Intermittent power generation and risk premia on electricity futures markets*

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Last modified version: May 2024

Abstract

We investigate the impact of an increase in the share of intermittent renewables' power generation (i.e., from wind and solar) in the production mix on prices, risk exposures, and hedging costs in electricity markets. Reduced form analysis on the German/Austrian market over 2013-2018 shows that intermittent power generation decreases spot prices and increases the risk premium embedded in futures contracts. To investigate this finding, we develop a model where retailers buy electricity from conventional and intermittent power generators on the spot market to match the final demand, and trade futures contracts to hedge their risk exposures. At equilibrium, futures prices encompass a risk premium whose sign and magnitude depend on the market participants' risk exposures. We structurally estimate the model's parameters to propose a counterfactual analysis in which we vary the characteristics of the distribution of intermittent power generation. Our simulations suggest that increasing the share of intermittent renewable power generation decreases spot prices. However, the effects on the risk premium can vary, depending on the characteristics of the intermittency distribution. We find higher risk premia when there is greater intermittency or when the integration of renewables into the system is less effective.

JEL classification: **G12, G23**

Keywords: electricity futures, risk premium, asset pricing, renewable energy

*Financial support from the ANR (ANR-16-CE26-0008 and ANR-17-EURE-0010 (Investissements d'Avenir program)) is gratefully acknowledged.

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1 Introduction

Growing concern about global warming has encouraged the adoption of environmental public policies (such as subsidies) that prioritize the development of clean, renewable energies to achieve net carbon neutrality. Following this process, which is facilitated by low marginal costs and dropping investment costs, renewables are expected to represent 40% of the production mix by 2030 (European Environmental Agency, 2022). However, their intermittent nature is challenging. On the operational side, intermittency generates physical risk, which management requires the development of transmission and backup plants and of command and control systems. Besides, it also affects spot prices, potentially impacting market participants' financial risk exposures. In particular, the variability of wind and solar power generation might increase price volatility, a primary concern in a market where prices can take negative values (see Würzburg et al. (2013), Paraschiv et al. (2014), de Lagarde and Lantz (2018), Figueiredo and da Silva (2019), Johnson and Oliver (2019)). To hedge against this financial risk, retailers and producers may lock in the price of part of their transactions by buying or selling power futures contracts.[1] This paper investigates the impact of renewable power generation on futures prices and risk sharing.

To this end, we first provide empirical evidence of the link between intermittent power generation and futures prices/risk premia. We then develop an equilibrium model of price formation on the futures markets to analyze the implications of intermittency in renewable power generation on risk exposures, hedging strategies, and risk premia. We finally structurally estimate the model's parameters and use them to propose a counterfactual analysis, enabling us to quantify the impact of increasing the share of intermittent power generation in the production mix on risk exposures and risk premia.

Our theoretical model builds on Bessembinder and Lemmon (2002). Since electricity cannot be stored on a large scale, electricity futures prices can not be determined through standard "cash and carry" arbitrage strategies. Instead, the pricing of power futures prices calls for

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

a market equilibrium approach, which requires understanding the market participants' 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 to price volatility than retailers, thus more or less willing to hedge by selling or buying futures. Bessembinder and Lemmon (2002) 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 the clearing futures prices encompass a risk premium whose sign and magnitude depend on the participants' hedging needs, risk exposures, and risk aversion.

We extend Bessembinder and Lemmon (2002) along two dimensions. First, the electricity supply on the spot market depends on the volume of wind and solar generation produced by "intermittent" power generators producing electricity alongside different dispatchable generators that we label as "conventional." Second, to capture the characteristics of the merit order curve, we assume that the supply curve of the conventional producers is inverse S-shaped, that is, first concave for low volumes (capturing the low marginal costs related to inflexible power generation), then convex for high volumes (capturing the high marginal costs related to the use of more flexible power plants). We identify market participants' revenue and cost risks, which determine their optimal demand in the futures market. At equilibrium, the aggregate retailers' cost risk matches the producers' revenue risk, so these risks cancel out and will, therefore, not be priced. Although diversifiable, their analysis remains relevant since they reveal the amount of risk shared among agents and, therefore, the usefulness of the futures market. Only the retailers' revenue risk and the producers' cost risk are non diversifiable and impact the futures prices.

Our model shows that the characteristics of producers' costs are crucial to understanding the direction and magnitude of intermittent power generation's impact on futures prices. To quantify the effects, we collect hourly limit order book data of the German/Austrian (day ahead) market (2013-2018). We use sell-side price schedules and the volume of intermittent power generation to structurally estimate the producers' cost parameters by non-linear least squares. We obtain a time series of monthly cost parameters, which we use to evaluate the participants' theoretical revenues and cost risk exposures on the spot market.

We confirm that producers' revenues and retailers' costs are highly and positively correlated with the spot price. This finding aligns with the fact that producers hold an overall long position while retailers hold an overall short position. Furthermore, conventional producers' revenue and retailers' cost risks are highly seasonal. These participants face the highest risk in winter when demand and prices are high. By contrast, intermittent power producers' revenue risk increases in summer, when demand is usually low while intermittent power production is high. While these risks influence the participants' demand in the futures markets, they balance each other at equilibrium.

By contrast, the correlations between the producers' costs or retailers' revenues and the spot price are crucial since they will impact the futures prices. When correlations are positive, they act as a natural hedge by reducing their initial long and short exposures. For instance, a high demand increases the spot price, thus retailers' costs, but simultaneously increases the volume sold by retailers and thus their revenues. We find that conventional producers' costs and retailers' revenues are, indeed, positive. However, the correlation between the intermittent power generators' costs and the spot price is negative. This finding may be explained by the fact that an increase in supply increases the intermittent power generators' cost while decreasing the residual demand served by conventional producers, thus the spot price. Overall, we show that the contributions of conventional or intermittent power producers to the risk premium on the futures markets are different. In terms of magnitude, participants' non-diversifiable risks also exhibit seasonality. In summer, the spot price often falls in the supply curve region with nearly zero marginal costs. Consequently, a shock on demand or on the supply of intermittent power has little impact on the spot price, which decreases its correlation with producers' costs and retailers' revenues. In contrast, those correlations are high in winter, when gas and coal-fired power generation set the price.

As a second step, we use our estimates of the structural parameters to examine the effects of a one percentage point increase in intermittent renewables in the energy mix on spot prices, futures, and risk premia. We run Monte Carlo simulations in five counterfactual cases, one calibrated on the entire sample period and four splitting it into summer/winter seasons and by the source of intermittent power generation (i.e., wind or solar). In each case, we assume that the increase of intermittent power in the mix also changes the characteristics of the renewable distribution, namely its intermittency (i.e., its volatility), and its system integration (i.e., its correlation with total demand). To understand the drivers of our main results, we analyze two alternative scenarios that decompose the effects obtained when combining intermittency and integration with the ones obtained when shutting down one channel.

Overall, we find that spot prices decrease by 1.63% following an increase of intermittent power by 1 percentage point in the production mix. This is due to the merit order effect, since intermittent power is characterized by lower marginal costs. However, the risk premia increase by 1.82%, inducing higher hedging costs. These two effects can be found, with different magnitudes, in the five cases we consider. In particular, when the risk premium is positive – which is the most frequently observed situation – indicating that retailers agree to buy power at a futures price that is higher than the average spot price, the decrease in spot prices is not fully reflected in futures prices. By contrast, when it is negative – which happens in Summer – indicating that producers agree to sell power at a futures price that is lower than the average spot price, the decrease in futures prices is exacerbated.

The decomposition into distinct intermittency and integration scenarios shows that the impact of intermittent power on risk premia is mostly driven by its increased intermittency. A higher volatility increases the participants' risk exposures, amplifying their impact on the risk premium. By contrast, a better integration, related to an increase in correlation with load demand, might exert an opposite force and reduce the risk premium. These findings explain the difference in the impact on the risk premium level depending on the season and power source found in the reduced form analysis: solar power generation is less intermittent than wind, and highly correlated with demand in Summer but not in Winter, while wind is highly correlated with demand in Winter but not in Summer.

1.1 Literature Review

There is a growing interest in studying the impact of variable 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), Keppler et al. (2016) 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 short-term 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 power futures cannot be determined based on "cost-of-carry" strategies and no-arbitrage conditions. To establish the future price, one must rely on the market equilibrium theory, in which the futures price can be determined via market clearing conditions. More precisely, the future price equals the expected value of the underlying commodity plus (or minus) a risk premium compensating 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. Bessembinder and Lemmon (2002) 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 the risk premium) that depends on producers' cost risk and retailers' revenue risk. 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 and tested Bessembinder and Lemmon (2002)'s theory, particularly the validity of the relation between the risk premia and the first moments of the spot price distribution. The results of these empirical studies mixed: Longstaff and Wang (2004), Diko et al. (2006), Douglas and Popova (2008), Viehmann (2011), and Fleten et al. (2015) support the theoretical predictions, Torró et al. (2008), Redl et al. (2009), Furió and Meneu (2010) find partial evidence, while Karakatsani and Bunn (2005), and Haugom and Ullrich (2012) find opposite results. However, concluding why these studies' findings differ is difficult. It remains unclear why results may be sensitive to the region of study, the analysis period, or the financial instrument's maturity. 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 Bessembinder and Lemmon (2002) to account for more heterogeneity in power generation and by directly testing the relation between the risk premia and the participants' risk exposures built from cost parameters' estimations instead of the approximated relation linking the risk premium to moments of the spot price distribution.

Undoubtedly, renewable power generation is changing market participants' price risk exposures. However, only some studies investigate its impact on hedging strategies and futures prices. Peura and Bunn (2021) theoretically show that wind generation affects the risk premia in a direction that depends on the amount fed into the system. Higher expected wind amounts lead to a less aggressive hedging strategy because the higher uncertainty causes producers to fear they may fail to deliver the quantity sold forward. Without solid selling pressure, futures prices remain high, and the risk premium is positive. By contrast, producers hedge more aggressively when they expect moderate expected wind amounts since the amount of power generated is more predictable, which leads to a negative risk premium. 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 and that risk premia increase in periods of low covariance. Koolen et al. (2021) separate the effects on the risk premium of large-scale renewable production technologies (i.e., solar and wind farms) from that of distributed renewable production technologies (i.e., rooftop solar). The authors find that both technologies affect the risk premium oppositely, resulting from asymmetries in information predicting renewable production.

We add to this new stream of research by developing a model that allows us to understand how combining different power generation sources impacts spot prices, hedging decisions, and risk premia. Additionally, our structural estimation of the model's parameters, based on the German/Austrian market (2013-2018), enables us to recover the production costs, analyze the risk exposures of the various market participants, and propose counterfactuals where we increase the share of intermittent power generation in the production mix.

2 Data and reduced form analysis

Our objective is to analyze the impact of power generation characteristics on prices and risk premia in electricity markets. This section describes the data, defines our variables, and reports descriptive statistics on the variables used in our analysis. We then show some reduced form empirical evidence of the links between the risk premia and the determinants of power generation.

2.1 Data and descriptive statistics

2.1.1 Spot market

Electricity spot demand and supply curves. The "spot" reference price at which electricity futures settle is the price on the so-called "day-ahead" market. On this market, a uniform price auction (organized every day at noon) sets prices for the electricity to be delivered within each of the 24 hours of the following day. From the European Power Exchange (EPEX SPOT), we collected the hourly aggregated supply and demand curves of the German/Austrian day-ahead electricity market from March 1, 2013 to August 31, 2018. In a given day, each of the 24 aggregated curves represents the sum of individual offers (for supply) or bids (for demand). These are a pair (price, Volume), where Volume is expressed in MWh and Price in Eur/MWh, expressing the producers/retailers' willingness to sell/buy electricity for a specific hour the following day.[2] We denote by $S_{T,d,h}$ the spot price of electricity delivered at hour h, on day d, in

[2] Prices range between Pmin=-500 and Pmax=3000, and the minimum order size is 0.1MW for each block of an hour.

month T. Our spot prices $S_{T,d,h}$ and quantity traded on the spot market $Q^S_{T,d,h}$ result from the intersection between the hourly aggregated supply and demand curves.[3] Let $\bar{S}_T$ be the monthly averaged spot price observed in month T, that is, $\bar{S}_T = \frac{1}{n_d \times 24} \sum_{d=1}^{n_{d_T}} \sum_{h=1}^{24} S_{T,d,h}$, where n_{d_T} is the number of days in month T.

Supply: the merit order curve In electricity spot markets, bids submitted by producers show their willingness to generate power for every possible market price. The aggregate supply curve is often named the "merit order curve," as it shows all producers' production ordered up according to their ascending marginal costs. The empirical evidence shows that this supply curve adopts an inverted S-shape (see Schneider (2011), He et al. (2013), Fanone et al. (2013), Wozabal et al. (2016)). The left-hand side of the curve captures the marginal costs of power plants choosing to give electricity at low or even negative prices – 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 inflexible production. The supply curve shape in this area is concave: marginal costs, typically negative, increase at a decreasing pace.[4] Moving along the curve, one finds the low, constant marginal costs of renewable production, such as biomass, geothermal, and biodiesel.[5] Next come the marginal costs of nuclear energy, which are low since small quantities of nuclear fuel, namely uranium or plutonium, can produce considerable amounts of energy, but higher than renewables. Finally, the right-hand side of the curve represents the marginal costs of fossil fuel plants such as coal, gas, and oil. These plants incur high marginal costs, as they must pay high fuel prices to produce electricity. Coal is usually cheaper than gas, and gas is cheaper than oil.[6] Oil plants are relatively small and inefficient, producing little at a very high price. In this area of the curve, the shape is convex, as marginal costs are increasing at an increasing rate.

[3]These prices are consistent with the spot prices published by EPEX SPOT.

[4]The phenomenon of negative marginal costs is also due to other factors such as network constraints (e.g., maintaining voltage), reserve requirements and inertia, heat supply (cogeneration), or the sale or loss of the electricity produced (unavoidable) from intermittent renewable sources.

[5]For instance, biomass is generated from low-cost organic materials such as plant or animal waste; geothermal energy harnesses the heat emanating from within the Earth; biodiesel is derived from a variety of low-cost renewable resources, such as plant oils and animal fats; wind power from the wind, and solar power from the sun.

[6]Even accounting for carbon prices, coal remains cheaper than gas and oil during our study period.

Figure 1: **Snapshot of (spot market) limit order book data**

Figure 1 represents a snapshot of limit order book data on the EPEX SPOT day-ahead market, namely the cumulative sell orders at each price level for delivery on January 02, 2018, at 12 a.m.

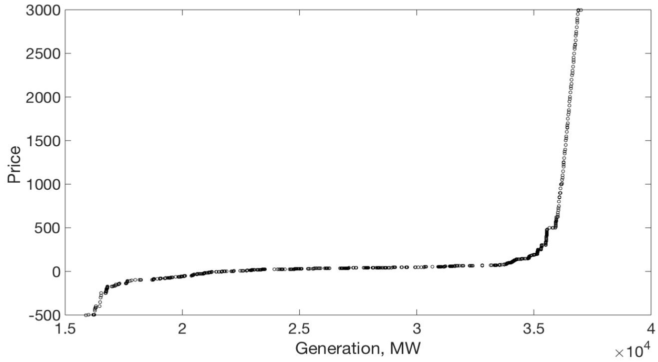


Figure 1 illustrates the S-shape nature of the supply with a snapshot of our data. We cannot precisely pin down the exact volume supplied from each energy source with our anonymous data, but we observe concave, flat, and then convex regions consistent with the merit order of power generation.

Load demand. To proxy for the total volume of electricity ultimately consumed at a given hour, $Q^D_{T,d,h}$, we collected the hourly load value from the European Network of Transmission System Operators for Electricity (ENTSO-E). The total demand, Q^D is different from the quantity that clears demand and supply on the spot market Q^S (defined above), as shown in Figure 2. Indeed, the total load is served by retailers who may have bought electricity in the spot and futures markets.

