O&M costs [eur/MWh]	4.4	3.2631 [GBP/MWh]	3

Table 2: Our values to compute the SRMC.
Source: We obtain efficiency percentages from an ECOFYS report (2018) and emission intensity factors from EIA (2005). We keep the operation and maintenance costs for coal and gas from Refinitiv. For oil, we employ those reported by DIW Berlin (2013).

Note that we change the efficiency and intensity emission values to keep the same reference sources among the three fuels and, thus, minimize possible distortions in the marginal costs derived from obtaining the data from different sources. Figures 7 and 8 show the comparison between the SRMC provided by Refinitiv and our time series. As can be seen, the differences are minimal. Our marginal costs capture the same upward and downward trends as those provided by Refinitiv. Figure 9 displays the marginal costs for the three fuels. The figure shows that the marginal costs of oil have remained significantly above the cost of the other two

[17] According to the EIA equivalences, 1 barrel of crude oil equals 5.691M of Btu while one metric ton of coal equals 18.856 of Btu. Also, 1M of Btu is equivalent to 0.29 MWh.

fuels while, most of the time of analysis, the marginal cost of coal has been the lowest. Only in the summer of 2017 did prices switch between gas and coal. In addition, marginal costs show a downward trend until February 2016 and continue with an upward trend until the end of our study period.

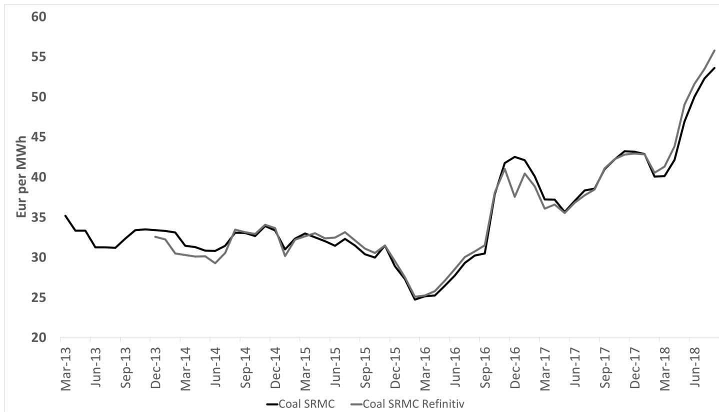


Figure 7: Marginal costs of coal power plants

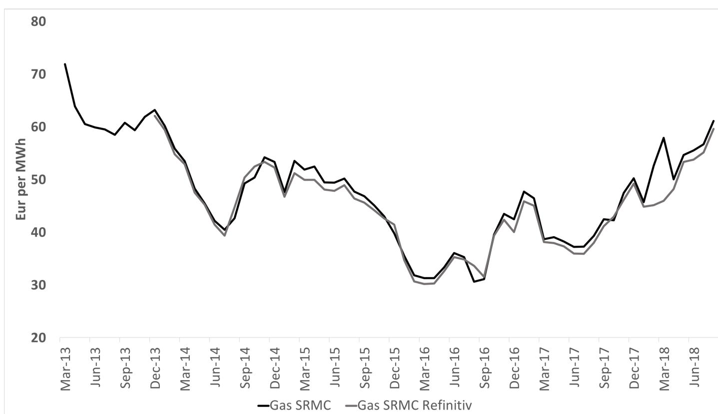


Figure 8: Marginal costs of gas power plants

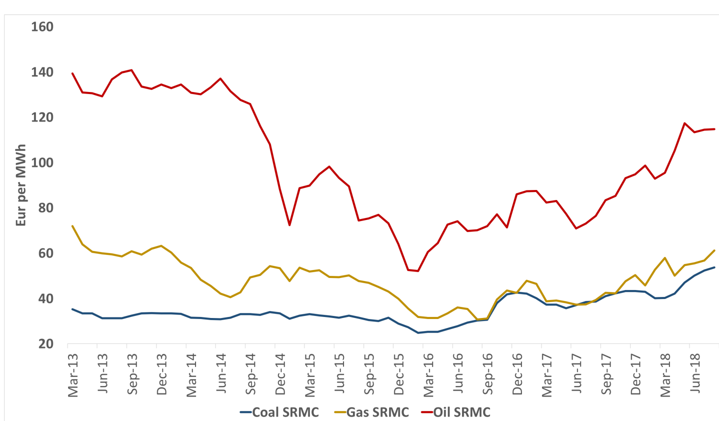


Figure 9: Marginal costs of oil, gas and coal power plants

4.4 Goodness of fit: supply curves and marginal costs

Table 3 shows the result of regression (22).This table reveals that an increase in the marginal cost of gas diminishes the convex curvature. This result, which at first glance seems counter-intuitive, points to a substitution effect between gas/coal production sources. When the marginal cost of gas increases, producers substitute this source for a cheaper one (i.e., coal). This leads to an increase in coal production and convex curvature. Also, note that the marginal cost of coal is not significant since coal is the fuel with the lowest marginal costs; an increase in cost does not cause a substitution effect of this source by gas. Moreover, since oil is the most expensive and least used source of electricity, an increase in its marginal cost translates directly into an increase in the convex curvature. Finally, residual demand is not significant. Table 3 also shows the results for regression (23). However, note that none of the marginal costs are significant in determining the b_B parameter, indicating that there are factors other than marginal costs and residual load that producers consider when deciding their bidding strategy in this area.

Table 3: g_B and b_B parameter regression

	g_B parameter	b_B parameter
Gas Marginal Cost	-0.00792**	-0.0142
	(0.00332)	(0.0212)
Oil Marginal Cost	0.00448***	0.0006
	(0.00143)	(0.00912)
Coal Marginal Cost	-0.00674	0.0290
	(0.00449)	(0.0287)
Residual Load in TWh	-0.00791	0.0468
	(0.0000119)	(0.0000758)
Time dummies included?	Yes	Yes
Observations	66	66

Standard errors in parentheses

* (p<0.1), ** (p<0.05), *** (p<0.01)

4.5 Structural estimation fit: Spot Prices

Once we estimate the first stage parameters, we reproduce the monthly spot prices using the spot equilibrium price equation (8). Then, we compare prices obtained from our model with the realized prices. Figure 10 shows the results. As can be seen, both prices exhibit seasonality, with maximum prices during the winter and minimum prices during the summer. Note that our prices follow the same upward and downward trend as the realized prices, with an average difference of around 6 Eur/MWh. In most of the analysis period, our prices are below the realized prices, indicating the possible existence of extreme positive prices that our model does not fully capture. Similarly, when our model's price is above the realized price, it points to the existence of negative price extremes not fully captured.