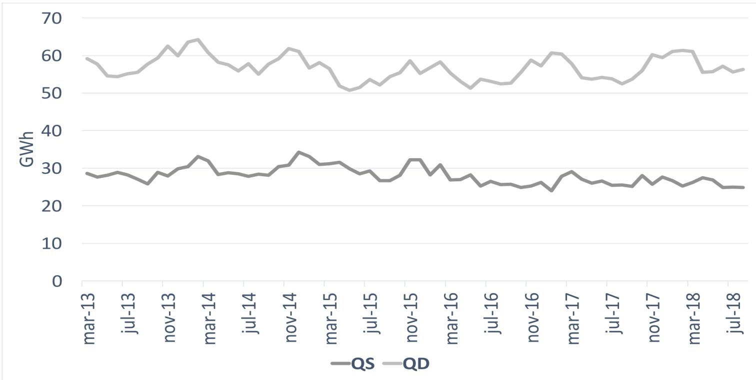
Figure 2 shows the monthly consumed volume during our analysis period averages 56.68 GWh, while the quantity traded on the spot market averages 28 GWh. Both time series exhibit seasonality around an average traded quantity that represents approximately 49% of the total load.

2.1.2 Futures markets and risk premia

Electricity futures prices. We collected the daily prices (in Euro/MWh) of one to six-month-ahead monthly base futures contracts (also called Phelix futures) from the European

Figure 2: **Load demand vs. Spot market trading volume**

Figure 2 compares the average monthly total consumption volume (Q_D) with the quantity traded on the spot market (Q^S). Q_D is the monthly averaged hourly load value from the European Network of Transmission System Operators for Electricity (ENTSO-E). Q^S is the volume resulting from the crossing between hourly supply and demand curves and is averaged monthly.



Energy Exchange (EEX) for 66 delivery months between March 2013 and August 2018.[7,8] We denote by $F_{d,T}$ the trading price at date d of a futures contract for delivery in month T.[9]

Electricity risk premia. In our analysis, we will focus on the risk premium of the one-month-ahead contract, computed from the averaged futures prices in month $T-1$, $F_{T-1,T} \equiv \frac{1}{n_{d_{T-1}}} \sum_{d=1}^{n_{d_{T-1}}} F_{d,T}$. The risk premium of a futures expiring at date T is defined as the difference between the average one-month-ahead futures price for a contract with delivery month T, $F_{T-1,T}$, and the expected spot price $E(S_T)$:

$$RP_{T-1,T} = F_{T-1,T} - E_{T-1}(S_T). \tag{1}$$

We assume perfect foresight and proxy the expectation during the month $T-1$ of the spot price for the delivery period T by the average spot price observed at date T, $\bar{S}_T$. Figure 3 shows the time series of one-month-ahead futures prices and average monthly spot prices for delivery in

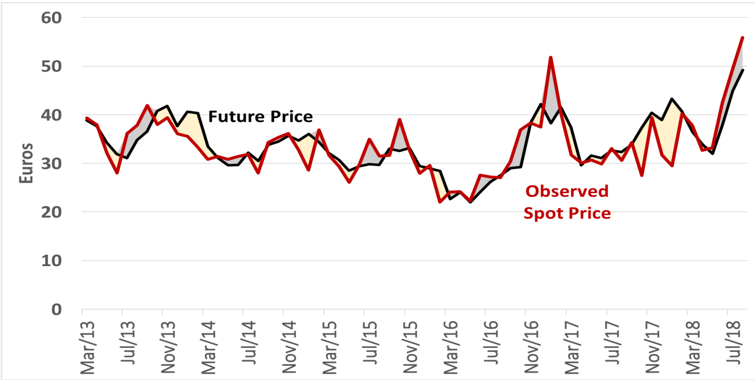
[7]Futures contracts are financial derivatives instruments enabling an economic agent to lock in the price at which they will sell or buy an (underlying) asset at a future maturity date. These contracts are traded on organized exchanges and specify standardized terms, including size, maturity, and delivery conditions.

[8]In electricity markets, contracts are typically categorized into three types (base, peak-load, and off-peak), each distinguished by the specific delivery times throughout the week. Peak-load contracts provide electricity from 8 am to 8 pm from Monday to Friday, when demand is typically at its highest. Off-peak contracts supply electricity from 8 pm to 8 am on weekdays and continuously over the 24 hours of weekends, aligning with periods of lower demand. Lastly, base contracts ensure a steady electricity supply 24 hours a day, seven days a week.

[9]The futures contract standard size 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 size is 720 MWh.

Figure 3: **One-month-ahead futures prices vs observed spot prices**

Figure 3 represents the monthly risk premia time series. The one-month-ahead futures prices (in black) are the monthly-averaged daily prices of one-month-ahead futures. The spot price (in red) is the monthly-averaged hourly price on the day-ahead market. The difference between the two curves represents the monthly risk premium, which can be positive (yellow area) or negative (grey area).



month T.

Figure 3 displays an average of future prices at 33.89 euros per MWh and spot prices at 33.60 euros per MWh. It also shows that risk premia may be either positive or negative. A positive risk premium is more frequently observed during winter when demand is high and more unpredictable.

2.1.3 Variables influencing power generation

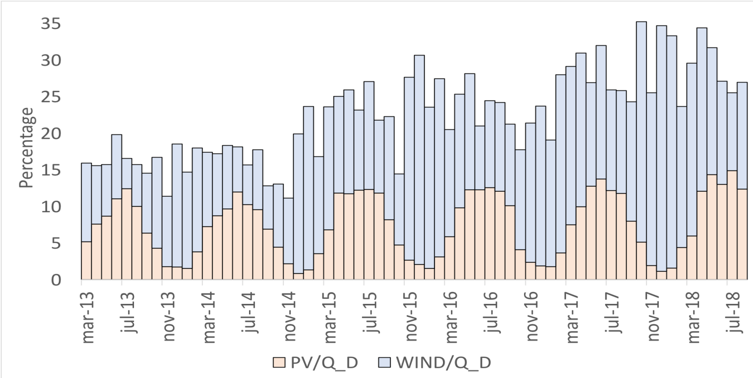
Generation of intermittent renewables. We obtained hourly solar and wind generation day-ahead forecasts from the German Transmission System Operators (TSOs): 50Hertz, Amprion, Transnet, and Tennet. The total solar and wind generation results from the sum of generation from the four operators.[10]

Figure 4 illustrates an increasing trend in the proportion of intermittent renewables in the production mix, rising from 16% to 35% by the end of the analysis period. Wind power generation experiences the highest growth rates, increasing by 20 percentage points during the study period (from 10% to 30%). Additionally, both production sources exhibit seasonality, with solar production showing a more pronounced pattern (i.e., being almost negligible in winter and representing up to 10% of the mix in summer).

[10] 50Hertz,Amprion, Transnet and Tennet data, last accessed on 27.08.2022.

Figure 4: **Share of intermittent power generation in the production mix**

Figure 4 represents the share of intermittent power generation in the production mix, defined as the sum of the volume originating from solar (or photovoltaic) and wind power generation, divided by the total demand. The bars are broken down into the share of solar power generation (in pink) and the share of wind power generation (in blue).



Short Run Marginal Costs. We construct the marginal costs of the three main fossil fuels (gas, coal, and oil) from the formula reported by Refinitiv, which is as follows:

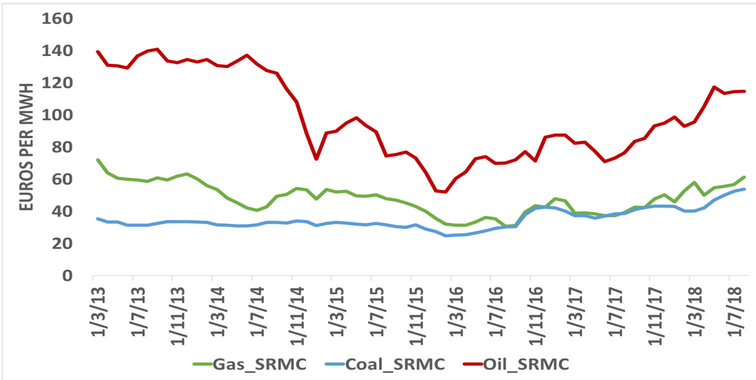
$$\begin{aligned} \text{SRMC[eur/MWh]} &= \text{O\&M costs[eur/MWh]} \\ &+ \frac{\text{Energy price[eur/ton or eur/therm]}}{\text{heat value[GJ/ton or GJ/therm]} \times \text{efficiency}} \times 3.6\text{[GJ/MWh]} \\ &+ \frac{\text{emission intensity[tCO2/GJ]} \times \text{carbon price[eur/tCO2]}}{\text{efficiency}} \times 3.6\text{[GJ/MWh]} \end{aligned} \tag{2}$$

We collected daily energy prices from Refinitiv. For gas, we used the price of the Dutch day-ahead gas contract (TRNLTTFD1 in EU/MWh). For coal, we used the price of coal delivered to the Amsterdam, Rotterdam, and Antwerp regions (Coal ICE API2 CIF ARA in Euros/MT). For oil, we used the price of Brent crude oil (BRT in EU/Bbl).[11] Appendix B.1 provides details on the measures of heat value, efficiency, carbon intensities, and Operation and Maintenance costs that we use in our computations. The time series of our estimates for SRMC are reported in Figure 5.

[11]Refinitiv provides SMRC for gas and coal after 2014. For consistency, we use our own measures of SMRC for the three energy sources, starting in 2013. We checked that our measures are similar to the Refinitiv time series whenever available in Figure B.1 in Appendix B.1. The gas and coal price series we describe here are the same used by Refinitiv to calculate its SRMCs.

Figure 5: **Short Run Marginal Costs of fossil energies**

Figure 5 presents the dynamics of the short-run marginal costs of coal, gas, and oil power plants computed following the formula in equation (2) (Source: Refinitiv-Power composite methodology and specification guide). We obtained efficiency percentages from an ECOFYS report (2018) and emission intensity factors from EIA (2005). We kept the operation and maintenance costs for coal and gas from Refinitiv. For oil, we employed those reported by DIW Berlin (2013).



Marginal cost of intermittent power generation. We assume that the marginal costs of wind and solar power generation only consist of Operation and Maintenance (hereafter O&M) costs, which we obtained from the EIA Annual Energy Outlook reports (expressed in USD per MWh, converted to EUR per MWh).[12,13]

Intermittent power generation is often subsidized. We collected the feed-in-tariffs (FIT) from the OECD database.[14] These tariffs are in dollars per kilowatt-hour (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 our focus on intermittent renewables. In addition, we convert the tariffs to euros per MWh. We calculate a weighted tariff according to the share of wind and solar monthly generation. We plot the evolution of renewable producers' marginal costs, Feed-in-tariffs, and net marginal costs in Figure 6.

[12]EIA Annual Energy Outlook reports,last accessed on 14.06.2023.

[13]The SRMCs of intermittent power sources (and particularly the O&M costs) are used in the monthly estimates. These costs do not influence the spot hourly price determination at any time.

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

Figure 6: **Marginal costs of wind and solar power and Feed-In-Tarrifs**

Figure 6 shows the Marginal costs of wind and solar power and Feed-In-Tariffs (FITs). Marginal costs represent the total expenses for operating and maintaining wind and solar power plants, excluding fuel costs. FITs are widely used policies to promote the expansion of renewable electricity generation. They are market-based instruments that provide renewable producers with long-term contracts, ensuring a fixed price per kWh of electricity supplied to the grid (Source: EIA Annual Energy Outlook reports and OECD database).

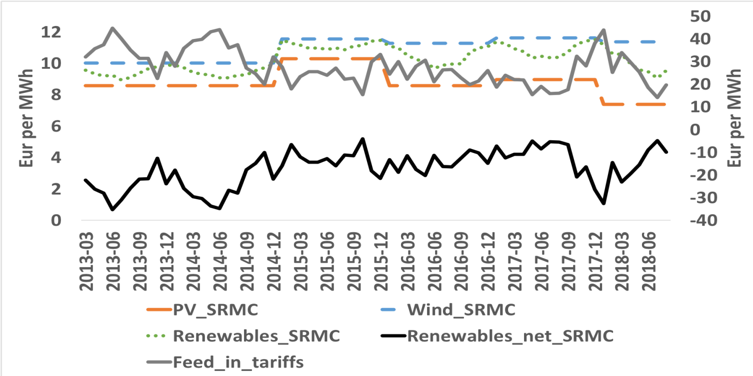


Figure 6 shows that marginal costs are nearly zero. According to the IRENA (2021) report, in the last decade, the O&M costs of renewables have been reduced mainly due to the increase of O&M service providers, better preventive maintenance programs, technological improvements, and higher capacity factors. Additionally, the marginal costs of solar generation are lower than those of wind, averaging 8.8 EUR/MWh compared to 10.24 EUR/MWh for wind. When comparing our estimates with the marginal costs of fossil fuels, we observe that the solar and wind costs are approximately 3, 4, and 9 times lower than the SRMC of coal, gas, and oil, respectively. The Figure also indicates that FITs are approximately three times higher than the marginal costs of both intermittent sources.

Retail Prices. We obtained the electricity prices for household consumers in Germany from Eurostat.[15] Data are bi-annual, in euros per kilowatt-hour, excluding taxes and levies, and describe the consumption data over a band DC between 2,500 KWh and 5,000 KWh.[16,17] To keep consistency with the rest of the data expressed in MWh, we convert the units to euros per MWh.

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

[16]Levies are charges or fees to fund specific energy programs to support renewable energy development.

[17]Eurostat uses a series of bands labeled from DA to DX to categorize electricity consumers based on the amount of electricity they consume annually. Band DC includes information about entities that consume between 2,500 and 5,000 kWh annually, a typical range for small to medium-sized households in many countries.

Weather. We collected monthly time series on temperature and sunshine duration in Germany from Deutscher Wetterdienst (DWD).[18] We completed our weather proxies with data on wind speed and velocity provided by the Deutscher Wetterdienst from the Climate Data Center.[19] We used reports from the Berlin Brandenburg station (Station 427) on "Hourly station observations of wind velocity ca. 10 m above ground in m/s" to capture wind velocity and on "Daily mean of station observations of wind speed at ca. 10 m above ground in m/s" as a proxy for wind speed.[20]

2.2 Reduced form analysis

To assess the impact of intermittent power generation (wind, solar) on electricity prices, we run the following regression:

$$Y_T = a_0 + a_1 Q\_I_T + X_T + \eta_T, \tag{3}$$

where our dependent variables Y are the monthly average spot price S or the one-month-ahead risk premium RP, our variable of interest Q_I is the volume of electricity generated from intermittent sources, and X is a set of control variables.[21,22]

To account for a potential spurious correlation between quantities and prices, we instrument the volume of power generated from intermittent sources using weather conditions as follows. We use wind speed, wind velocity, and precipitation for wind power generation. We use the average sunshine duration observed in Germany in the delivery month for solar power generation.

Besides year-fixed effects, our control variables consist of a series of variables that capture variations in supply and another series that controls for variations in demand. For the supply side, we include the short-run marginal costs of fossil energies and intermittent renewables, and feed-in tariffs. For the demand side, we control for temperatures and seasons (with three seasonal dummies for summer, fall, and winter).

[18]See Deutscher Wetterdienst (DWD), last accessed on 15.06.2023.

[19]See Climate Data Center, last accessed on 15.06.2023.

[20]The Climate Data Center reports daily or hourly statistics per station but no aggregate statistics for Germany.

[21]Consistently with our assumption of perfect foresight on spot prices, we also assume that participants' expectation of intermittent power generation, $E_{T-1}[Q\_I_T]$, corresponds to the observed value Q_I_T.

[22]As a consistency check, we regress the spot price and the risk premium on the marginal costs of oil, gas, coal and intermittent power generation in Appendix B.3. The results, reported in Table B.3, show that spot prices are positively and significantly related to the costs of coal and gas and negatively related to feed-in-tariffs, as expected. However, only the costs of intermittent power and the feed-in tariffs are related to the risk premium.

The results of the first stage are reported in Table B.2 in the Appendix. As expected, solar power generation is significantly and positively related to sunshine duration. By contrast, wind power generation is not significantly related to either wind speed or wind velocity but is significantly and positively related to both the marginal costs of renewable power generation and the feed-in-tariffs. Table 1 shows the estimates from regression (3) with our instrumented variables, first pooling wind and solar power, then independently for each instrumented variable, and finally decomposing the effects of wind and solar.[23]

Consistent with renewables having lower marginal costs, we find that a higher amount of intermittent renewables is associated with lower spot prices (in column (1)). However, it has a significantly positive impact on the risk premia (in column (5)). Looking at the decomposition between wind and solar in the following columns, these effects seem to be mainly driven by wind power. The signs of the coefficients for solar power generation, though not significant, are the opposite. This suggests that all intermittent power sources might not have the same impact on the risk premium, which could explain the mixed results in the literature. To shed light on the economic mechanisms underlying these contrasting effects, we develop and structurally estimate an equilibrium model for electricity futures prices in section 3.

Table 1 further shows that the short-run marginal costs of coal, gas, and renewables are positively related to spot prices, while the feed-in-tariffs are negatively related, as expected. In all regressions, only the SRMC of coal appears to be significant; this result is in line with Paraschiv et al. (2014), Bublitz et al. (2017), and Mosquera-López and Nursimulu (2019), who also find that coal prices have the highest impact on electricity prices. By contrast, risk premia do not seem to be affected by the costs of conventional power generation but seem sensitive to subsidies on intermittent power generation. Our analysis will shed light on this finding.

3 The model

Our model builds on the equilibrium model initially proposed by Bessembinder and Lemmon (2002) and analyzes interactions of producers and retailers on the spot and futures electricity

[23]In specifications (1) and (2), and (5) and (6), intermittent power generation is instrumented by all instruments, namely sunshine duration, wind speed, wind velocity, and precipitation.

Table 1: **Electricity prices and intermittent power generation**

Table 1 reports coefficients (z-statistics) from the second stage regressions of spot prices (in column (1)-(3)) and one-month-ahead futures risk premium (in column (4)-(8)) on intermittent power generation. WIND POWER (resp. SOLAR POWER) is instrumented by wind speed, wind velocity, and precipitation (resp. by sunshine duration). Control variables include the short-run marginal costs of coal, gas, oil, and intermittent power, feed-in-tariffs, temperature, three dummies, SUMMER, FALL, and WINTER that capture seasonality and Year-Fixed Effects. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. We report (i) the Anderson canonical correlations LM statistic of an underidentification test and its p-value, (ii) the Cragg-Donald Wald F statistic of a weak identification test and the Stock-Yogo critical values at 10%, and (iii) the Sargan statistic of an overidentification test and its p-value.

	Spot Price S_T			**Risk premium** $F_{T-1,T} - S_T$		
	(1)	(2)	(3)	(4)	(5)	(6)
SOLAR POWER	2.216		0.848	-2.205		-0.994
	(1.48)		(0.58)	(-1.42)		(-0.66)
WIND POWER		-1.009***	-0.919**		1.003**	0.880**
		(-2.58)	(-2.14)		(2.50)	(2.00)
SRMC_COAL	0.696***	0.679***	0.728***	-0.099	-0.081	-0.136
	(3.21)	(3.88)	(3.66)	(-0.44)	(-0.45)	(-0.67)
SRMC_GAS	0.053	0.149	0.125	-0.026	-0.122	-0.093
	(0.35)	(1.14)	(0.89)	(-0.17)	(-0.91)	(-0.64)
SMRC_OIL	0.031	-0.002	-0.012	0.005	0.038	0.048
	(0.47)	(-0.04)	(-0.19)	(0.08)	(0.63)	(0.75)
SRMC_INTMT	0.760	-0.206	1.249	1.457	2.423	0.778
	(0.17)	(-0.07)	(0.31)	(0.32)	(0.76)	(0.19)
Feed_in_tariffs FIT	-0.270***	-0.035	-0.060	0.180*	-0.053	-0.020
	(-2.64)	(-0.28)	(-0.44)	(1.70)	(-0.41)	(-0.14)
Dummy SUMMER	5.719***	3.679**	4.106**	-3.970**	-1.942	-2.462
	(3.16)	(2.31)	(2.28)	(-2.11)	(-1.19)	(-1.33)
Dummy FALL	7.903***	4.790***	6.041**	-5.568*	-2.470	-3.933
	(2.76)	(3.04)	(2.24)	(-1.88)	(-1.53)	(-1.42)
Dummy WINTER	5.755**	4.202***	5.238**	-2.447	-0.900	-2.090
	(2.18)	(2.68)	(2.18)	(-0.89)	(-0.56)	(-0.85)
TEMPERATURE	-0.796***	-0.438**	-0.561**	0.665**	0.309	0.453
	(-2.69)	(-2.34)	(-1.96)	(2.16)	(1.60)	(1.54)
Constant	3.768	15.67	0.964	-11.29	-23.18	-6.510
	(0.09)	(0.52)	(0.02)	(-0.25)	(-0.75)	(-0.16)
Year FE	yes	yes	yes	yes	yes	yes
Observations	66	66	66	66	66	66
R-squared	0.732	0.789	0.775	0.349	0.499	0.467
(i) Underident. test	28.493	39.793	28.931	28.493	39.793	28.931
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(ii) Weak ident. test	37.983	24.295	9.171	37.983	24.295	9.171
Critical values (10%)	16.38	9.08	7.56	16.38	9.08	7.56
(iii) Overident. test	0	1.486	1.056	0	3.046	2.473
p-value	.	0.4757	0.5898	.	0.2180	0.2904

markets. Our objective is to investigate how power generation characteristics impact the risk premium. Our extension includes electricity generation from intermittent renewables and inflexible sources such as nuclear power, the impact of which is contrasted to that of conventional power sources (i.e., fossil fuels).

3.1 Timing and participants

3.1.1 Model setup

The model has three periods. Date 3 corresponds to the consumption/production date when the end-customers' total demand must be served and when power is generated. We take consumption decisions made by final consumers as given and assume that total demand $\widetilde{Q}_D$ is a random variable with mean μ_D and volatility σ_D. To capture its intermittent nature and its dependence on weather conditions, we assume that the volume of intermittent power supplied (i.e., generated from solar and wind), $\widetilde{Q}_I$, is also a random variable with mean μ_I and volatility σ_I. These two random variables may be correlated, and we denote by $\sigma_{D,I}$ their covariance.

At date 2, market participants observe the realizations Q_D and Q_I of both random variables. To satisfy the total demand to be delivered at the retail fixed price P_R, N_R retailers (without production facility) must each purchase a volume Q_{R_i} of electricity from producers (without end-customers). Total demand is first satisfied by power generated from intermittent sources. Let N_I the number of power generators using intermittent sources to supply a volume Q_{I_i} each. N_N conventional producers using non-intermittent sources serve the residual demand Q_{RD} (i.e., $Q_D - Q_I$). We assume that intermittent and conventional producers and retailers are competitive and equally share, respectively, the total volume of intermittent power generation Q_I, residual demand Q_{RD}, and total demand Q_D, each generating or distributing the following volume:

$$Q_{I_i} \quad = \quad \frac{Q_I}{N_I}; Q_{N_i} = \frac{Q_{RD}}{N_N}; Q_{R_i} = \frac{Q_D}{N_R}.$$

Retailers and producers may buy or sell power on the spot market, open at date 2. Spot prices $\tilde{S}$ may be volatile due to uncertainty in demand and intermittent power generation. To hedge against these variations, participants can lock in the price F at which they would buy or sell electricity by trading futures contracts on the futures market, open at date 1. The futures market is also populated by financial intermediaries, who have neither power generation facilities nor end-customers. We assume that markets are competitive and that all participants are price takers in both markets.

3.1.2 Market participants' expected utility

We assume that participants are risk averse with a mean-variance expected utility:

$$\max_{q_i^F} EU\left(\tilde{\pi}_i\right) = E\left(\tilde{\pi}_i\right) - \frac{A}{2} Var\left(\tilde{\pi}_i\right), \tag{4}$$

where A represents the coefficient of risk aversion, and $\tilde{\pi}_i$ is the participant i's final profit, defined as follows.

Let Q_{P_i} be the volume of power generated by producer P_i, and Q_{R_i} the volume delivered by retailer R_i to her end-customers. If they trade q_i^F on the futures market, where $q_i^F > 0$ for a purchase and $q_i^F < 0$ for a sale, participant i's final profit $\tilde{\pi}_i$ writes:

$$\tilde{\pi}_i = \underbrace{\rho_i(\tilde{S}, Q_i)}_{\text{But-for-hedging-profits}} + \underbrace{q_i^F \times \left(\tilde{S} - F\right)}_{\text{Futures market's gains/losses}}, \tag{5}$$

where $\rho_i(\tilde{S}, Q_i)$ denotes the "but-for-hedging" profit, that is, the profit participant i makes by trading the total quantity they must produce or deliver, Q_i, at the random spot price $\tilde{S}$. More precisely, a retailer R_i delivers to her end-customers a volume Q_{R_i} of power at the retail price P_R, that she buys on the spot or the futures markets, yielding a final profit of:

$$\begin{aligned}
\tilde{\pi}_{R_i} &= \underbrace{P_R \times Q_{R_i}}_{\text{Revenues}} - \underbrace{(Q_{R_i} - q_{R_i}^F) \times \tilde{S}}_{\text{Cost of purchases on spot market}} - \underbrace{q_{R_i}^F \times F.}_{\text{Cost of purchases on futures market}} \\
&= \underbrace{Q_{R_i}\left(P_R - \tilde{S}\right)}_{\rho_{R_i}(\tilde{S}, Q_{R_i})} + q_{R_i}^F \left(\tilde{S} - F\right). \qquad (6)
\end{aligned}$$

Symmetrically, a producer P_i generates a volume Q_{P_i} of power at a total cost $TC(Q_{P_i})$.[24]

[24] See Appendix C.2.1 for the details of the computation of Producers' but-for-hedging-profits.

His final profit is thus:

$$
\begin{aligned}
\tilde{\pi}_{P_i} &= \underbrace{\left(Q_{P_i} - (-q^F_{P_i})\right) \times \tilde{S}}_{\text{Revenues from sales on spot market}} + \underbrace{\left(-q^F_{P_i}\right) \times F}_{\text{Revenues from sales on futures market}} - \underbrace{TC_{P_i}(Q_{P_i})}_{\text{Cost of production}} \\
&= \underbrace{\tilde{S} \times Q_{P_i} - TC_{P_i}(Q_{P_i})}_{\rho_{P_i}(\tilde{S}, Q_{P_i})} + q^F_{P_i}\left(\tilde{S} - F\right).
\end{aligned} \tag{7}
$$

Finally, we assume that N_f financial intermediaries may be willing to participate in the futures markets to speculate or diversify their investors' portfolios.[25] We assume that their initial wealth W_{f_i}, is invested in the market portfolio, that provides a return $\tilde{r}_M$ at date 3. Since they neither generate nor distribute power, all the power bought or sold in the futures market must be sold or bought back in the spot market. Their final profit is thus:

$$
\tilde{\pi}_{f_i} = \underbrace{W_{f_i} \times \tilde{r}_M}_{\rho_{f_i}(\tilde{S})} + q^F_{f_i}\left(\tilde{S} - F\right).
$$

3.1.3 Producers' cost structure

The two types of producers are characterized by heterogeneous marginal costs. First, intermittent power producers have constant, small marginal costs and receive "feed-in-tariffs" for each unit of electricity produced. We assume that their total cost function for generating a volume Q_{I_i} of intermittent power is such that:

$$
TC_{I_i}(Q_{I_i}) = F_I + \delta Q_{I_i} - \theta Q_{I_i}, \tag{8}
$$

where F_I are the fixed costs, δ the constant marginal cost, and θ the feed-in-tariff.

Second, we assume that the marginal costs of conventional producers, who serve the residual demand $\widetilde{Q}_{RD} = \widetilde{Q}_D - \widetilde{Q}_I$ using non-intermittent energy sources, are inverted S-shape, in line with the characteristics of generation slack described in Section 2.1.1. The total cost of a representative conventional producer N_i who produces a quantity Q_{N_i} from non-intermittent

[25] Gorton and Rouwenhorst (2006) have shown that over the period 1959-2004, commodity futures returns were negatively correlated with stock returns, suggesting potential gains from diversification, especially at longer horizons. Many papers document and analyze the "financialization of commodity markets" that started in the 2000s (see, for instance, Tang and Xiong (2012).)

energy sources is given by:

$$
TC_{N_i}(Q_{N_i}) = F_N + \begin{cases} \frac{c^L}{\gamma^L} \exp(\gamma^L Q_{N_i}) & \text{if } Q_{N_i} < \underline{Q}_{N_i} \\ \\ \frac{c^M}{2} \left(Q_{N_i}\right)^2 & \text{if } \underline{Q}_{N_i} < Q_{N_i} < \overline{Q}_{N_i} \\ \\ \frac{c^R}{\gamma^R} \exp(\gamma^R Q_{N_i}) & \text{if } Q_{N_i} > \overline{Q}_{N_i} \end{cases}, \tag{9}
$$

where F_N are fixed costs, and c^L, γ^L, c^M, c^R and γ^R are variable cost parameters.

Each segment of the cost function, namely convex, linear, and convex, represents a producer's marginal costs fulfilling the last unit of demand.[26] The first segment (i.e., $Q_{N_i} < \underline{Q}_{N_i}$) captures the concavity of the marginal costs of inflexible producers: total costs are increasing at decreasing rates ($c^L < 0$ and $\gamma^L < 0$). The second segment (i.e., $\underline{Q}_{N_i} < Q_{N_i} < \overline{Q}_{N_i}$) represents the low and constant marginal costs of power generation from efficient nuclear power plants or non-intermittent renewables ($c^M \geq 0$). The last segment (i.e., $Q_{N_i} > \overline{Q}_{N_i}$) captures the convex marginal costs of fossil fuel producers such as coal, gas, and oil ($c^R > 0$ and $\gamma^R > 0$). Note that our model almost perfectly nests Bessembinder and Lemmon (2002)'s with no intermittent power (that is, $\mu_I = \sigma_I = 0$) and convex costs (that is, $\overline{Q} = 0$.)

We solve for the equilibrium backward, starting with the equilibrium in the spot market at date 2. Then, we compute the optimal positions of market participants on the futures market and the futures price that clears the market.

3.2 Equilibrum on the Spot Market

We first search for the equilibrium on the spot market, at date 2, when exogenous shocks are realized. Since futures contracts are in zero-net supply, the price S^* such that the market-clearing condition holds on the spot market guarantees that conventional producers' power

[26]Instead of considering heterogeneous producers, we assume that producers are homogenous but with heterogeneous costs. We choose exponential costs as the 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)). Our data regarding the electricity supply curve confirm this function as the best fit.

generation equilibrates the wholesale market:

$$\sum_{i=1}^{N_N} Q^S_{N_i}(S^*) + \sum_{i=1}^{N_I} Q^S_{I_i}(S^*) + \sum_{i=1}^{N_f} Q^S_{f_i}(S^*) = \sum_{i=1}^{N_R} Q^S_{R_i}(S^*) \tag{10}$$
$$\iff \sum_{i=1}^{N_N}\left(Q_{N_i} + q^F_{N_i}\right) + \sum_{i=1}^{N_I}\left(Q_{I_i} + q^F_{I_i}\right) + \sum_{i=1}^{N_f} q^F_{f_i} = \sum_{i=1}^{N_R}\left(Q_{R_i} - q^F_{R_i}\right) \iff \sum_{i=1}^{N_N} Q_{N_i} = Q_D - Q_I,$$

where $Q^S_{N_i}(S^*)$ and $Q^S_{I_i}(S^*)$ are the quantities sold by a conventional and intermittent producer i, $Q^S_{f_i}(S^*) \equiv q^F_{f_i}$ is the quantity sold by financial intermediaries i, and $Q^S_{R_i}(S^*)$ the quantity bought by retailer i on the spot market at price S^*.