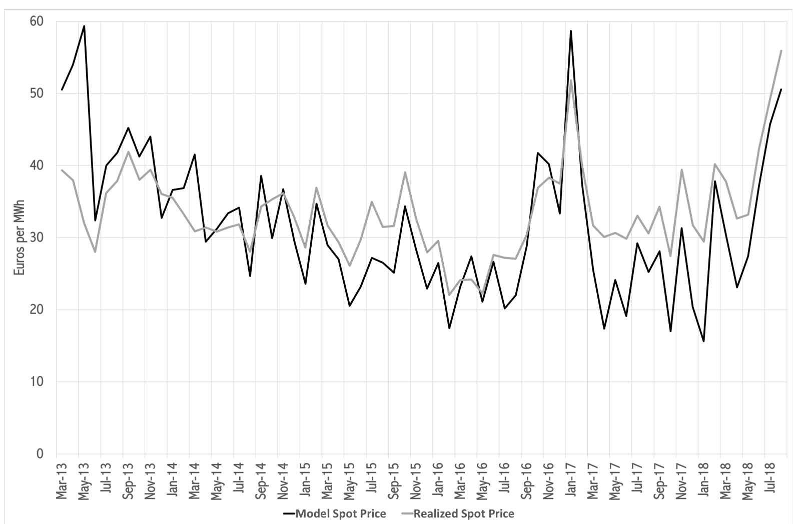


Figure 10: Model spot prices vs realized spot prices

5 Second stage estimation

5.1 Percentage of spot prices within each region

We estimate the probability α_j $\forall j, j = 1, .., 3$ as the percentage of times the residual demand falls in each region within a month. Note that this percentage is the same as the number of times the spot price falls in each region.[18]

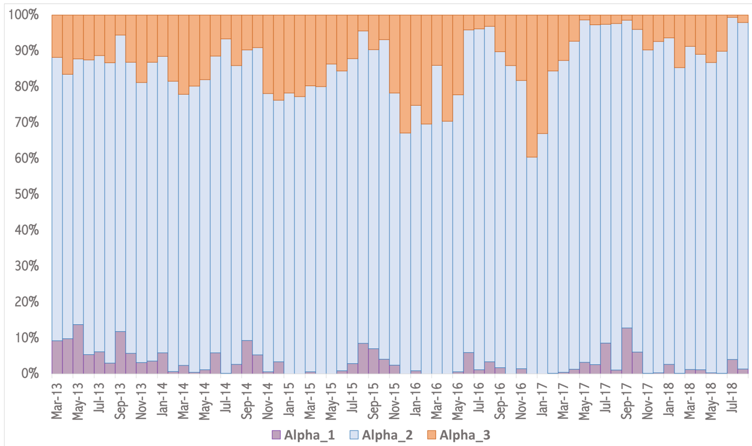


Figure 11: % times the spot price falls in the different areas of the supply curve.

Figure 11 shows the results. There is a downward trend in the probability of falling into region 1. This means that market participants anticipate residual demand more accurately, showing that they improve their production expectations during the study period. In addition, there is an increase in the frequency of equilibrium prices in the convex area of the supply curve. This generally happens during winter, the season with the highest demand.

5.2 Diversifiable Risks Estimation

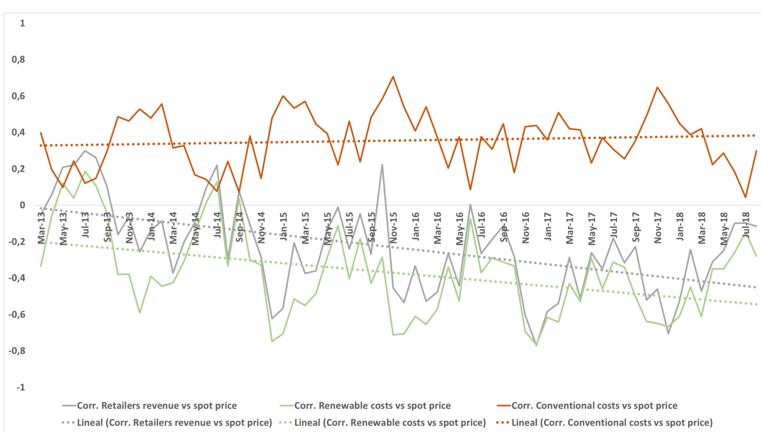


Figure 12: Time series of estimated (diversifiable) risks

[18]The sorting will be the same, considering that total demand represents a curve shift to the right. For each point in the total demand, there is a corresponding equilibrium price.

To better understand the intuition behind equation (20), we compute both the diversifiable and non-diversifiable risks using the parameter estimates. Figure 12 depicts diversifiable risks. In order to compare the relationship between these risks and the spot price, we convert the covariances into correlation coefficients. As the figure exhibits, given their high correlation with the spot price, the retailers' cost and the conventional producers' revenue risks are a hedging priority in the market. In turn, the renewable revenue risk is lower, more seasonal, and volatile. Since the correlation coefficients are positive, revenue risk points towards a need for short hedging for both producers, while cost risk points towards a need for a long position for retailers.

Note how the positions between the two producers are opposed in summer and winter. In winter, the conventional producers' revenue correlation is positive and close to 1, while for renewables close to zero. In other words, during winter, the revenue short-hedging needs for conventional producers are more significant than those of renewables. The reason is that, in winter, the high price levels are located in the convex area of supply and are driven by conventional production. Thus, the volume of conventional production is more sensitive to price changes, which is reflected in their pressing need to hedge revenues. In contrast, the volume of renewable production is not very sensitive to a price change. In fact, given that prices are high in winter, this price level more than proportionally offsets potential variations in renewables production. Hence, green producers are naturally hedged in winter.

In summer, the correlation between conventional producers' revenue and spot prices remains positive but lower than during winter, while the renewable correlation becomes positive. In summer, price levels are located in the flat and concave area of supply, driven by baseload production. Additionally, during this season, there is a higher correlation between renewable energy production and total demand. As a result, volume and price risks increase, and so do their hedging needs. Given the low price level, conventional producers' revenue risk is still significant, which is why they still short-hedge.