Once intermittent power generation and demand are realized, intermittent power generators' supply and retailers' demand on the spot market is price inelastic: they trade whatever remains to be bought or sold to meet their target, given the volumes q^F_i already traded on the futures market. The former each sell $Q^S_{I_i} = \frac{Q_I}{N_I} - \left(-q^F_{I_i}\right)$, while the latter buy $Q^S_{R_i} = \frac{Q_D}{N_R} - \left(q^F_{R_i}\right)$. The spot price will, however, depend on the conventional producers' marginal costs, computed from their total cost function in (9). Under the zero-profit condition imposed by perfect competition, the quantity supplied by conventional producers on the spot market at a price S is thus $Q^S_{N_i}(S)$ such that:

$$Q_{N_i} \equiv Q^S_{N_i}(S) + \left(-q^F_{N_i}\right) = \begin{cases} \frac{1}{\gamma^L}\ln\left(\frac{S}{c^L}\right) & \text{if } Q_{N_i} < \underline{Q}_{N_i} \\ \left(\frac{S}{c^M}\right) & \text{if } \underline{Q}_{N_i} < Q_{N_i} < \overline{Q}_{N_i}. \\ \frac{1}{\gamma^R}\ln\left(\frac{S}{c^R}\right) & \text{if } Q_{N_i} > \overline{Q}_{N_i} \end{cases} \tag{11}$$

Substituting the quantities found in equation (11) into the market clearing condition in (10), and given that $Q_{N_i} = \frac{Q_{RD}}{N_N}$, we find the equilibrium spot price:

$$S^* = \begin{cases} c^L \exp(\gamma^L \frac{Q_{RD}}{N_N}) & \text{if } \widetilde{Q}_{RD} < \underline{Q} \\ c^M\left(\frac{Q_{RD}}{N_N}\right) & \text{if } \underline{Q} < \widetilde{Q}_{RD} < \overline{Q} \\ c^R \exp(\gamma^R \frac{Q_{RD}}{N_N}) & \text{if } \overline{Q} < \widetilde{Q}_{RD} \end{cases}, \tag{12}$$

where $\underline{Q} = N_N \underline{Q}_{N_i}$ and $\overline{Q} = N_N \overline{Q}_{N_i}$. The equilibrium price resumes some characteristics of the electricity market, such as the non-monotonic relationship between the demand and the price skewness.[27] Also note that, as prices depend on residual demand, the spot price is a decreasing function of renewable production. A higher realization of intermittent renewables strongly displaces conventional production in the provisioning order.

3.3 First Period: futures hedging positions

Having determined the equilibrium price on the spot market, we now turn to the equilibrium on the futures market at date 1.

3.3.1 Producers and retailers hedging position

Participant i chooses the optimal quantity q_i^F that maximizes their expected utility:

$$\max_{q_i^F} EU(\tilde{\pi}_i) = E(\tilde{\pi}_i) - \frac{A}{2} Var(\tilde{\pi}_i), . \tag{13}$$

where profits $\tilde{\pi}_i$ are defined in (5).

Market participants (i.e., producers and retailers) know that spot prices may be related to various parameters of the conventional producers' cost function depending on whether the realization of the residual demand is low and falls into the concave region (i.e., when $\widetilde{Q}_{RD} < \underline{Q}$), intermediate and in the linear region (i.e., when $\underline{Q} < \widetilde{Q}_{RD} < \overline{Q}$), or high and in the convex region (i.e., when $\widetilde{Q}_{RD} > \overline{Q}$), as characterized in (12). We label these events $\mathcal{R}_1$, $\mathcal{R}_2$ and $\mathcal{R}_3$ respectively, corresponding to a state of nature $j \in \{1, 2, 3\}$, with a probability of occurrence denoted α_j. Applying the laws of iterated expectations and of total variance to decompose the unconditional expectation and variance in (13), the outcome of the maximization problem is given in the following lemma.

Lemma 1 *Market participant i trades a quantity q_i^{F*} (positive for a purchase, negative for a*

[27] When the residual demand is normally distributed, when it is low, the realizations of the spot price take an exponential shape where c^L and $\frac{\gamma^L}{N_N}$ are negative. Thus, as $\widetilde{Q}_{RD}$ increases, the exponential increases of S^* are smaller. Consequently, the residual demand realizations can result in S^* values more concentrated around prices close to 0, with outliers or extreme negative values showing negative skewness. Conversely, when demand is high, prices increase exponentially, and skewness is positive.

sale) on the futures market, where

$$q_i^{F*} = \frac{E(\tilde{S}) - F}{A\sum_{j=1}^{3}\alpha_j Var(\tilde{S}|\mathcal{R}_j)} - \frac{\sum_{j=1}^{3}\alpha_j Cov(\tilde{\rho}_i, \tilde{S}|\mathcal{R}_j)}{\sum_{j=1}^{3}\alpha_j Var(\tilde{S}|\mathcal{R}_j)}. \tag{14}$$

Equation (14) consists of two parts. The first part corresponds to a speculative position: a futures price below the expected spot price (i.e., $E(\tilde{S}) - F > 0$) induces market participants to buy more futures (i.e., $q_i^F > 0$) to benefit from this difference. The second component corresponds to the incentive to hedge. When the covariance between the but-for-hedging profits $\tilde{\rho}_i$ and the spot price $\tilde{S}$ is positive, which is more likely to be the case for producers who have a long position, participants are induced to sell futures (i.e., $q_i^F < 0$). Conversely, when the covariance between the but-for-hedging profits $\tilde{\rho}_i$ and the spot price $\tilde{S}$ is negative, which is more likely to be the case for retailers who have a short position or if electricity prices enable financial intermediaries to diversify their portfolios, 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 being low, medium, or high.

3.3.2 First Period: futures price equilibrium

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

$$\sum_{i=1}^{N_N} q_{N_i}^F + \sum_{i=1}^{N_I} q_{I_i}^F + \sum_{i=1}^{N_R} q_{R_i}^F + \sum_{i=1}^{N_f} q_f^F = 0. \tag{15}$$

We substitute the participants' optimal demands $q_{N_i}^{F*}$, $q_{I_i}^{F*}$, $q_{R_i}^{F*}$ and q_f^{F*} from equation (14) into equation (15) and decompose the participants' profits into their revenue and cost components to characterize the equilibrium futures price in the following Lemma.

Lemma 2 *The equilibrium price in the futures market, F^*, is such that:*

$$F^* - E(\tilde{S}) = \overline{A}\left[\underbrace{cov(TC_N(\tilde{Q}_{RD}), \tilde{S})}_{Conv.\ Producers'\ Cost\ Risk} + \underbrace{[\delta - \theta]\sum_{j=1}^{3}\alpha_j Cov\left(\tilde{Q}_I, \tilde{S}|\mathcal{R}_j\right)}_{Intermittent\ producers'\ Cost\ Risk} - \underbrace{P_R\sum_{j=1}^{3}\alpha_j Cov\left(\tilde{Q}_D, \tilde{S}|\mathcal{R}_j\right)}_{Retailers'\ Revenue\ Risk} - W_0 Cov(\tilde{r}_M, \tilde{S})\right], \tag{16}$$

where $\overline{A} = \frac{A}{N_N+N_I+N_R+N_f}$, $W_0 = \sum_{i=1}^{N_f} W_{f_i}$ *and*

$$cov(TC_N(\tilde{Q}_{RD}), \tilde{S}) = \begin{pmatrix} \alpha_1 N_N Cov\left(\frac{c^L}{\gamma^L}\exp\gamma^L\left(\frac{\tilde{Q}_{RD}}{N_N}\right), \tilde{S}\right) + \alpha_2 N_N Cov\left(\frac{c^M}{2}\left(\frac{\tilde{Q}_{RD}}{N_N}\right)^2, \tilde{S}\right) \\ +\alpha_3 N_N Cov\left(\frac{c^R}{\gamma^R}\exp\gamma^R\left(\frac{\tilde{Q}_{RD}}{N_N}\right), \tilde{S}\right) \end{pmatrix}.$$

Equation (16) results from the optimal hedging demand of the wholesale market participants, which depends on the covariance between the revenue and cost components of their profits. We refer to these components as the revenue and cost risk exposures, and we develop and discuss them in the proof reported in Appendix C.2. From the zero net supply condition, since the aggregate producers' revenues ($S\times Q$) correspond to the aggregate retailers' costs ($-S\times Q$), the corresponding risks cancel each other out: we call these risks "diversifiable." The risk premium ends up being a function of the sole producers' cost risk and the retailers' revenue risk that do not cancel out in the aggregate, which we call "non-diversifiable" risks. As standard in asset pricing theory, only the aggregate risk is priced. The presence of financial intermediaries influences the risk premium: if electricity prices negatively correlate with the market portfolio, financial intermediaries are induced to buy power futures to diversify their portfolios, which increases futures prices. The sign of the risk premium $F^* - E(\tilde{S})$ depends on that of the various covariances, which can be summarized in the following corollary.

Corollary 1 *The risk premium's expected sign is as follows:*

Participant	***Component***	***Exp. sign***	***Exp. impact on RP***
Conv. prod. Cost Risk (+)	$cov(TC_N(\tilde{Q}_{RD}), \tilde{S})$	> 0	> 0
Int. prod. Cost Risk (+)	$\delta - \theta$ $\sum_{j=1}^{3}\alpha_j Cov\left(\tilde{Q}_I, \tilde{S}\vert\mathcal{R}_j\right)$	- < 0	*sign of* $-(\delta-\theta)$
Ret. Revenue Risk (-)	P_R $\sum_{j=1}^{3}\alpha_j Cov\left(\tilde{Q}_D, \tilde{S}\vert\mathcal{R}_j\right)$	> 0 > 0 *or* < 0	*sign of* $-Cov\left(\tilde{Q}_D, \tilde{S}\right)$ *(depending on* $\sigma_{D,I}$*)*
Fin. intermed. (-)	W_0 $Cov(\tilde{r}_M, \tilde{S})$	> 0 -	*sign of* $-Cov(\tilde{r}_M, \tilde{S})$

As in Bessembinder and Lemmon (2002), the sign of the risk premium depends positively on the producers' cost risk and negatively on the retailers' revenue risk.[28] If prices covary positively with demand, as might be intuitive, one would expect the conventional producers' cost risk and the retailers' revenue risk to be positive. In the absence of intermittent power generation and financial intermediaries, the sign of the risk premium consequently depends on the extent to which producers' and retailers' risks offset each other.

The presence of intermittent power generators, however, alters this balance for two reasons. The first effect is direct: their hedging demand creates additional pressure on futures prices, which can be positive or negative depending on the sign of $\theta - \delta$, that is, on how feed-in-tariffs compensate for the marginal costs of intermittent power generation. The second effect is indirect: the presence of intermittent power generation can alter the risk exposures of other participants. Indeed, since the residual demand now depends on the volume of intermittent power generation, the covariance between the load demand and the spot price that captures the retailers' revenue risk may no longer be positive, unlike in Bessembinder and Lemmon (2002). This would, for instance, be the case if the total demand and the volume of intermittent power generated were highly positively correlated.

Finally, the risk premium is impacted by the participation of financial intermediaries. One would expect the returns of their wealth invested in a market portfolio to correlate positively with electricity prices, reflecting higher commodities' prices during periods of economic growth, thus a negative price pressure.

Overall, both the sign and magnitude of the risk premium expressed in equation (16) are related to the extent to which risk exposures offset or reinforce each other, which in turn depends on the parameters of the model, particularly those of the conventional producers' cost function and those of the joint distribution of demand and intermittent power generation. In the following section, we structurally estimate the model's parameters to analyze the sign and economic determinants of the equilibrium future risk premium and develop some counterfactuals.

[28] After some manipulation, they show both the producers' cost risk and the retailers' revenue risk can be expressed as functions of the variance and skewness of prices, which provides them with a clear prediction that they test empirically.

4 Structural estimation

We estimate the model in two stages. In the first stage, we obtain the conventional producers' cost parameters from the supply curves on the spot market. In the second stage, we obtain the remaining parameters from prices on the futures market.

4.1 Step 1: Conventional producers' costs

We first estimate the cost parameters of conventional producers (i.e., $c^L, \gamma^L, c^M, c^R, \gamma^R, \underline{Q}$ and $\overline{Q}$) from the supply curves on the spot market. To this end, we estimate the parameters of the spot market supply curves:

$$S = \begin{cases} \hat{c}^L \exp(\frac{\hat{\gamma}^L}{N_N} Q) & \text{if } Q < \underline{\hat{Q}} \\ \frac{\hat{c}^M}{N_N} Q & \text{if } \underline{\hat{Q}} < Q < \overline{\hat{Q}} \\ \hat{c}^R \exp(\frac{\hat{\gamma}^R}{N_N} Q) & \text{if } \overline{\hat{Q}} < Q \end{cases}, \tag{17}$$

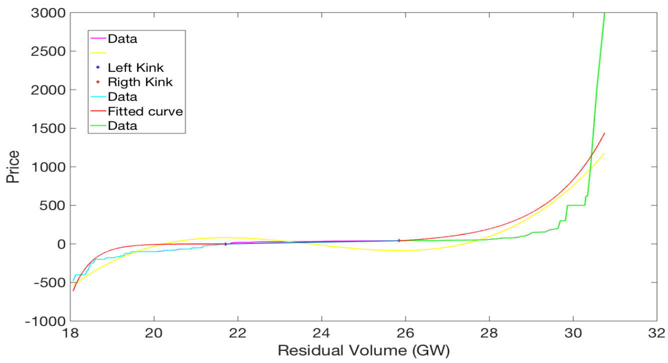
A note in section C.3 in the appendix shows that there is a one-to-one mapping (given in equation (37)) between the parameters of the spot supply curve ($\hat{c}^L, \hat{\gamma}^L, \hat{c}^M, \hat{c}^R, \hat{\gamma}^R, \underline{\hat{Q}}$ and $\overline{\hat{Q}}$) and those characterizing the conventional producers' costs in our model ($c^L, \gamma^L, c^M, c^R, \gamma^R, \underline{Q}$ and $\overline{Q}$).

4.1.1 Methodology

Hourly estimates. We proceed with each hourly aggregate supply curve from EPEX SPOT in four steps. First, we subtract the volume corresponding to intermittent power generation obtained from the German Transmission System Operators (TSOs) to find the residual supply. Second, we use a linear interpolation to smooth the data since the supply curves are defined for discrete prices and quantities. Third, we fit the data into a third-degree polynomial, and we define the kinks ($\underline{\hat{Q}}$ and $\overline{\hat{Q}}$) as those points on the curve where the first derivative of the polynomial is equal to zero. Fourth, having determined the left and right kinks, we fit the first concave (i.e., where $Q < \underline{\hat{Q}}$) and the last convex (i.e., where $Q > \overline{\hat{Q}}$) segments of the piecewise function (17) using nonlinear least squares. For each hourly fitted curve, we obtain values of the parameters $\hat{c}^L$, $\frac{\hat{\gamma}^L}{N_N}$, $\hat{c}^R$, $\frac{\hat{\gamma}^R}{N_N}$, 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 and find $\hat{c}^M$, we obtain the line that passes through the two kink points. We estimate a total of $64,909$ sets of parameters.[29,30] Figure 7 illustrates the estimation for the market supply curve on June 5, 2017, at 4 pm.

Figure 7: **Illustration of our curve fit**

Figure 7 illustrates how we fit the aggregate supply curve from the EPEX-SPOT day-ahead market for delivery on June 5, 2017, at 4 p.m. net from the volume of intermittent power generation to estimate the cost parameters of conventional producers structurally. The blue, pink, and green curves show the interpolated data for each segment $[0, \underline{\hat{Q}}]$, $[\underline{\hat{Q}}, \overline{\hat{Q}}]$, and $[\overline{\hat{Q}}, \infty]$ respectively. The yellow curve represents the third-degree polynomial, and the red curve shows the piecewise function fitting curve. Source: EPEX SPOT and German Transmission System Operators (TSOs).



Monthly averages. 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 horizon. The second is that we are interested in constructing monthly spot prices to ensure consistency with the definition of monthly futures contracts. Once we obtain the hourly estimates, we compute a weighted average to obtain monthly parameters, which should be interpreted as the hourly average for each month of the period analyzed. To this end, we first winsorize the estimates at 90% on a monthly basis to avoid outliers; then, we weigh the hourly estimates by the adjusted R2 of the estimation when computing the monthly weighted

[29] We remove 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).

[30] To obtain $N_N = N_I = N_R$, we use the list of trading participants from EEX in the German market in 2018. This list reports that 58 companies were trading in the futures market. Since we cannot classify them between conventional and intermittent power producers or retailers, we assume that 20 are retailers, 20 are intermittent power producers, and 20 are conventional producers. Our results are rather insensitive to this assumption.