In contrast, retailers increase production costs during winter because they buy their electricity at higher spot prices. Thus, their long positions rise during winter and, during summer, decline. Finally, the figure also shows that, over time, the cost risk of retailers increases and, on average, has a higher correlation coefficient than both producers. In other words, by the end of the study period, retailers have the greatest hedging needs in the market.

5.3 Non-diversifiable Risks Estimation

Figure 13: Time series of estimated (non-diversifiable) risks

Figure 13 shows the non-diversifiable risks involved in equation (20). The figure reveals that all risks, in absolute value, have increased. Therefore, we should expect a rise in risk premium during our study period. If we compare diversifiable versus non-diversifiable risks, we can see that the former, in absolute value, are bigger than the latter. This suggests that the futures market still ensures the priority risks.

Additionally, the correlation sign denotes a specific position for each market participant. Thus, when producers' cost risk is positive, producers go long, while when it is negative, they go short. In contrast, when retailers' revenue risk is positive, they go short, while when it is negative, they go long. In other words, moving from -1 to 1 for producers represents a decrease in their futures sales (as they are net sellers in the market), while for retailers means a decrease in purchases (as they are net buyers in the market).

The correlation between conventional producers' costs and the spot price remains positive and shows a strong seasonality. Given that most conventional sources are in operation in winter, their production costs also rise. Hence, the correlation between these costs and the spot price is positive and indicates a need for long hedging. In turn, since conventional production is low in summer, their production costs are not impacted by changes in spot prices. Hence, during the summer, conventional producers are naturally hedged and do not take a position in the futures market.

It is interesting to see that the hedging position of renewable producers is opposed to conventional producers. Notably, the correlation of renewables costs reaches figures close to -1 during winter and 0 during summer. This means that during winter, renewables hedge against potential cost increases derived from a sharp fall in price. During winter, prices are determined by the residual demand on the steeper convex side of the supply. Hence, an increase in renewable production (and, therefore, in their costs) could lead to a steeper price drop. By taking a short position, they hedge against this risk. In summer, when prices are low, an increase in renewable production does not cause a significant fall in prices (as most of the time, the spot price falls on the flat side of the supply curve). In this case, renewable producers are naturally hedged, as the cost increase does not covary with spot prices. In short, it is in winter that its non-diversified cost risk is the highest. Note that their revenue correlation has become progressively more negative, reaching minimums near -1 during winter. We attribute this effect to the increase in renewables. As a result, the correlation between revenues and spot price has become much closer to -1. As a result, retailers' need for hedging (with long positions) has increased, especially during winter.

5.4 Regression results

The non-diversifiable risks from the previous section were used to estimate the remaining parameters (i.e., $\overline{A}$, a_G, and N_B) using the following equation:

$$\begin{aligned}\overbrace{F_{t,T} - E_t(S_T)}^{\text{Risk Premium}} &= \beta_1 \times cov\,(\text{Conv. cost}_T, S_T) + \beta_2 \times cov\,(\text{Renewable cost}_T, S_T) \\ &+ \beta_3 \times cov\,(\text{Retailers revenue}_T, S_T) + X_T + \varepsilon_t,\end{aligned} \tag{25}$$

Where $F_{t,T}$ is the future monthly price at time t of a contract with delivery T. $E_t(S_T)$ is the monthly expected spot price at T and X_T are quarterly fixed effects. For simplicity, we assume that market participants have rational expectations and $E_t(S_T) = \overline{S}_T$.[19] To overcome autocorrelation problems, we aggregate the future series to monthly prices. By doing so, we reduce 30 daily observations per month to one monthly

[19]By assuming rational expectations, we avoid specifying a spot price model, which could be very sensitive to assumptions and bring misleading conclusions.

average observation. Since we have futures prices six months before delivery, we end up with six monthly prices for each contract. Similarly, we compute the monthly average of the 720 hourly spot prices each month. Thus, the risk premium time series consists of the difference between the monthly futures and realized spot prices.

We employ the non-diversifiable risks as the independent variables for equation (25). The sign of the coefficients responds to the change in the supply or demand of futures. In other words, for producers, the increase in the covariance between costs and spot prices represents a decrease in futures sales, which increases futures prices and the risk premium (i.e., $\beta_1 > 0$ and $\beta_2 > 0$). For retailers, an increase in the covariance between revenues and spot price means a diminish in futures purchases, a decrease in futures prices and, consequently, in risk premium (i.e., $\beta_3 < 0$).We provide the main results in Table 4 with and without controlling by quarterly fixed effects.

	(2013-2018) RP	RP
Cov(Conv. $cost_T, S_T$)	1.40e-09***	1.04e-09***
$[\overline{A}N_B]$	(4.33)	(3.34)
Cov(Green $cost_T, S_T$)	0.0603***	0.0913***
$[\overline{A}(a_G - \theta)]$	(3.50)	(4.91)
Cov(Retailers $revenue_T, S_T$)	-0.0386***	-0.0376***
$-\overline{A} = -\left[\frac{A}{N_B+N_G+N_R}\right]$	(-4.66)	(-4.45)
Constant	0.0416	4.722***
	(0.10)	(5.31)
Delivery Quarter FE	No	Yes
Adjusted R-squared	0.104	0.198
N	396	396

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Risk Premium regression results

The coefficients sign is in line with the expectations of our model. The regression coefficients define the following key parameter:

$$\beta_1 = \overline{A}N_B$$

$$\beta_2 = \overline{A}(a_G - \theta)$$

$$\beta_3 = -\overline{A}$$

Weighted risk aversion coefficient ($\overline{A}$) The coefficient is positive and precisely estimated at 0.0386. A low value of $\overline{A}$ could be due to a low-risk aversion A or a high number of players $(N_G + N_R + N_B)$. According to a Thomson & Reuters technical report, there has been a steady growth of renewable generators in Germany while conventional producers and retailers have remained stable (see Scholz and Wessling (2021)).

Marginal cost of renewable producers (a_G) Using the weighted risk aversion coefficient and the Feed-in-tariffs values from the OECD, we can plot the evolution of the marginal costs of renewable producers, a_G is in the following figure:[20]

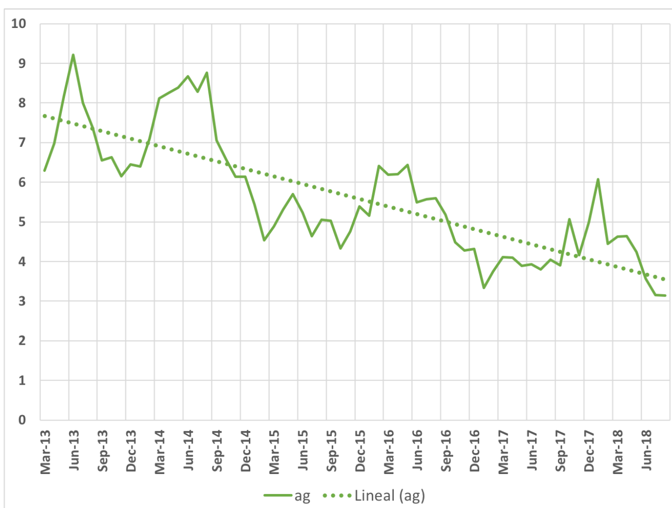


Figure 14: a_g parameter

Figure 14 shows that marginal costs are close to zero and have decreased over time. If we take the short-run marginal cost formula from equation (24), we can determine that SRMC for renewables equals to O&M costs. According to the IRENA (2021)report, in the last decade, the O&M costs of renewables have been reduced mainly due to the increase of O&M service providers, better preventive maintenance programs,

[20]To obtain the theta parameter, we first calculate a weighted tariff according to the share of wind and solar monthly generation. Then, we divide this representative tariff by the monthly spot price.

technological improvements, and higher capacity factors. If we compare our estimate with the marginal costs obtained for fossil fuels, we find that they are approximately 7, 9, and 16 times lower than the SRMC of coal, gas, and oil, respectively.

6 Counterfactual Simulations

We perform counterfactual simulations where we shift the renewable production percentage fulfilling total demand (varying from 0 to 100%). In this way, we can compare the hedging behavior of market participants, futures/spot prices, and risk premium under different scenarios. Our starting point assumes the following parameters values.

Parameter	**Value**
$\underline{Q}$	12.26
$\overline{Q}$	17.49
a_B	-60
$\frac{b_B}{N_B}$	-0.6
$\frac{c_B}{N_B}$	8.5
d_B	7.8
$\frac{g_B}{N_B}$	0.6
a_G	5.61
θ	4× S
P_R	4.34× S
α_1	0.03
α_2	0.84
$\overline{A}$	0.0386
$N_B = N_G = N_R$	20

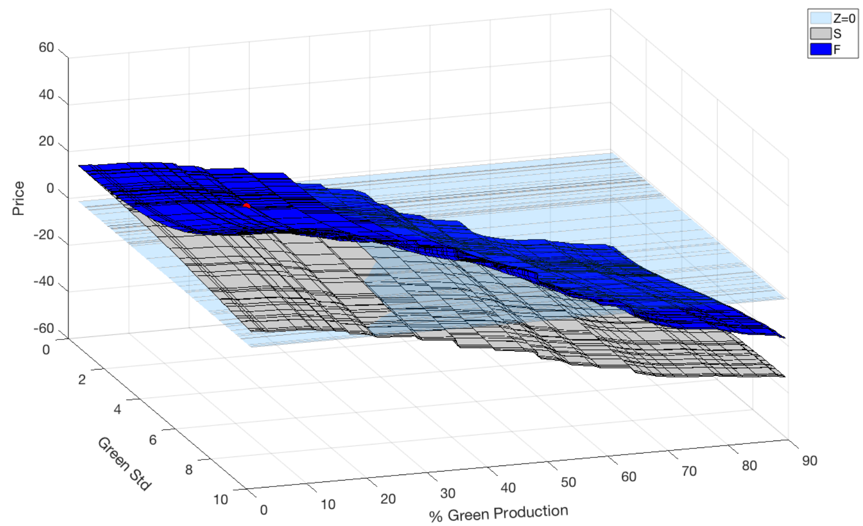
Parameters $\underline{Q}, \overline{Q}, a_B, \frac{b_B}{N_B}, c_B, d_B, \frac{g_B}{N_B}, \alpha_1$ and α_2 come from the first stage estimation of the structural model. Parameters $\overline{A}$ and a_G come from the second stage estimation of the structural model. θ and P_R are from the feed-in-tariffs and retail tariffs databases and, we obtain $N_B = N_G = N_R$ from the list of trading participants from EEX in the German market in 2018. This list reports that 58 companies were transacting in the futures market. Since we cannot classify them between conventional and green producers orretailer, we assume that 20 are retailers, 20 are green producers, and 20 are conventional producers.

As a first exercise, based on the above values, we performed 10000 Monte Carlo simulations by only changing the mean and variance of the normal renewable distribution and keeping the total demand fixed at 28 GWh. Although total demand does not vary, changing the renewable distribution still adds risk to the economy since equilibrium prices depend on $\widetilde{Q}_N$ and $\widetilde{Q}_G$. Specifically, we vary the mean $\mu_G \in [0, 28]$ and standard deviation $\sigma_G \in [0, 10]$. We employ this range of values since it corresponds to the maximum and minimum values for renewable production forecast within our study period.[21] We exhibit the results in the following figure.