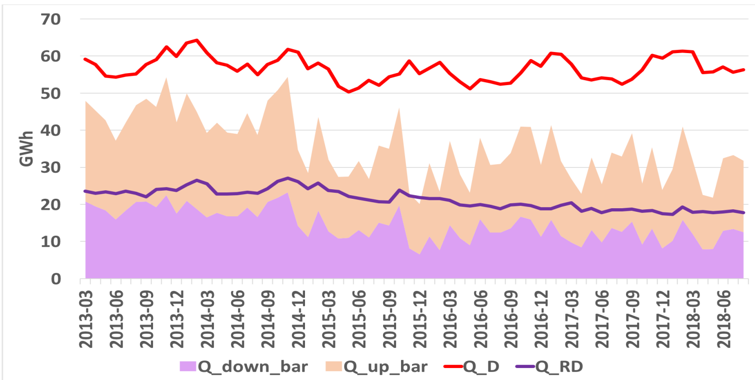
averages. Thus, the closer the adjusted R2 is to 1, the more weight the hourly estimate has in the monthly parameter.[31] Finally, we use equation (37) to obtain the cost parameters of interest.

4.1.2 Estimates of the kinks $\hat{\underline{Q}}$ and $\hat{\overline{Q}}$

Figure 8 shows the results of the estimates for the right and left kinks.

Figure 8: **Monthly estimates of parameters $\underline{Q}$ and $\overline{Q}$**

Figure 8 shows the average monthly estimates of parameters $\underline{Q}$ and $\overline{Q}$, following the approach described in section 4.1.1. First, we perform a linear interpolation to smooth the hourly cumulated bids on the spot market. Second, we fit the data into a third-degree polynomial, and we define the kinks ($\hat{\underline{Q}}$ and $\hat{\overline{Q}}$) as those points on the curve where the first derivative of the polynomial is equal to zero. Third, we compute the monthly weighted averages after windsorizing at 90%. Fourth, we recover the model parameters $\underline{Q}$ and $\overline{Q}$ from equation (37) in Appendix C.3. The purple area represents the parameter $\underline{Q}$, and the orange one is the parameter $\underline{Q}$. For comparison purposes, we plot the total demand Q_D in red and the residual demand Q_{RD} in blue.



The figure shows that in the short run, parameters remain relatively stable. It also illustrates the long-run evolution of conventional producers' costs. Take, for example, an hourly supply level of 20GW. By the end of 2014, this quantity was in the concave area (as $\underline{Q}_{2014-01} > 20$ for instance), but as of 2016, it was already in the middle segment (as $\underline{Q}_{2016-01} < 20 < \overline{Q}_{2016-01}$ for instance). The total and residual demand displayed in Figure 8 remain relatively constant over time, ruling out the possibility that such a reduction results from a drop in demand. The long-term decrease in $\underline{Q}$ may be due to the increase in intermittent power generation throughout the analysis period, leading to a decrease in conventional production. Consistently, Figure A.1 in Appendix A, which reports the net installed electricity capacity in Germany, shows an increase in wind and solar, a slight growth in gas, and a reduction in nuclear and hard coal installed

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

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.[32]

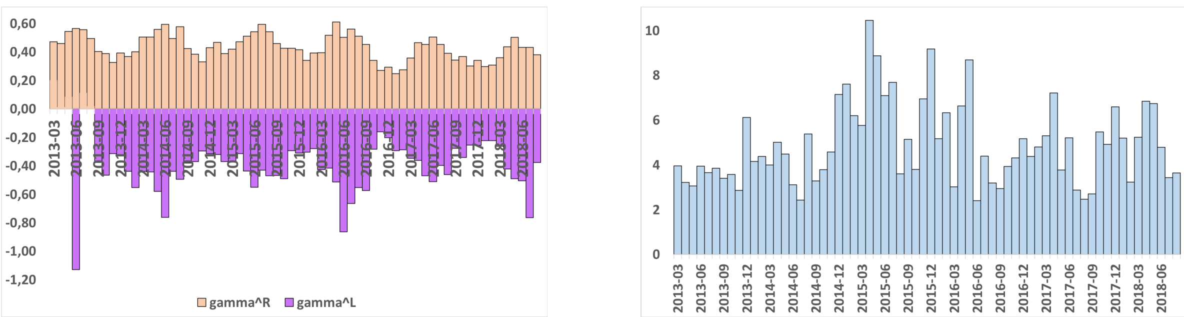
4.1.3 Estimates of the marginal cost parameters

Figure 9 shows the estimates for our main parameters of interest, namely γ^L, γ^R, and c^M. Parameters γ^L and γ^R indicate the degree of concavity and convexity of the supply curve: provided that $c^L < 0$ and $\gamma^L < 0$, a higher $|\gamma^L|$ indicates greater concavity for low residual demand, while provided that $c^R > 0$ and $\gamma^R > 0$, a higher γ^R denotes greater convexity for high residual demand. The parameter c^M depicts the linear marginal cost of conventional producers when residual demand is between these two extreme cases. It should be positive, capturing increasing marginal cost in line with the merit order effect. The estimates for the remaining parameters (c^L and c^R) are provided in the Appendix D.

Figure 9: **Monthly estimates of cost parameters**

Figure 9 shows the average monthly estimates of parameters $\gamma^L \gamma^R$, and c^M, following the approach described in section 4.1.1. Having identified the parameters $\underline{\hat{Q}}$ and $\overline{\hat{Q}}$, we fit the first concave (i.e., where $Q < \underline{\hat{Q}}$) and the last convex (i.e., where $Q > \overline{\hat{Q}}$) segments of the piecewise function (17) using nonlinear least squares. For each hourly fitted curve, we obtain values of the parameters $\hat{c}^L$, $\frac{\hat{\gamma}^L}{N_N}$, $\hat{c}^R$, $\frac{\hat{\gamma}^R}{N_N}$ and the Adjusted R-Squared. To adjust the middle segment of the piecewise function and find $\hat{c}^M$, we obtain the line that passes through the two kink points. We recover the model parameters γ^L, γ^R, and c^M from equation (37) in Appendix C.3. We compute the monthly weighted averages after windsorizing at 90%. In panel (a), the purple bars represent the parameter γ^R, and the orange ones the parameter γ^R. The blue bars in panel (b) represent the parameter c^M.

(a) γ^L and γ^R (curvatures) (b) c^M (linear part)



With a few exceptions, all parameters are aligned with our model expectations (i.e., $c_L < 0$ and $\gamma^L < 0$, c_R and $\gamma^R > 0$, and $c^M > 0$).[33] Furthermore, they show seasonality, where

[32] Germany exiting nuclear before 2011, we observe a minor decrease of nuclear in our data after 2013.

[33] The estimates of the c_L and γ^L parameters for March, April, May, July, and August 2013 take positive

parameters γs show maximum curvatures during summer. The γ^L parameter shows values between -1.12 and 0.20, averaging -0.38, while the γ^R parameter ranges between 0.25 and 0.61 and averages 0.43.

4.2 Step 2: Spot Prices and generation slack

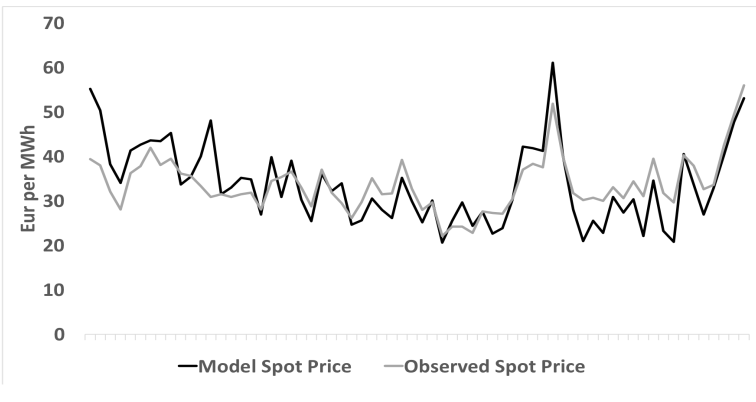
As a second step, we use the cost parameters estimated in section 4.1 to determine the conventional producers' theoretical supply curve, which we match with the residual demand computed from our data on the realized load demand and intermittent power generation to identify the clearing prices and quantities. Time series of spot prices are necessary to evaluate the participants' risk exposures that enter the theoretical risk premium in (16), while time series of quantities enable us to assess the frequencies of prices falling into the three regions of the supply curves.

4.2.1 Spot prices

For each hour, we compute the spot price (S_h) that clears the market, i.e., such that the supply from conventional producers equals the residual demand following the equilibrium price equation (12). This enables us to perform a consistency check by comparing the theoretical prices obtained from our model with the observed prices. Figure 10 shows the results.

Figure 10: **Model spot prices vs. observed spot prices**

Figure 10 compares the observed prices (in grey, computed as the monthly average of hourly prices reported by EPEX-SPOT) and the theoretical spot price (in black. The theoretical spot price is computed hourly from equation (12), using the monthly cost parameters estimated in section 4.1 and hourly data on load demand and intermittent power generation, then averaged across hours for each month.)



values, which violates the constraint $\gamma^L < 0$ and c_L of our model.

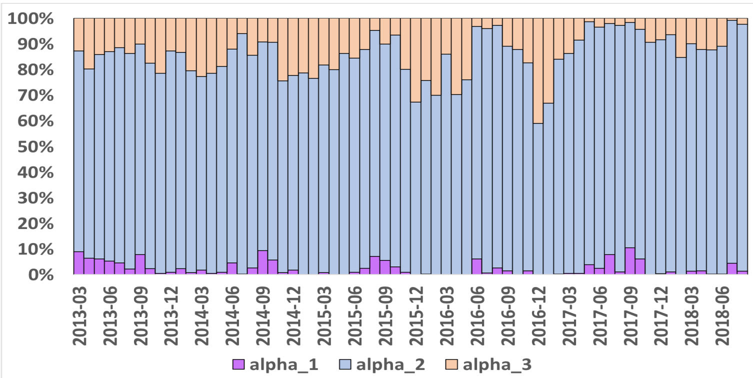
Our theoretical prices follow the same trends and seasonality as the realized prices, with an average difference of around 6 Eur/MWh and a correlation of 0.803.

4.2.2 Percentage of spot prices within each region

For each hour, we define three dummies that are equal to one if the clearing volume Q_h falls respectively below $\underline{Q}$, above $\overline{Q}$, or in-between. Averaging these dummies monthly, we find the percentage of times the residual demand is low, high, or medium within a month, corresponding to the parameters α_1, α_3, and α_2, respectively. Note that this percentage is the same as the number of times the spot price falls in each region. Figure 11 shows the results.

Figure 11: **Monthly estimates of parameters** $\alpha_{j\in\{1,2,3\}}$

Figure 11 shows the percentage of times the spot price falls in the different segments of the supply curve. The left (concave) segment of the curve is shown in purple, the middle (linear) segment in blue, and the right (convex) segment in orange.



We observe that approximately 85% of the time, the equilibrium spot price falls within the middle residual demand zone. This suggests that conventional producers are generally effective in anticipating residual demand and avoiding extreme regions where they are forced to sell at negative prices or switch on their inefficient power plants. We also observe seasonality: prices fall more frequently into the convex region during winter, when residual demand is high.

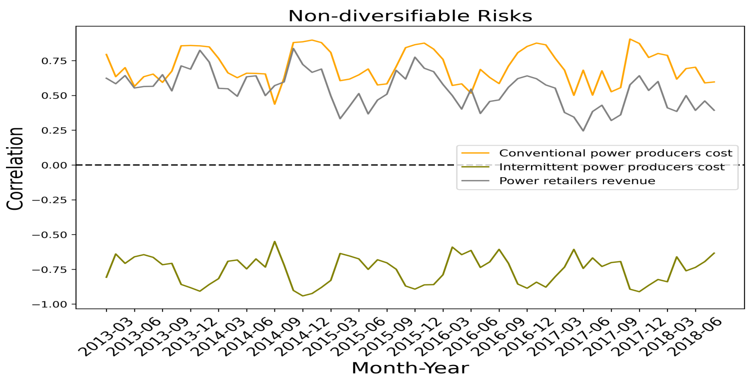
Besides, this percentage α_2 shows an increasing trend. The decrease in the probability α_1 characterizing the concave region since 2013 may be related to the EEG 2014 reform and the decrease in nuclear and hard coal installed capacity. After March 2017, the decrease in the probability α_3 characterizing the convex region suggests that producers' capacity to generate power more efficiently may have improved over time. Also already pointed out, this is consistent with the observed increasing trend in $\overline{Q}$ that is likely to be related to the increasing wind and solar net installed capacity in Germany reported in Figure A.1 of Appendix A.

4.3 Step 3: participants' risk exposures

We use the retail price, the marginal costs of wind and solar, and the feed-in-tariffs collected from the databases listed in section 2 to calibrate parameters P_R, δ, and θ, respectively. As a third step, having estimated the cost parameters and the probabilities $\alpha_{j\in\{1,2,3\}}$, we now can assess the participants' non-diversifiable risks introduced in (16), which determine the futures risk premium. We compute the covariances between conventional producers' cost and the spot price, intermittent power volume and the spot price, and residual demand and the spot price. Figure 12 displays the time series of the corresponding correlations (to ease comparability.)[34]

Figure 12: **Time series of non-diversifiable risks**

Figure 12 shows the evolution of non-diversifiable risks across time. For comparability, we plot correlations instead of covariances. The conventional producers' cost risk, in brown, is computed here as $\alpha_1 N_N Corr\left(\frac{c^L}{\gamma^L}\exp\gamma^L\left(\frac{\widetilde{Q}_{RD}}{N_N}\right),\tilde{S}\right)+\alpha_2 N_N Corr\left(\frac{c^M}{2}\left(\frac{\widetilde{Q}_{RD}}{N_N}\right)^2,\tilde{S}\right)+\alpha_3 N_N Corr\left(\frac{c^R}{\gamma^R}\exp\gamma^R\left(\frac{\widetilde{Q}_{RD}}{N_N}\right),\tilde{S}\right)$. The intermittent power producers' cost risk, in green, is computed here as $(\delta-\theta)\,Corr\left(\widetilde{Q}_I,\tilde{S}\right)$. The retailers' revenue risk, in grey, is computed here as $P_R\times Corr\left(\widetilde{Q}_D,\tilde{S}\right)$. Parameters c^L, γ^L, c^M, c^R, γ^R, $\alpha_{j\in\{1,2,3\}}$ are estimated as described in sections 4.1 and 4.2.2, and used to compute time series of theoretical spot prices.



The figure first reveals that the retailers' revenue risk is positive, suggesting that load demand still drives the clearing spot prices. While the conventional producers' cost risk is positive, as expected, the intermittent power producers' cost risk is negative. This suggests that the en-

[34]For completeness, their diversifiable risks (i.e., producers' revenue risk and retailers' cost risk) are reported in Appendix D.1.2. The comparison between diversifiable and non-diversifiable risks shows that, in absolute value, the former is more significant than the latter. This suggests that the futures market enables participants to hedge their main risk exposure, which are the diversifiable risks.

try of these producers is not innocuous, as their hedging behavior is unlike that of conventional producers.

The three series further exhibit a strong seasonality. The magnitude of market participants' risk exposures is higher in winter. For conventional producers and retailers, this is in line with the seasonality of the frequencies of extremely high prices in the convex region when the load demand is high. For intermittent power generators, it is likely due to the characteristics of intermittent power in Germany, which exhibits a strong seasonality as shown in Figure 4.

4.4 Step 4: Risk aversion

To identify the final parameter $\overline{A}$ corresponding to the market participants' risk aversion level, we start from the risk premium's equation (16). Using average monthly observations or estimates over the sample period, the model implies that:

$$\overline{A} = \frac{\frac{1}{N_m}\sum_{T=1}^{N_m}\left(F_{T-1,T} - S_T\right)}{\frac{1}{N_m}\sum_{T=1}^{N_m}\left(cov(TC_{N_T}, S_T) + cov((\delta_T - \theta_T)Q_{I_T}, S_T) - cov(P_{R,T}Q_{D_T}, S_T) - cov\left(W_0\tilde{r}_M, \tilde{S}\right)\right)}, \tag{18}$$

where N_m is the number of delivery month observations in our data. The numerator is the average one-month-ahead risk premium. The denominator is computed from the average monthly risk exposures reported in section 4.3 after retrieving the total number of participants (N), Feed-in-Tariffs (θ), retail price (P_R), and marginal costs of renewables (δ) from external sources. We collect data on the annual market capitalisation of the Frankfurt Stock Exchange for Statistica and daily adjusted prices for the DAX index to compute the covariance $cov\left(W_0\tilde{r}_M, \tilde{S}\right)$. We find $\overline{A} = 0.011$.[35]

5 Counterfactual Analysis

With counterfactual simulations, we study the impact of increasing intermittent renewable power generation in the production mix by 1 percentage point (p.p.) on electricity spot prices and futures risk premia.

[35] Since Figures 3 and 12 respectively show the time series of the risk premium and the risk exposures, we do not report their summary statistics in a Table.

5.1 Simulations

We run $n_F = 1,000$ simulations for futures prices and risk premia in the various cases we analyze. These simulations are each based on beliefs relative to demand and supply and the induced expected spot price at the delivery date. To characterize these beliefs, we generate $n_S = 1,000$ observations of production and consumption variables affecting the spot price.

Spot prices at the delivery date. We first draw a realization m of total demand and intermittent production (Q_D, Q_I) from the following multivariate normal distribution:

$$\begin{pmatrix} \tilde{Q}_D \\ \tilde{Q}_I \end{pmatrix} \sim N \left[\begin{pmatrix} \mu_D \\ \mu_I \end{pmatrix}, \begin{pmatrix} \sigma_D^2 & \sigma_{D,I} \\ \sigma_{D,I} & \sigma_I^2 \end{pmatrix} \right].$$

With the realized values of Q_D and Q_I, we use our parameters' estimates to determine the theoretical spot price that clears the market S_m using equation (12), and compute the participants' costs and revenues.

Futures prices. To form a belief k, we compute the following statistics based on n_S realizations of demand, supply and the induced prices in the spot market: the average spot price $(\bar{S}_k = \frac{1}{n_S} \sum_{m=1}^{n_S} S_m)$, and the covariances between participants' costs or revenues and the spot prices. We use these statistics and apply equation (16) to find the futures price F_k and the risk premium RP_k in each simulation $k \in [1, n_F]$. Our counterfactuals compare the futures price $\bar{F} = \frac{1}{n_F} \sum_{k=1}^{n_F} F_k$, risk premia, and risk exposures averaged across n_F series of simulations.

5.2 Scenarios in the counterfactual analysis.

The key feature of our counterfactual analysis is an increase of the mean of intermittent power from μ_I to $\mu_I^{1\%} = \mu_I + 1\% \times \mu_D$ in our simulations, that is, an increase in one percentage point in the total production mix (keeping total demand constant).

However, we are aware that an increase in the level of intermittent power generation is likely to impact the variability of the volume of intermittent power (measured by its standard deviation, σ_I), as well as its correlation $r_{D,I} = \frac{\sigma_{D,I}}{\sigma_D \sigma_I}$ with the load demand, as illustrated in

Figure 13, panels (a) and (b) (see also Figure D.3 in time series). An increase in the standard deviation indicates greater intermittency of renewables, while an increase in correlation with the load demand suggests a better integration of intermittent renewables into the system.[36]

Figure 13: **Moments of intermittent power generation**

Figure 13 plots the standard deviation of the intermittent renewable energy generation (σ_I) in panel (a) (resp. the correlation between intermittent power generation and demand ($r_{D,I} = Corr(Q_D, Q_I)$) in panel (b)) against the percentage of intermittent renewable generation in the energy mix ($\frac{Q_I}{Q_D}\%$). Each dot represents the monthly standard deviation (resp. correlation with load demand) computed from hourly power generation data. We split months of observation by season. Blue (resp. green, yellow, orange) dots show the standard deviation (resp. correlation) for the months in Winter (resp. Spring, Summer, Fall) season. Winter (resp. Spring; Summer; and Fall) corresponds to December, January, February (resp. March, April, May; June, July, August; and September, October, November). Additionally, a gray dashed line shows the linear regression fit, estimating the relationship between the percentage of intermittent renewable generation and its standard deviation (resp. the correlation with load demand). The slope of this line, labeled as $\hat{a_1}$ (resp. $\hat{b}_1$), indicates the estimated variability in Q_I (resp. in $Corr(Q_D, Q_I)$) relative to the percentage of intermittent renewable generation in the energy mix ($\frac{Q_I}{Q_D}\%$).

(a) Monthly $\sigma_{\widetilde{Q}_I}$ **(b) Monthly** $Corr(\widetilde{Q}_D, \widetilde{Q}_I)$

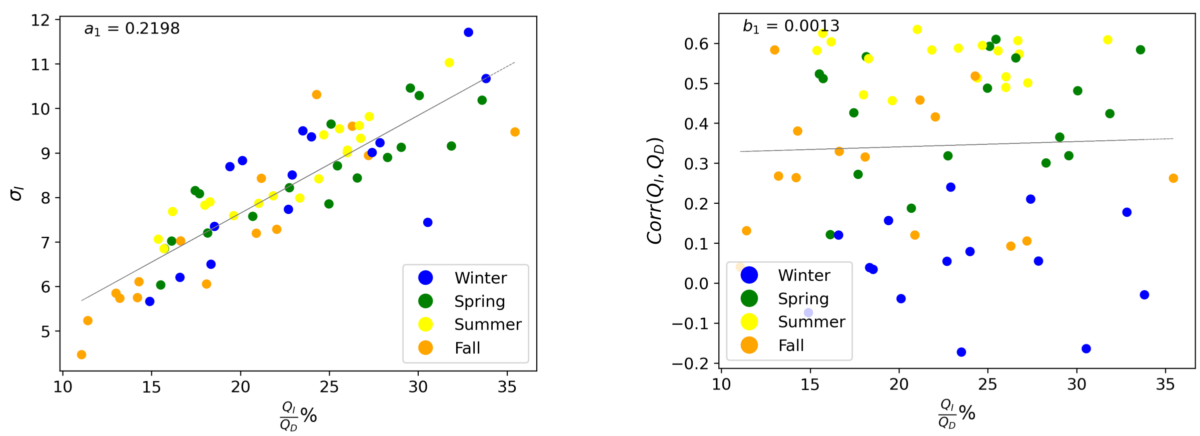


Figure 13, panel (a) shows that the volatility of intermittent power production is positively related to the percentage of intermittent renewable generation in the mix, which may be due to the challenges of integrating this source into the system. Figure 13, panel (b) illustrates a positive correlation between intermittent renewables Q_I and total load Q_D, with higher values

[36]We acknowledge the complex relationship between spot prices and variable costs of generation as several factors, such as ramping costs, minimum operational constraints, and portfolio dynamics, contribute to the divergence between spot prices and variable costs. Our approach simplifies this complex relationship.

observed in spring/summer (around 0.56) and lower values in autumn/winter (around 0.05). It is interesting to observe values close to zero during autumn/winter despite this being the season simultaneously characterized by the highest wind production and the highest demand in the German-Austrian region. This low correlation could be linked to the grid's limitations in managing wind energy intermittency, which may lead to curtailments and blackouts, or to the increasing demand for conventional power during high-demand periods such as winter, thus weakening the correlation between total demand and intermittent renewable production.

To capture these empirical features, our counterfactual analysis consists of shocking moments of intermittent power generation. ¿e assume that an increase by 1 p.p. of intermittent production would change the variance-covariance matrix of the multinormal distribution as follows:

$$\begin{pmatrix} \tilde{Q}_D \\ \tilde{Q}_I \end{pmatrix} \sim N\left[\begin{pmatrix} \mu_D \\ \mu_I + 1\% \times \mu_D \end{pmatrix}, \begin{pmatrix} \sigma_D^2 & a_2 r_{D,I}\sigma_D(a_1\sigma_I) \\ a_2 r_{D,I}\sigma_D(a_1\sigma_I) & (a_1\sigma_I)^2 \end{pmatrix}\right],$$

where parameters a_1 and a_2 represent the correlation between volatility or correlation with load demand and the share of intermittent power in the production mix.

5.3 Calibration

Overall. We first conduct a counterfactual analysis based on the structurally estimated parameters averaged over the full sample. We calibrate the characteristics of the distribution based on the means μ_D and μ_I, volatilities σ_D and σ_I, and covariance $\sigma_{D,I}$ of the load demand and volume of intermittent power observed in our data. We estimate the coefficients a_1 and a_2 (defined in equation (19)) that relate the share of intermittent power in the production mix with its volatility and covariance with demand, respectively, from the following OLS regressions:

$$\begin{aligned} \sigma_I &= a_0 + a_1 \frac{Q_I}{Q_D} + \varepsilon_1 \\ r_{D,I} &= b_0 + b_1 \frac{Q_I}{Q_D} + \varepsilon_2. \end{aligned} \tag{19}$$

The corresponding parameters are provided in column (1) of Table 2.

Table 2: **Values of the parameters used in the simulations**

Table 2 reports the parameter values for the Monte Carlo simulations. In Column (1), estimates are averaged over the sample period. In Columns (2) and (3), we focus on one source of intermittent power generation: solar or wind. In Columns (4) and (5), we split the sample into a Summer and a Winter season. We adjust our OLS regression estimating parameters a_1 and a_2 defined in (19) as follows: $\sigma_I^{\text{summer}} = a_0^{\text{summer}} + a_1^{\text{summer}} \frac{Q_{PV}}{Q_D} + a_2^{\text{summer}} \frac{Q_{Wind}}{Q_D} + \varepsilon$, $r_{D,I}^{\text{summer}} = b_0^{\text{summer}} + b_1^{\text{summer}} \frac{Q_{PV}}{Q_D} + b_2^{\text{summer}} \frac{Q_{Wind}}{Q_D} + \varepsilon$, $\sigma_I^{\text{winter}} = a_0^{\text{winter}} + a_1^{\text{winter}} \frac{Q_{PV}}{Q_D} + a_2^{\text{winter}} \frac{Q_{Wind}}{Q_D} + \varepsilon$, and $r_{D,I}^{\text{winter}} = b_0^{\text{winter}} + b_1^{\text{winter}} \frac{Q_{PV}}{Q_D} + b_2^{\text{winter}} \frac{Q_{Wind}}{Q_D} + \varepsilon$.
In panel (a), the monthly time series of the parameters P_R, δ,and θ come from the databases listed in section 2. We report their average ratio over the monthly observed spot price. In panel (b), parameters $\underline{Q}, \overline{Q}, c^L, \gamma^L/N_N, c^M/N_N, c^R, \gamma^R/N_N$, come from the structural model's estimation in section 4.1, α_1 and α_2 are obtained after computing the spot price in section 4.2, and parameter $\overline{A}$ is estimated from futures prices using formula (16) as described in section 4.4. In panel (c), we report the descriptive statistics of power generation and load demand, that is, the mean load demand and its volatility, the share of intermittent renewables in the mix, the mean volume of intermittent power generation, its volatility, and the correlation between demand and intermittent power generation. Panel (d) shows the variation in volatility σ_I and correlation $r_{D,I}$ following a 1 p.p. increase in intermittent power generation, using the estimates $\hat{a}_1$ and $\hat{b}_1$ from regressions in (19), reported in Table D.2 in Appendix D.3.

Parameter	**Overall**	**Summer**		**Winter**	
	All (1)	**Wind** (2)	**Solar** (3)	**Wind** (4)	**Solar** (5)
(a) External data sources					
P_R/S	4.31	4.34		4.26	
δ/S	0.3	0.33	0.27	0.33	0.27
θ/S	0.77	0.84		0.9	
(b) Parameters from the structural estimation					
$\underline{Q}$	14.45	14.58		13.28	
$\overline{Q}$	21.31	20.52		21.13	
c^L	-278.79	-358.51		-211.31	
γ^L/N_N	-0.38	-0.51		-0.31	
c^M/N_N	12.33	4.05		5.7	
c^R	3.84	2.75		5.32	
γ^R/N_N	0.43	0.51		0.36	
α_1	2.3%	3.1%		0.5%	
α_2	83.6%	89.4%		78.1%	
$\overline{A}$	0.011	0.011	0.011	0.011	0.011
(c) Parameters of the distribution $\left(\tilde{Q}_D, \tilde{Q}_I\right)$ *(baseline)*					
μ_D	28	26.83		29.39	
σ_D	9.86	9.70		4.41	
$\frac{Q_I}{Q_D}$	23.75%	11.85%	11.7%	22.24%	2.18%
μ_I	6.65	3.18	3.14	6.87	0.64
σ_I	8.18	4.24	7.48	8.09	2.45
$r_{D,I}$	0.34	-0.01	0.63	0.67	0.38
(d) Parameters of the distribution $\left(\tilde{Q}_D, \tilde{Q}_I\right)$ *after the 1 p.p. increase in* μ_I					
$\hat{a}_1$	0.213	0.186	0.376	0.200	-0.078
$\hat{b}_1$	0.0013	-0.0069	0.0255	0.0003	0.0616
$\frac{Q_I}{Q_D}^{1\%}$	24.75%	12.85%	12.7%	23.15%	3.18%
$\mu_I^{1\%}$	13.23	6.35	7.06	13.25	1.93
$\sigma_I^{1\%}$	8.39	4.43	7.86	8.29	2.37
$r_{D,I}^{1\%}$	0.341	-0.015	0.655	-0.060	0.370

Integration and intermittency Scenarios. Column (1) of Table 2, panel (d) shows the variation in parameters μ_I, σ_I and $r_{D,I}$ in the counterfactual analysis. To understand which parameters drive the effects, we decompose them as follows. The "Intermittency" scenario focuses on the impact when only the volatility σ_I changes while the correlation $r_{D,I}$ remains the same, while the "Integration" scenario does the opposite. Our decomposition can be summarized as follows:

"Intermittency & Integration"	$\mu_I^{1\%} = \mu_I + 1\%\mu_D$	$\sigma_I^{1\%} = a_1\sigma_I$	$r_{D,I}^{1\%} = b_1 r_{D,I}$
"Intermittency"	$\mu_I^{1\%} = \mu_I + 1\%\mu_D$	$\sigma_I^{1\%} = a_1\sigma_I$	
"Integration"	$\mu_I^{1\%} = \mu_I + 1\%\mu_D$		$r_{D,I}^{1\%} = b_1 r_{D,I}$

Cases focusing on specific seasons or power source. Because an increase in wind and solar power have different intermittency and integration characteristics, we run our counterfactual analysis distinctly for these two power generation sources by considering that the one p.p. increase of intermittent power in the mix solely stems from one power source and keeping the other parameters constant. Table 1 indeed suggests that wind and solar may have different impacts on the risk premia. Besides, Figure 3 shows seasonality in the risk premium, which may be related to the strong seasonality in intermittent power generation (see Figure 4), in demand (see Figure 8), or in cost parameters (see Figure 9). As a second step, we thus split our sample and compute parameter values averaged by season (winter vs. summer) and the source of intermittent power (wind vs. solar).

Table 2, Columns (2) to (5) report the parameter values used in our simulations. Parameters used for each season are computed from averages of the months in the season or based on values obtained from the separate seasonal estimations. In Winter (i.e., December, January, and February), the amount of intermittent power is slightly higher (24.42%); it is mostly generated from wind power; the supply curve is characterized by low curvatures; and demand is high. In Summer (i.e., June, July, August), the amount of intermittent power is slightly lower (23.55%); approximately half of it is generated from wind and the other half from solar; and the supply curve is characterized by high curvatures.

Inspecting Columns (2) and (3) (resp. (4) and (5)) of Table 2 allows for a comparison between wind and solar statistics during Summer (resp. Winter). A one p.p. increase in either wind or solar has a different impact on the parameters of the multivariate normal distribution. While an increase in wind power increases volatility, an increase in solar power might reduce it. Besides, while solar power is highly correlated to load demand, an increase in wind power yields a lower correlation. These variations, though small, show that wind is a more intermittent source than solar, and that solar integrates better into the system.

5.4 Main results

Table 3: **Counterfactual analysis**

Table 3 reports the average Spot price, Futures price and risk premium across n_F simulations in the baseline case and counterfactual scenarios where the share of intermittent power in the production mix increases by 1 p.p. The Intermittency & Integration, Intermittency, and Integration scenarios reported in Columns (1), (2), and (3) are described in section 5.3. Columns (4) to (7) report the results when parameter estimates are calibrated on a subsample of the data, focusing on Seasons or the source of intermittent power generation. We report the spot and futures prices observed in our data for comparability.