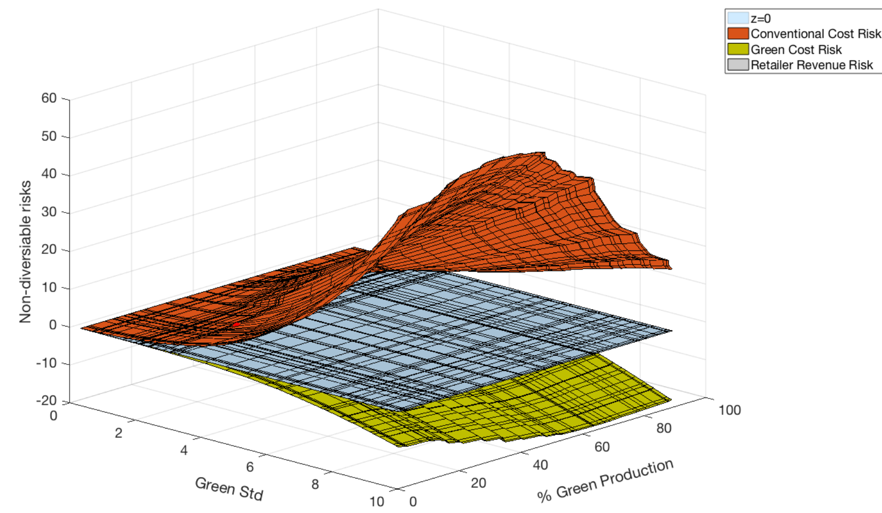
The results in Figure 15 confirm the findings of the previous sections. The top left panel shows the futures and the spot prices. Both prices decrease with the share of renewables, which confirms that, as renewables increase, the merit order effect dominates. In addition, the panel shows that the spot price decreases as the standard deviation of renewables rises while the futures price increases. The top right panel shows the non-diversiable risks. The covariance between conventional producers' costs and spot price remains positive and diminishes as the share of renewables rises. When there is a high residual production (low renewables), conventional production costs increase with the spot price, decreasing their need to hedge by selling futures. Conversely, as residual production decreases (high renewables), this natural hedge vanishes, inducing them to sell more futures which creates a downward pressure on futures prices. In turn, the covariance of green producers' cost with the spot price is negative and grows in magnitude with the share of renewables, which induces them the sell more futures. Again, our simulation confirms that the impact of an increase in intermittent power generation in the production mix have opposite effects on the cost risk of conventional and green producers. Under the set of assumptions chosen for the simulations represented on Figure 15 , the retailers' covariance remains constant since the demand Q_D is constant. By assuming a constant total demand, we also neutralize the retail risk, since the covariance between renewable generation and spot price is precisely the inverse of the residual demand and spot price. This is equivalent to claiming that, under a scenario in which total demand is fixed, retailers' non-diversifiable risk is non-existent.

[21] As total demand remains fixed, the residual and renewable variances are equal:

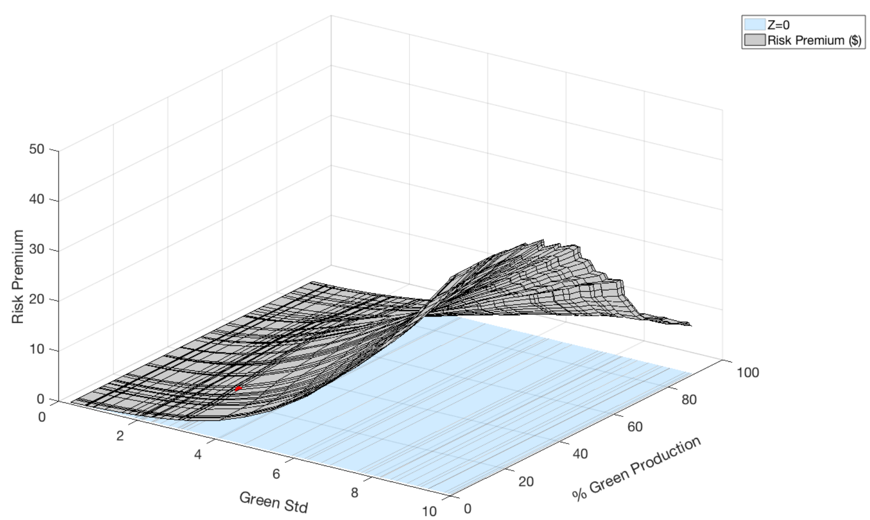
$$\begin{aligned} Var(Q_N) &= Var(Q_D - Q_G) \\ &= Var(Q_D) + Var(Q_G) - 2Cov(Q_D, Q_G) \\ \text{Assuming } Cov(Q_D, Q_G) = 0 \text{ and because } Var(Q_D) = 0 \text{ then,} \\ &= Var(Q_G) \end{aligned}$$



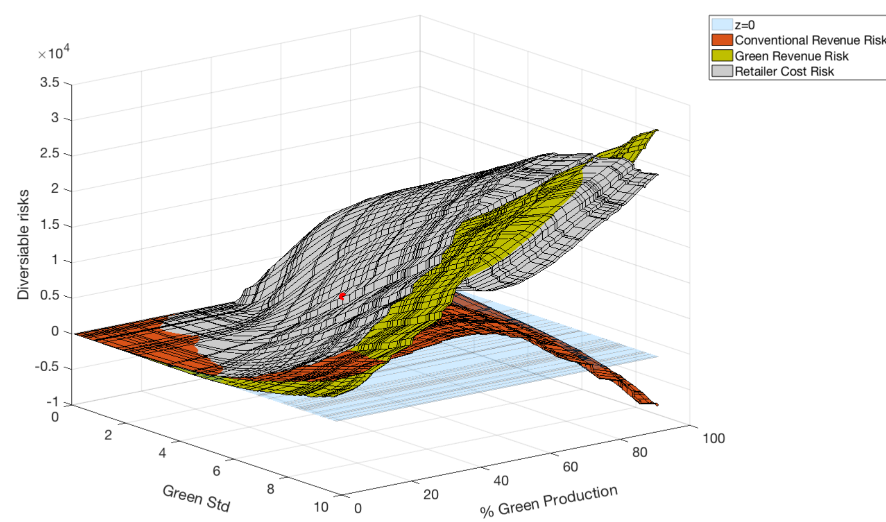
(a) Future and Spot prices



(b) Non-diversifiable risks



(c) Risk premium



(d) Diversiable risks

Figure 15: Monte Carlo simulations (n=10000) with parameters that equal the estimates and a fixed total demand. The red dot marks the average values of renewable production forecasts based on our study period.

The risk premium (on panel (c)) depends on the difference between the conventional producers and the green cost risks. We find that the risk premium is positive and declines as the share of renewables grows. Moreover, the risk premium increases as the volatility of renewable production rises.

Finally, the bottom right panel shows the diversifiable risks. This panel confirms the results of Figure 12. First, these risks are significantly higher than the non-diversifiable ones. Second, producers' revenue risks cancel out retailers' cost risks. In addition, as the proportion of renewables increases, the revenue risk of renewables rises and ends up being more significant than the other risks. In turn, increasing the share of renewables reduces conventional producers' income risk and retailers' cost risk. Also, all diversifiable risks are increasing as the volatility of renewable production increases.

A second simulation exercise consists of varying the standard deviation of the total demand. We keep the mean total demand at 28GWh while varying the standard deviation according to values found in the data (i.e., between 0 and 6) and assuming that $Cov(Q_D, Q_G) = 0$.[22] Figure 16 shows the results.