	Overall			**Splitting the data**			
				Summer		Winter	
				Wind	Solar	Wind	Solar
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(a) Average Spot Price							
Baseline	29.80	29.78	29.78	37.53	37.89	35.33	42.10
One p.p. increase	29.30	29.27	29.32	37.19	37.51	34.66	41.89
Diff.	-0.50	-0.50	-0.46	-0.34	-0.39	-0.66	-0.22
Average % variation	-1.63	-1.65	-1.50	-0.88	-1.01	-1.86	-0.51
(b) Average Futures Price							
Baseline	38.30	38.26	38.33	28.91	33.19	39.31	42.67
One p.p. increase	37.90	37.85	37.57	28.43	32.69	39.10	42.47
Diff.	-0.40	-0.41	-0.76	-0.47	-0.50	-0.22	-0.19
Average % variation	-0.98	-1.01	-1.92	-1.57	-1.47	-0.55	-0.45
(c) Average Risk Premium							
Baseline	8.50	8.48	8.56	-8.63	-4.70	3.99	-0.56
One p.p. increase	8.60	8.57	8.25	-8.76	-4.81	4.43	0.59
Diff.	0.10	0.10	-0.30	-0.14	-0.11	0.45	0.02
Average % variation	1.82	1.73	-2.95	1.78	2.74	11.92	4.28
Scenario							
Intermittency ($\sigma_I^{1\%} = a_1\sigma_I$)	Yes	Yes	No	Yes	Yes	Yes	Yes
Integration ($r_{D,I}^{1\%} = b_1 r_{D,I}$)	Yes	No	Yes	Yes	Yes	Yes	Yes
Data							
Observed Spot Price		33.69		34.03		34.27	
Observed Futures Price		38.39		32.51		37.03	

Overall. Table 3, column (1) displays the impact when the model's parameters estimates and the calibration of the distributions are based on the entire sample (see Column (1) of Table 2). Panel (a) shows that increasing intermittent power in the production mix decreases spot prices. More precisely, one p.p. increase of intermittent power in the mix yields a decrease of 1.63% in the spot price, or approximately €0.50. This is consistent with renewables having low marginal costs, which decreases prices. Panel (b) shows that futures prices also experience a decrease in prices, by 0.98% or approximately €0.40.

Our main object of interest, the risk premium, is reported in Panel (c). On average, it is positive across the entire sample. Here, it is key to note that the feed-in tariffs outweigh the marginal costs of intermittent power generation over the period 2013-2018, i.e., $\delta < \theta$. Consequently, while the correlation between intermittent power generation $\tilde{Q_I}$ and the spot price $\tilde{S}$ is negative, the intermittent power producers' cost risks positively contribute to the risk premium. Consistently with our results reported in Panels (a) and (b), we observe an increase in the risk premium by €0.10 or 1.82%. Although both prices decrease, the price shift observed on the spot market is not fully transmitted into futures prices.

Intermittency vs Integration. A comparison across scenarios shows the increase in the risk premium is mostly driven by the increase in volatility in the Intermittency scenario reported in Table 3, column (2).[37]

By contrast, the risk premium decreases in the Integration scenario reported in column (3) when the higher share of renewables increases the covariance between load demand and intermittent power generation. The latter effect is, however, offset by the increased intermittency in the Intermittency & Integration scenario.[38]

Besides, the finding that better integration does not necessarily reduce the risk premia, or insufficiently to compensate the impact of increased intermittency is driven by the fact that in our data, average feed-in-tariffs are higher than the marginal cost of renewables.[39] This distort risk exposures and increase futures prices. If subsidies for renewables were reduced, improved

[37] An inspection of the components of the risk premium (building on the theoretical risk premium formula (16)), unreported here, suggests that the increase in the risk premium is driven by an increase in the intermittent power producers' cost risk – which is related to the increased volatility in intermittent power generation.

[38] Again inspecting the components of the risk premium, we find that the better integration of intermittent power in the system decreases the non-diversifiable risk exposures of all participants. The reduction in conventional and intermittent power producers' cost risks outweighs the one in retailers' revenue risks, resulting in a significant decrease in the risk premium.

[39] It is important to consider the changing nature of renewable subsidies over time. For instance, during our study period (2013-2018), Germany introduced Feed-in Premia (FIP).

system integration would induce a larger decrease in risk premia.

Summer vs Winter. Table 3, Columns (4) to (7) report the results when the model is calibrated using parameter estimates averaged over the Summer or Winter season. Consistent with the seasonality already mentioned, risk premia are, on average, negative in Summer (when retailers are at risk due to low demand) and positive in Winter (when producers are at risk due to potentially high demand). As in the overall case, we find that increasing intermittent power reduces both the spot and futures prices – an effect likely to be driven by its lower marginal costs. However, panel (c) shows that it always increases the risk premium: when it is negative, as in Summer, its impact on Futures prices amplifies the decrease in Futures prices relative to spot prices, while when it is positive in Winter, Futures prices do not decline as much as spot prices.

Besides, prices and risk premia respond more to an increase in intermittent power in Winter than in Summer. In Winter, intermittent power displaces power produced at higher marginal costs since demand is large. Further decomposition shows that this result remains driven by the increased intermittency. During Winter, the increase in intermittent power producers' cost risk is the primary factor affecting the positive risk premium. The better integration of renewables into the system during both seasons, but more particularly in Summer, causes risks to decrease for all market participants, but this effect does not balance the impact of increased intermittency on the risk premium.

Wind vs solar. We now compare Table 3, Columns (4) and (5) or Columns (6) and (7) to assess how the sign and magnitude of the impact of intermittent power generation depend on the energy source. In line with the findings observed in the reduced form in Table 1, we find that wind and solar have different impacts on the risk premium. In Winter, an increase of one p.p. in intermittent power increases the risk premium by 4.28% when generated by solar power but by 11.92% when generated by wind power. Conversely, the impact of solar is larger than wind in Summer.

These differences between the magnitude of the impacts of the two energy sources can be explained by a higher integration between solar generation and demand, which lowers the non-diversifiable risks for all market participants. Although the intermittency in both sources is very similar, we observe a higher increase in the intermittent power producer's cost risk related to intermittency for wind than for solar power, contributing to a higher and positive risk premium when the increase in intermittent power stems from wind power.

6 Conclusion

This paper studies the impact of the growth of intermittent renewables on hedging strategies, futures prices, and risk premia in power markets. We develop a simple equilibrium model that we structurally estimate to perform a counterfactual analysis, in which we look at the effects of a 1% increase in renewable energy production, both in terms of the intermittency of the renewable source and its integration into the system. According to our simulations, this change could lower the spot price by about 1.6% due to a merit order effect – a value which can vary depending on the impact of intermittency and integration on prices. However, this decrease in spot prices also comes with a rise in the risk premium of around 1.8%. We also find that the impact on the premium is stronger when intermittency is higher and there is less integration of intermittent power in the system.

Our results shed light on the mixed empirical findings in the literature that has analyzed the impact of an increase in intermittent power on the volatility of power prices. We show that this impact is dependent on the characteristics of the source of intermittent power generation, and its correlation with load demand in a region. One of the key takeaways from our analysis is that enhancing the integration of renewable sources decreases not only the spot price but also the risk premium. This better integration reduces non-diversifiable risks for all market participants, possibly outweigthing the negative effects of its increased intermittency.

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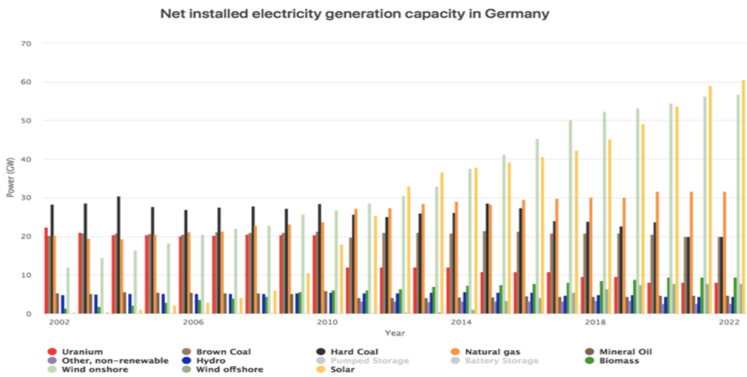
Appendices

A Appendix: Characteristics of power generation in Germany

A.1 Net installed electricity generation capacity in Germany

Figure A.1: **Net installed electricity generation capacity in Germany**

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



B Appendix: Reduced form analysis

B.1 Recovering Short Run Marginal Costs

This section explains our computations on the Short-Run Marginal Cost of fossil energies. 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. 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. Again, Refinitiv considers the plant's efficiency in this calculation. The third part of the formula accounts for the operation and maintenance costs. Table B.1, Panel A shows the values used by Refinitiv in the SRMC over the period from 2014 onwards:

Table B.1: **Short Run Marginal Costs**

In Panel A, we report values from Refinitiv-Eikon to compute the SRMC (Source: Refinitiv-Power composite methodology and specification guide). In Panel B, we report the values from our own computations. 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).

Panel A: Refinitiv-Eikon reported values to compute the SRMC

	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]

Panel B: Our values to compute the SRMC

	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

We use this formula to complete coal and gas and to create oil time series. However, we first convert the original units into MWh since coal is expressed in metric tons and oil in barrels. 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.).[40] Once we convert prices to MWh, we apply the formula (2) using the following values for all the sample periods.

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. Figure B.1 shows the comparison between the SRMC provided by Refinitiv and our time series, for coal (Panel (a)) and gas (Panel (b)) power plants respectively.[41] As can be seen, the differences are minimal. Our marginal costs capture the same upward and downward trends as Refinitiv's. Panel C displays the marginal costs for the three fuels from our computations. The figure shows that the marginal costs of oil have remained significantly above the cost of the other two 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.

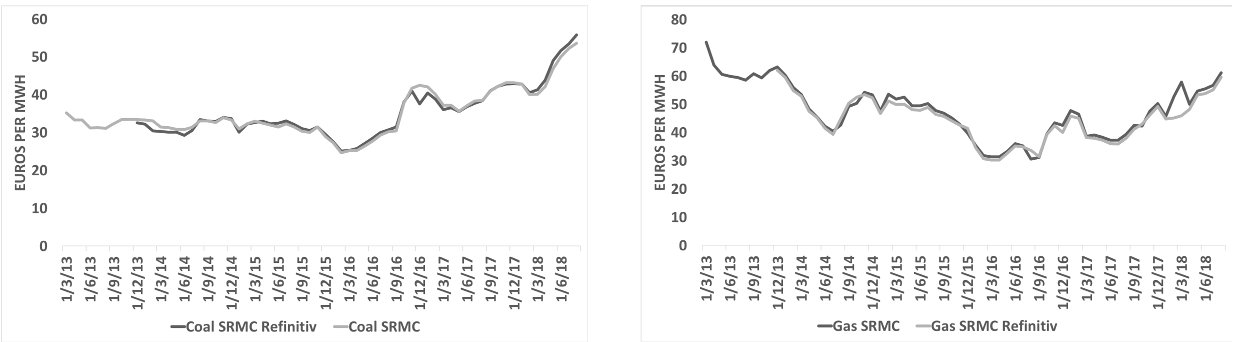
[40]According to the EIA equivalences, 1 barrel of crude oil equals 5.691M of Btu while one metric ton of coal equals 18.856 of Btu. Also, 1M of Btu is equivalent to 0.29 MWh.

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

Figure B.1: **Short Run Marginal Costs: Comparison of Refinitiv (when available) vs. our own computations**

Figure B.1 presents the dynamics of the short-run marginal costs of coal and gas power plants computed following the in (2) (Source: Refinitiv-Power composite methodology and specification guide). 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). In subfigures (a) and (b), we compare our estimate with the values provided by Refinitiv for coal and gas, respectively, after 2014.

(a) Marginal costs of coal power plants **(b) Marginal costs of gas power plants**



B.2 First stage

B.3 Electricity Prices and marginal costs of power generation

As a consistency check, we first analyze whether the short-run marginal costs of the various energy sources used in power generation influence the electricity spot price and the risk premium on futures markets. Using monthly data, we run the following OLS regression:

$$Y_T = a_0+a_1 SRMC\_COAL_T+a_2 SRMC\_GAS_T+a_3 SRMC\_OIL_T+a_4 SRMC\_INTMT_T+a_5 FIT_T+\varepsilon_T, \tag{20}$$

where $SRMC\_j$ are the short-run marginal costs from source j, and FIT the feed-in-tariffs of wind and solar power generation. Our dependent variables Y are the monthly average spot price S, and the one month ahead risk premium $RP \equiv F_{T-1,T}$. Table B.3 reports the results.

Table B.3 shows that the short-run marginal costs of coal, gas, and renewables positively impact the spot prices, while the feed-in-tariffs negatively impact them, as expected. Spot prices do not appear significantly related to the short-run marginal cost of oil, which may not be surprising since the latter is last in the merit order. Risk premia do not seem to be affected by the costs of conventional power generation. However, the risk premium seems sensitive to both the costs and subsidies on intermittent power generation.

Table B.2: **Determinants for intermittent power generation**

Table B.2 reports coefficients (t-statistics) from the first stage regressions of spot prices and the futures risk premium on intermittent power generation. SOLAR POWER and WIND POWER are instrumented by sunshine duration and wind speed, wind velocity, and precipitation, respectively. The control variables of the second stage regression are included and consist of the short-run marginal costs of coal, gas, oil, renewables, feed-in-tariffs, temperature, three dummies SUMMER, FALL, and WINTER that capture seasonality, and year fixed effects. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	SOLAR POWER	WIND POWER	SOLAR POWER	WIND POWER
	(1)	(2)	(3)	(4)
SUNSHINE DURATION	0.0119***		0.0126***	-0.00751
	(6.163)		(5.152)	(-1.281)
WIND VELOCITY		5.738	-1.123	3.288
		(0.968)	(-0.433)	(0.531)
WIND SPEED		-3.094	1.132	-0.763
		(-0.526)	(0.442)	(-0.125)
PRECIPITATION		-0.00894	0.00257	-0.0113*
		(-1.424)	(0.944)	(-1.735)
SRMC_COAL	-0.0505**	0.0911*	-0.0493**	0.0839
	(-2.455)	(1.801)	(-2.328)	(1.660)
SRMC_GAS	0.0171	-0.0179	0.0197	-0.0145
	(1.080)	(-0.445)	(1.170)	(-0.360)
SMRC_OIL	0.00875	-0.0328**	0.00929	-0.0301*
	(1.349)	(-2.011)	(1.358)	(-1.840)
SRMC_INTMT	-1.350***	2.664***	-1.429***	2.251***
	(-3.756)	(2.963)	(-3.595)	(2.371)
Feed_in_tariffs FIT	0.00560	0.123***	0.00520	0.131***
	(0.509)	(4.124)	(0.411)	(4.328)
Dummy SUMMER	-0.279	0.0122	-0.307	-0.104
	(-1.492)	(0.0246)	(-1.465)	(-0.208)
Dummy FALL	-0.905***	0.902*	-0.859***	0.487
	(-4.217)	(1.885)	(-3.567)	(0.847)
Dummy WINTER	-1.005***	0.669	-0.958***	0.464
	(-5.363)	(1.474)	(-4.783)	(0.969)
TEMPERATURE	0.0781***	-0.0116	0.0677**	0.0342
	(3.149)	(-0.198)	(2.380)	(0.503)
Dummy_ 2014	0.447*	-0.174	0.503*	-0.150
	(1.872)	(-0.288)	(1.995)	(-0.249)
Dummy_ 2015	3.224***	-3.602**	3.413***	-2.553
	(4.394)	(-2.011)	(4.163)	(-1.304)
Dummy_ 2016	2.722***	-1.427	2.912***	-0.673
	(4.293)	(-0.900)	(4.138)	(-0.400)
Dummy_ 2017	3.741***	-0.462	3.884***	0.528
	(4.958)	(-0.256)	(4.757)	(0.271)
Dummy_ 2018	2.842***	1.775	2.929***	2.549*
	(5.161)	(1.385)	(4.964)	(1.808)
Constant	13.67***	-30.93***	13.93***	-26.30***
	(3.900)	(-3.686)	(3.664)	(-2.894)
Observations	66	66	66	66