The top left panel shows the simulations related to prices. In this case, spot prices require a higher share of renewables to become negative. As before, an increase in the standard deviation of renewables decreases the spot price. However, it now increases the futures price.

To understand the impact on futures prices, we turn to panel (b) that shows the non-diversified risks. The cost risk of producers behaves similarly as in the previous exercise. However, as renewables increase, retailers' revenue risk begins to fluctuate and reaches significantly negative values. This is because, at times of high renewable production, the portion of revenue risk related to renewables ($cov(\widetilde{Q}_G, S)$ in equation (21)) increases, and this negative covariance dominates. Consequently, while retailers' revenue risk and cost risk evolve in opposite direction in the absence of renewables, providing retailers with a natural hedge, this is no longer the case when renewables consistute a large portion of the mix, inducing retailers to purchase more futures contracts, which generates an upward pressure on prices.

[22] As total demand varies, the residual standard deviation is:

$$\begin{aligned} Var(Q_N) &= Var(Q_D - Q_G) \\ &= Var(Q_D) + Var(Q_G) - 2Cov(Q_D, Q_G) \\ &\text{Assuming } Cov(Q_D, Q_G) = 0 \text{ then,} \\ &= Var(Q_D) + Var(Q_G) \end{aligned}$$

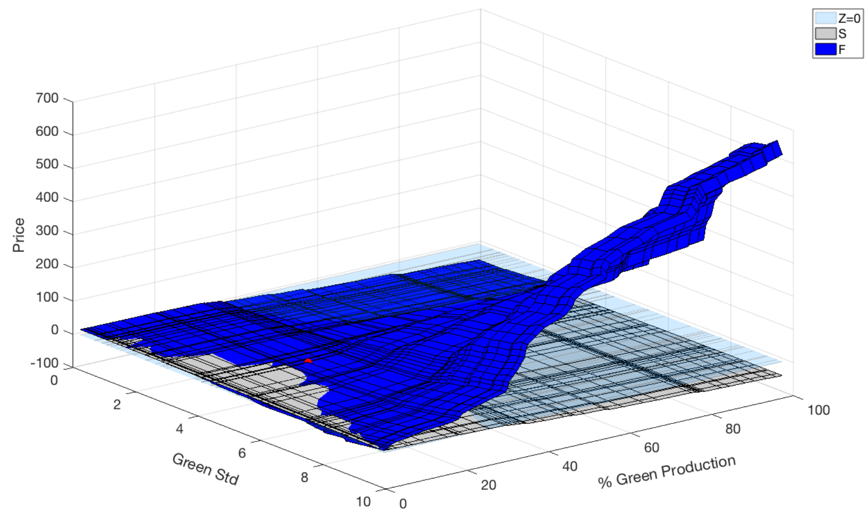
The bottom left panel shows the risk premium implications. Note how the risk premium becomes more positive by including retailers' revenue risk, mainly when the share of renewables is high. Again, when the share of renewables is low, the conventional producers' cost risk dominates and drives the risk premium. However, as the share of renewables increases, both the conventional producers' cost risk and the retailers' revenue risk drive the positive sign of the risk premium. This exercise highlights the critical role of retailer revenue risk. This risk prevails as the share of renewables increases, and it is also the risk that reinforces and dictates the positive sign of the risk premium.

Finally, diversifiable risks show a similar evolution as in the previous exercise. Specifically, as the share of renewables increases, their revenue risk increases while the risks of the other market participants decline. Similarly, as the volatility of renewables increases, all diversifiable risks increase.

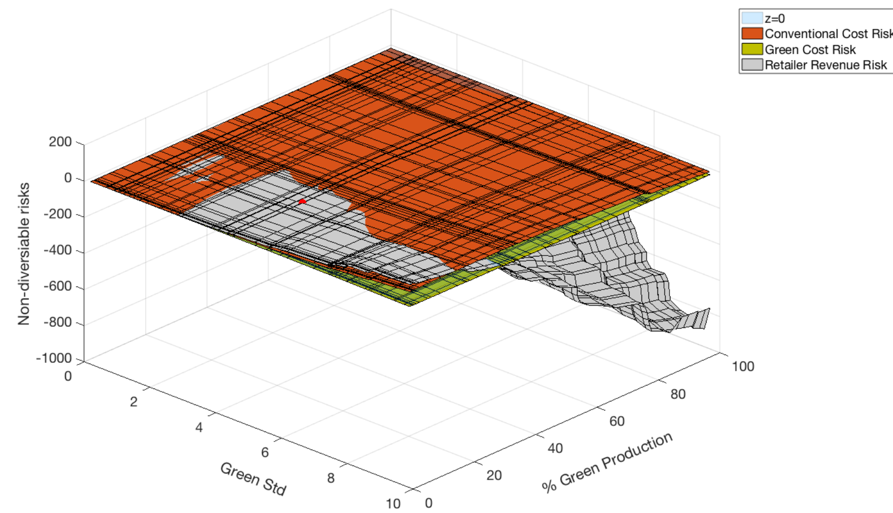
7 Conclusion

This paper studies the impact of the growth of renewable power generation on the futures price, the risk premium forward, and hedging strategies in the electricity market. Our results suggest that the growth in the share of renewable energy increases the uncertainty in the electricity market. Thus, market participants experience an increase in both their diversifiable and non-diversifiable risks. The increase in diversifiable risks indicates a growing need to hedge potential losses through the use of the forward market. However, the results of our research could also be extended to the use of alternative markets (such as the balancing market) to hedge the increasing risks in the market.

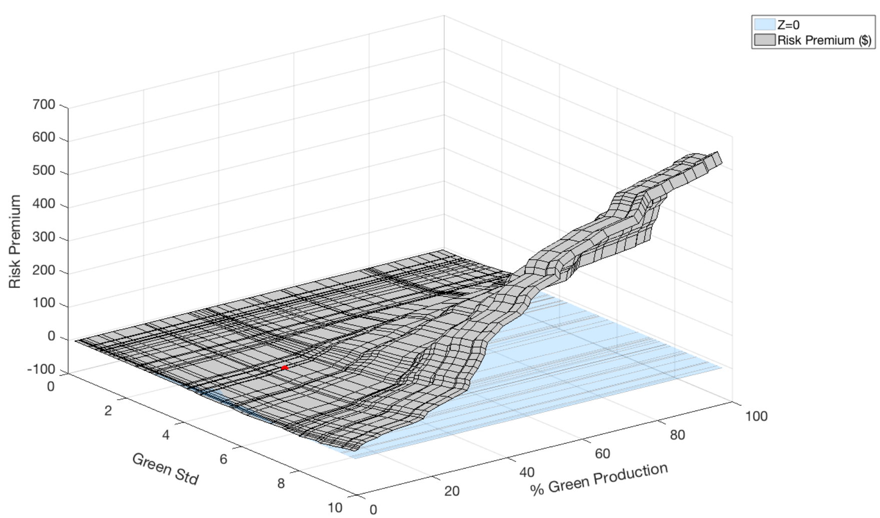
Moreover, our results show that although the increase in renewable generation reduces spot prices, it also increases both futures and risk premium. We find evidence that the cost risks of conventional producers positively affect the risk premium, as opposed to the negative impact derived from renewable producers' cost risk. However, the retailers' income risk prevails and drives the positive risk premium.



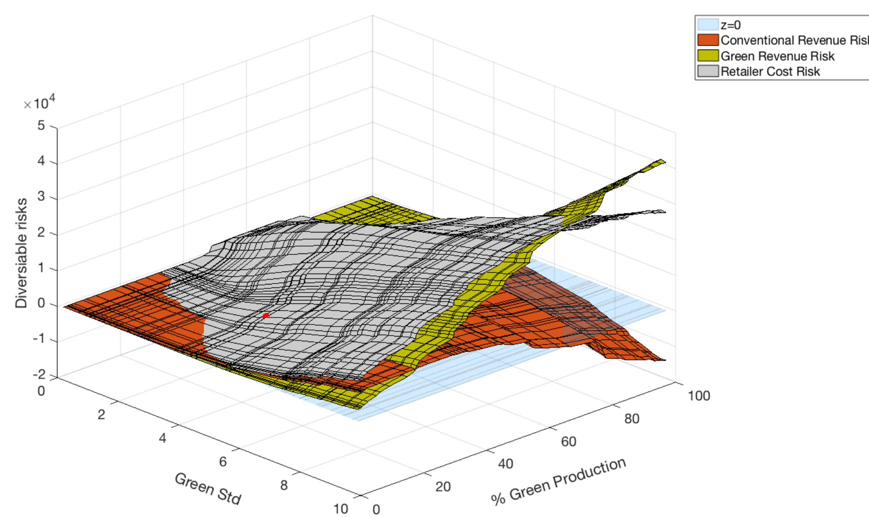
(a) Future and Spot prices



(b) Non-diversifiable risks



(c) Risk premium



(d) Diversifiable risks

Figure 16: Monte Carlo simulations (n=10000) with parameters that equal the estimates and a total demand with $\mu_D = 28$ and small variations of standard deviation $\sigma_D \in [0, 6]$. The red dot marks the average values of renewable production forecasts based on our study period.

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Appendices

A Appendix: "But-for-hedging profits"

A.1 Conventional Producers

Conventional Producer's profits are given by equation (3):

$$\pi_{B_i} = \begin{cases} SQ^w_{B_i} + FQ^F_{B_i} - F_B - \frac{a_B}{b_B}\exp\left[Q^w_{B_i} + Q^F_{B_i}\right] & \text{if } Q_{B_i} < \underline{Q}_{B_i} \\ \\ SQ^w_{B_i} + FQ^F_{B_i} - F_B - \frac{c_B}{2}\left[Q^w_{B_i} + Q^F_{B_i}\right]^2 & \text{if } \underline{Q}_{B_i} < Q_{B_i} < \overline{Q}_{B_i} \\ \\ SQ^w_{Bi} + FQ^F_{Bi} - F_B - \frac{d_B}{g_B}\exp\left[Q^w_{Bi} + Q^F_{Bi}\right] & \text{if } \overline{Q}_{B_i} < Q_{B_i} \end{cases}$$

Substituting the quantity offered by each producer in the spot market, $Q^w_{Bi} = \left[\frac{\widetilde{Q}_D - \widetilde{Q}_G}{N_B}\right] = \left[\frac{\widetilde{Q}_N}{N_B}\right]$, into conventional producers' profit, we get:

$$\pi_{B_i} = \begin{cases} S\left[\frac{\widetilde{Q}_N}{N_B}\right] + Q^F_{B_i}\left[F - S\right] - F_B - \frac{a_B}{b_B}\exp b_B\left[\frac{\widetilde{Q}_N}{N_B}\right] & \text{if } \widetilde{Q}_N < \underline{Q} \\ \\ S\left[\frac{\widetilde{Q}_N}{N_B}\right] + Q^F_{B_i}\left[F - S\right] - F_B - \frac{c_B}{2}\left[\frac{\widetilde{Q}_N}{N_B}\right]^2 & \text{if } \underline{Q} < \widetilde{Q}_N < \overline{Q} \\ \\ S\left[\frac{\widetilde{Q}_N}{N_B}\right] + Q^F_{B_i}\left[F - S\right] - F_B - \frac{d_B}{g_B}\exp g_B\left[\frac{\widetilde{Q}_N}{N_B}\right] & \text{if } \overline{Q} < \widetilde{Q}_N \end{cases}$$

Under the absence of any hedging position ($Q^F_{B_i} = 0$), we get the "But-for-Hedging" profits for conventional producers:

$$\rho_{B_i} = \begin{cases} S\left[\frac{\widetilde{Q}_N}{N_B}\right] - F_B - \frac{a_B}{b_B}\exp b_B\left[\frac{\widetilde{Q}_N}{N_B}\right] & \widetilde{Q}_N < \underline{Q} \\ \\ S\left[\frac{\widetilde{Q}_N}{N_B}\right] - F_B - \frac{c_B}{2}\left[\frac{\widetilde{Q}_N}{N_B}\right]^2 & \underline{Q} < \widetilde{Q}_N < \overline{Q} \\ \\ S\left[\frac{\widetilde{Q}_N}{N_B}\right] - F_B - \frac{d_B}{g_B}\exp g_B\left[\frac{\widetilde{Q}_N}{N_B}\right] & \overline{Q} < \widetilde{Q}_N \end{cases}$$

A.2 Green Producers

Green Producer's profits are given by equation (4):

$$\pi_{Gi} = SQ^w_{Gi} + FQ^F_{Gi} - F_G - a_G(Q^w_{Gi} + Q^F_{Gi}) + \theta(Q^w_{Gi} + Q^F_{Gi})$$

Since in the spot market the production of renewables is a random variable, we assume that it is split between the N_G green producers minus the production already sold in the futures market:

$$\widetilde{Q}^{w}_{G_i} = \left[\frac{\widetilde{Q}_G}{N_G}\right] - Q^F_{G_i}$$

Substituting this equation into green producer's profit, we get the conditional profit:

$$[\pi_{G_i}|\mathcal{R}_j] = \left[(S - a_G + \theta)\left[\frac{\widetilde{Q}_G}{N_G}\right] + Q^F_{G_i}\left[F - S\right] - F_G|\mathcal{R}_j\right]$$

Under the absence of any hedging position ($Q^F_{G_i} = 0$), we get the "But-for-Hedging" profits for green producers:

$$\left[\rho_{G_i}|\mathcal{R}_j\right] = \left[\left(\frac{\widetilde{Q}_G}{N_G}\right)\left[S - a_G + \theta\right] - F_G|\mathcal{R}_j\right]$$

Note that total and "but-for-hedging¨" profits depend on the spot market equilibrium price realization.

A.3 Retailers

Retailers' conditional profits are given by:

$$\left[\pi_{R_i}|\mathcal{R}_j\right] = \left[Q^w_{R_i}\left[P_R - S\right] + Q^F_{R_i}\left[F - S\right]|\mathcal{R}_j\right]$$

Under the absence of any hedging position ($Q^F_{R_i} = 0$), we get the "But-for-Hedging" profits for retailers:

$$\left[\rho_{R_i}|\mathcal{R}_j\right] = \left[Q^w_{R_i}\left[P_R - S\right]|\mathcal{R}_j\right]$$

Note that total and "but-for-hedging" profits depend on the spot market equilibrium price realization.

B Appendix: Optimal quantity traded on futures markets

Applying the law of iterated expectations, we find the unconditional expected value:

$$E\left[\pi\right] = \sum_{i=j}^{3} \alpha_j \mu_j, \tag{26}$$

where α_j is the probability that the residual demand falls in region $j \in \{1, 2, 3\}$ and $\alpha_3 = 1 - \alpha_1 - \alpha_2$.

Applying the law of total variance, we obtain the unconditional variance:

$$Var[\pi] = \sum_{i=j}^{3} \alpha_j \sigma_j^2 + \sum_{j=1}^{3} \alpha_i \mu_j^2 - \left[\sum_{j=1}^{3} \alpha_j \mu_j .\right]^2 \tag{27}$$

Then, the participant's maximization problem becomes:

$$\max_{Q_F} Z = E[\pi] - \frac{A}{2} Var[\pi] = \sum_{j=1}^{3} \alpha_j \mu_j - \frac{A}{2} \left(\sum_{j=1}^{3} \alpha_j \sigma_j^2 + \sum_{j=1}^{3} \alpha_j \mu_j^2 - \left[\sum_{j=1}^{3} \alpha_j \mu_j \right]^2 \right) \tag{28}$$

From the F.O.C, we can determine the optimal quantity to be sold/buy on the futures market, Q^F:

$$\frac{dZ}{dQ^F} = \sum_{j=1}^{3} \alpha_j \mu_j^{'} - \frac{A}{2} \left(\sum_{j=1}^{3} \alpha_j \sigma_j^{2'} + 2 \sum_{j=1}^{3} \alpha_j \mu_j \mu_j^{'} - 2 \left[\sum_{j=1}^{3} \alpha_j \mu_j \right] \mu_j^{'} \right) = 0 \tag{29}$$

We know that $\forall j$:

$$\mu_j = E[\pi|\mathcal{R}_j] = E\left[\rho|\mathcal{R}_j\right] + Q^F \left(F - E[S|\mathcal{R}_j]\right) \tag{30}$$

which yields:

$$\mu_j' = F - E[S|\mathcal{R}_j] \tag{31}$$

Besides,

$$\sigma_j^2 = Var[\pi|\mathcal{R}_j] = Var\left[\rho|\mathcal{R}_j\right] + \left[Q^F\right]^2 Var\left[S|\mathcal{R}_j\right] - 2Q^F Cov\left[\rho, S|\mathcal{R}_j\right] \tag{32}$$

which yields

$$\sigma_j^{2'} = 2Q^F Var\left[S|\mathcal{R}_j\right] - 2Cov\left[\rho, S|\mathcal{R}_j\right] \tag{33}$$

Replacing (30), (31), (32) and (33) we obtain:

$$\begin{aligned}\frac{dZ}{dQ^F} &= \underbrace{\sum_{i=j}^{3} \alpha_j F}_{F} - \underbrace{\sum_{i=j}^{3} \alpha_j E[S|\mathcal{R}_j]}_{E[S]} \\ &- \frac{A}{2}\left[\begin{array}{l} 2Q^F \sum_{j=1}^{3} \alpha_j Var(S|\mathcal{R}_j) - 2\sum_{j=1}^{3} \alpha_j Cov(\rho, S|\mathcal{R}_j) \\ +2\sum_{j=1}^{3} \alpha_j E[\rho|\mathcal{R}_j](F - E[S|\mathcal{R}_j]) + 2Q^F \sum_{j=1}^{3} \alpha_j (F - E[S|\mathcal{R}_j])^2 \end{array}\right] \\ &- \frac{A}{2}\left[-2\left[\sum_{j=1}^{3} \alpha_j \left(E\left[\rho|\mathcal{R}_j\right] + Q^F\left(F - E[S|\mathcal{R}_j]\right)\right)\right]\left[F - E[S|\mathcal{R}_j]\right]\right] \\ &= F - E[S] - \frac{A}{2}\left[2Q^F \sum_{j=1}^{3} \alpha_j Var(S|\mathcal{R}_j) - 2\sum_{j=1}^{3} \alpha_j Cov(\rho, S|\mathcal{R}_j)\right]\end{aligned}$$

Finally, the FOC condition (29) yields:

$$Q^{F*} = \frac{F - E[S]}{A\sum_{i=1}^{3} \alpha_i Var[S|E_i]} + \frac{\sum_{i=1}^{3} \alpha_i Cov(\rho_i, S|E_i)}{\sum_{i=1}^{3} \alpha_i Var[S|E_i]} \tag{34}$$