Table B.3: **Electricity prices and short-run marginal costs**

Table B.3 reports coefficients (t-statistics) from OLS regressions of spot prices (in column (1)), and futures risk premium (in column (2)) on short-run marginal costs of coal, gas, oil, renewables, and feed-in-tariffs. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	Spot price S_T (1)	One month-ahead risk premium $F_{T-1,T} - S_T$ (2)
$SRMC\_COAL$	0.402***	0.0708
	(4.776)	(0.850)
$SRMC\_GAS$	0.241***	-0.0659
	(2.722)	(-0.753)
$SRMC\_OIL$	0.0655	0.00993
	(1.320)	(0.203)
$SRMC\_INTMT$	0.259	2.066**
	(0.263)	(2.120)
Feed_in_tariffs FIT	-0.320***	0.298***
	(-4.024)	(3.795)
Constant	7.791	-29.39**
	(0.692)	(-2.640)
N	66	66
R^2	0.684	0.304

C Appendix: Proofs

C.1 Proof of Lemma 1

To determine the optimal quantity to be sold/buy on the futures market, q_i^F, we solve the participant's maximization problem $\max_{q_i^F} EU[\tilde{\pi}_i] = E[\tilde{\pi}] - \frac{A}{2}Var[\tilde{\pi}_i]$. Let α_j define the probability that the residual demand falls in region $j \in \{1, 2, 3\}$ and $\alpha_3 = 1 - \alpha_1 - \alpha_2$ and let $\mathcal{R}_j$ denote the corresponding event. The unconditional expectation and variance of the participants' profits $\tilde{\pi}_i$ depend on the probabilities of prices falling in these regions. We calculate them using the law of iterated expectations and the law of total variance, respectively, as follows:

$$E[\tilde{\pi}] = \sum_{j=1}^{3} \alpha_j E[\tilde{\pi}_i | \mathcal{R}_j] \tag{21}$$

$$
\begin{aligned}
Var[\tilde{\pi}_i] &= E[Var[\tilde{\pi}_i|\mathcal{R}_j]] + Var[E[\tilde{\pi}_i|\mathcal{R}_j]] \\
&= \sum_{j=1}^{3} \alpha_j Var[\tilde{\pi}_i|\mathcal{R}_j] + \sum_{j=1}^{3} \alpha_j \left(E[\tilde{\pi}_i|\mathcal{R}_j]\right)^2 - \left(\sum_{j=1}^{3} \alpha_j E[\tilde{\pi}_i|\mathcal{R}_j]\right)^2 \qquad (22)
\end{aligned}
$$

With these expressions, the participant's expected utility becomes:

$$
EU[\tilde{\pi}_i] = \sum_{j=1}^{3} \alpha_j E[\tilde{\pi}_i|\mathcal{R}_j] - \frac{A}{2}\left(\sum_{j=1}^{3} \alpha_j Var[\tilde{\pi}_i|\mathcal{R}_j] + \sum_{j=1}^{3} \alpha_j \left(E[\tilde{\pi}_i|\mathcal{R}_j]\right)^2 - \left(\sum_{j=1}^{3} \alpha_j E[\tilde{\pi}_i|\mathcal{R}_j]\right)^2\right)
$$

The F.O.C. of the maximization problem is such that $\frac{dEU[\tilde{\pi}_i]}{dq_i^F} = 0$, with:

$$
\begin{aligned}
\frac{dEU[\tilde{\pi}_i]}{dq_i^F} &= \sum_{j=1}^{3} \alpha_j \frac{dE[\tilde{\pi}_i|\mathcal{R}_j]}{dq_i^F} \\
&\quad - \frac{A}{2}\left(\sum_{j=1}^{3} \alpha_j \frac{dVar[\tilde{\pi}_i|\mathcal{R}_j]}{dq_i^F} + 2\sum_{j=1}^{3} \alpha_j E[\tilde{\pi}_i|\mathcal{R}_j] \frac{dE[\tilde{\pi}_i|\mathcal{R}_j]}{dq_i^F} - 2\left[\sum_{j=1}^{3} \alpha_j E[\tilde{\pi}_i|\mathcal{R}_j]\right] \frac{dE[\tilde{\pi}_i|\mathcal{R}_j]}{dq_i^F}\right)
\end{aligned}
$$

which simplifies as follows:

$$
\frac{dEU[\tilde{\pi}_i]}{dq_i^F} = \sum_{j=1}^{3} \alpha_j \frac{dE[\tilde{\pi}_i|\mathcal{R}_j]}{dq_i^F} - \frac{A}{2}\left(\sum_{j=1}^{3} \alpha_j \frac{dVar[\tilde{\pi}_i|\mathcal{R}_j]}{dq_i^F}\right). \qquad (23)
$$

Next, we decompose the participant i's profit π into their but-for-hedging profit, ρ_i, and their hedging profit. First, we have:

$$
E[\tilde{\pi}_i|\mathcal{R}_j] = \sum_{j=1}^{3} \alpha_j E\left[\tilde{\rho}_i|\mathcal{R}_j\right] + q_i^F \left(E[\tilde{S}|\mathcal{R}_j] - F\right) = E\left[\tilde{\rho}_i|\mathcal{R}_j\right] + q_i^F \left(E[\tilde{S}|\mathcal{R}_j] - F\right)
$$

where $\tilde{\rho}_i$ is independent of q_i^F. Hence

$$
\frac{dE[\tilde{\pi}_i|\mathcal{R}_j]}{dq_i^F} = E[\tilde{S}|\mathcal{R}_j] - F. \qquad (24)
$$

Second, we also know that:

$$
Var\left[\tilde{\pi}_i|\mathcal{R}_j\right] = Var\left[\tilde{\rho}_i|\mathcal{R}_j\right] + \left(q_i^F\right)^2 Var\left[\tilde{S}|\mathcal{R}_j\right] + 2q_i^F Cov\left[\tilde{\rho}_i, \tilde{S}|\mathcal{R}_j\right].
$$

Hence

$$\frac{dVar[\tilde{\pi}_i|\mathcal{R}_j]}{dq_i^F} = 2q_i^F Var\left[\tilde{S}|\mathcal{R}_j\right] + 2Cov\left[\tilde{\rho}_i, \tilde{S}|\mathcal{R}_j\right] \tag{25}$$

Plugging (24) and (25) in (23), we obtain:

$$\frac{dEU[\tilde{\pi}_i]}{dq_i^F} = \underbrace{\sum_{i=1}^{3}\alpha_i E[\tilde{S}|\mathcal{R}_j] - \sum_{i=1}^{3}\alpha_i F}_{\equiv E[\tilde{S}]-F} - \frac{A}{2}\left(2q_i^F\sum_{j=1}^{3}\alpha_j Var[\tilde{S}|\mathcal{R}_j] + 2\sum_{j=1}^{3}\alpha_j Cov[\tilde{\rho}_i, \tilde{S}|\mathcal{R}_j]\right).$$

Finally, the FOC condition yields:

$$q_i^{F*} = \frac{E[\tilde{S}] - F}{A\sum_{j=1}^{3}\alpha_j Var[\tilde{S}|\mathcal{R}_j]} - \frac{\sum_{j=1}^{3}\alpha_j Cov[\tilde{\rho}_i, \tilde{S}|\mathcal{R}_j]}{\sum_{j=1}^{3}\alpha_j Var[\tilde{S}|\mathcal{R}_j]}$$

C.2 Proof of Lemma 2

Substituting the participants' optimal demands $q_{N_i}^{F*}$, $q_{I_i}^{F*}$ and $q_{R_i}^{F*}$ from equation (14) into equation (15), we obtain:

$$F^* - E(\tilde{S}) = -A\left(\begin{array}{l}\sum_{i=1}^{N_N}\left(\sum_{j=1}^{3}\alpha_j Cov[\tilde{\rho}_{N_i}, \tilde{S}|\mathcal{R}_j]\right) + \sum_{i=1}^{N_I}\left(\sum_{j=1}^{3}\alpha_j Cov[\tilde{\rho}_{I_i}, \tilde{S}|\mathcal{R}_j]\right)\\ +\sum_{i=1}^{N_R}\left(\sum_{j=1}^{3}\alpha_j Cov[\tilde{\rho}_{R_i}, \tilde{S}|\mathcal{R}_j]\right)\end{array}\right) \tag{26}$$

To compute the covariances in (26), we first express the participants' but-for-hedging profits, which we then use to develop the risk exposures of individual participants before finally applying the market-clearing condition to find the equilibrium price F^*.

C.2.1 "But-for-hedging profits"

Retailers We substitute the quantity delivered by each retailer, $\tilde{Q}_{R_i} = \frac{\tilde{Q}_D}{N_R}$, into the retailers' profit given by equation (6). Under the absence of any hedging position ($q_{R_i}^F = 0$), we obtain the "But-for-Hedging" profits for retailers:

$$\tilde{\rho}_{R_i} = \left(\frac{\tilde{Q}_D}{N_R}\right)\left(P_R - \tilde{S}\right)$$

Intermittent Power Producers We substitute the quantity offered by each intermittent power producer, $\tilde{Q}_{I_i} = \frac{\tilde{Q}_I}{N_I}$, into the producers' profit given by equation (7). Given the total costs of intermittent producers given by equation (8), and under the absence of any hedging position ($q^F_{I_i} = 0$), we obtain the "But-for-Hedging" profits for intermittent power producers:

$$\tilde{\rho}_{I_i} = \left(\frac{\widetilde{Q}_I}{N_I}\right)\left(\tilde{S} - \delta + \theta\right) - F_I.$$

Conventional Producers We substitute the quantity offered by each conventional producer, $\widetilde{Q}_{N_i} = \frac{\widetilde{Q}_{RD}}{N_N}$, into the producers' profit given by equation (7). Given the total costs of conventional producers given by equation (9), and under the absence of any hedging position ($q^F_{N_i} = 0$), we obtain the "But-for-Hedging" profits for conventional producers:

$$\tilde{\rho}_{N_i} = \begin{cases} \tilde{S}\left(\frac{\widetilde{Q}_{RD}}{N_N}\right) - F_N - \frac{c^L}{\gamma^L}\exp\gamma^L\left(\frac{\widetilde{Q}_{RD}}{N_N}\right) & \text{if } \widetilde{Q}_{RD} < \underline{Q} \\ \tilde{S}\left(\frac{\widetilde{Q}_{RD}}{N_N}\right) - F_N - \frac{c^M}{2}\left(\frac{\widetilde{Q}_{RD}}{N_N}\right)^2 & \text{if } \underline{Q} < \widetilde{Q}_{RD} < \overline{Q}, \\ \tilde{S}\left(\frac{\widetilde{Q}_{RD}}{N_N}\right) - F_N - \frac{c^R}{\gamma^R}\exp\gamma^R\left(\frac{\widetilde{Q}_{RD}}{N_N}\right) & \text{if } \overline{Q} < \widetilde{Q}_{RD} \end{cases}$$

where $\underline{Q} = N_N \underline{Q}_N$ and $\overline{Q} = N_N \overline{Q}_N$.

C.2.2 Participants' risk exposures

Taking a detailed look at the covariance components in equation (14), we decompose the participants' but-for-hedging-profits $\tilde{\rho}_i$ into costs and revenues, which translates into components of the covariance with the spot price as follows:

$$\sum_{i=j}^{3} \alpha_j Cov(\tilde{\rho}_{R_i}, \tilde{S}|\mathcal{R}_j) = Cov(\tilde{\rho}_{R_i}, \tilde{S}) = \underbrace{P_R \times Cov\left(\frac{\widetilde{Q}_D}{N_R}, \tilde{S}\right)}_{\text{Retailers' revenue risk}} - \underbrace{Cov\left(\tilde{S} \times \frac{\widetilde{Q}_D}{N_R}, \tilde{S}\right)}_{\text{Retailers' cost risk}} \tag{27}$$

$$\begin{aligned}\sum_{j=1}^{3} \alpha_j Cov(\tilde{\rho}_{N_i}, \tilde{S}|\mathcal{R}_j) = & \underbrace{Cov\left(\tilde{S} \times \frac{\widetilde{Q}_{RD}}{N_N}, \tilde{S}\right)}_{\text{Conventional producers' revenue risk}} \underbrace{- \alpha_1 \left(\frac{c^L}{\gamma^L}\right) Cov\left(\exp^{\gamma^L\left(\frac{\widetilde{Q}_{RD}}{N_N}\right)}, \tilde{S}\right)}_{\text{Conventional producers' cost risk in } \mathcal{R}_1} \\ & \underbrace{- \alpha_2 \left(\frac{c^M}{2}\right) Cov\left(\left(\frac{\widetilde{Q}_{RD}}{N_N}\right)^2, \tilde{S}\right)}_{\text{Conventional producers' cost risk in } \mathcal{R}_2} \underbrace{- \alpha_3 \left(\frac{c^R}{\gamma^R}\right) Cov\left(\exp^{\gamma^R\left(\frac{\widetilde{Q}_{RD}}{N_N}\right)}, \tilde{S}\right)}_{\text{Conventional producers' cost risk in } \mathcal{R}_3}\end{aligned} \tag{28}$$

$$\sum_{i=j}^{3} \alpha_j Cov(\tilde{\rho}_{I_i}, \tilde{S}|\mathcal{R}_j) = Cov(\tilde{\rho}_{I_i}, \tilde{S}) = \underbrace{Cov\left(\tilde{S} \times \frac{\widetilde{Q}_I}{N_I}, \tilde{S}\right)}_{\text{Intermittent producers' revenue risk}} - \underbrace{(\delta - \theta)\, Cov\left(\frac{\widetilde{Q}_I}{N_I}, \tilde{S}\right)}_{\text{Intermittent producers' cost risk}} \tag{29}$$

All market participants' risks are related to the magnitude and expected signs of the covariation between their revenues/costs and the spot price. For a retailer in (27), one would expect her cost risk to be positive as higher demand will likely induce her to buy a larger volume while simultaneously exerting a buying pressure which would increase prices. Her cost risk corresponds to the main (short) exposure a retailer is typically willing to hedge by buying futures. Similarly, one would expect her revenue risk to be positive as higher demand increases the volume sold to end-customers at a fixed price, thus increasing her revenues. Her (expected) positive revenue risk partly offsets her cost risk: because revenues are high when costs are high, the retailer's revenue risk acts as a "natural hedge," potentially reducing her overall (short) risk exposure.

A similar reasoning applies to a conventional producer in (28): one would expect his revenue risk to be positive as lower residual demand simultaneously leads to decreased volume – thus, less revenue – and to lower prices. This revenue risk, which corresponds to the main (long) exposure a producer is typically willing to hedge by selling futures, is similarly partially naturally hedged by his cost risk with a covariance also expected to be positive – since higher residual demand increases costs, progressively taking a positive exponential shape. Given the shape of their marginal costs, conventional producers must also weigh their cost risk according to the probability of low, medium, or high residual demand.

Intermittent power generation has two potential impacts on participants' risk exposures. By contrast with the straightforward logic developed above for conventional producers, the intermittent power generators' revenue and cost risk exposures in (29) may not be positive. First, for the revenue risk, the sign of the covariance will depend on whether the volume effect dominates the price effect. Given the merit order, an increase in intermittent renewable generation decreases the spot price. However, this price effect may be offset by a volume effect. The latter may dominate the former when intermittent generation is high enough to compensate for the impact of this price drop on their revenues, but it may not necessarily be the case. Second, for the cost risk, we might expect a negative covariance between intermittent generation and spot prices due to the merit order effect. However, the cost risk is also affected by the marginal cost parameter, δ, and the feed-in tariffs, θ. When the feed-in tariffs exceed the marginal cost, the cost risk will be positive, and vice versa.

However, note that intermittent power generation may further impact risk exposures if highly and positively correlated with demand. If this were the case, indeed, an increase in demand may become negatively correlated with spot price variations.

C.2.3 Equilibrium futures price

Finally, individual risk exposures are aggregated to satisfy the market-clearing condition (26). Lemma 2 follows from the observation that:

$$\sum_{i=1}^{N_R}\left(\underbrace{-Cov\left(\tilde{S}\times\frac{\widetilde{Q}_D}{N_R},\tilde{S}\right)}_{\text{Retailers' cost risk}}\right)+\sum_{i=1}^{N_N}\underbrace{Cov\left(\tilde{S}\times\frac{\widetilde{Q}_{RD}}{N_N},\tilde{S}\right)}_{\text{Conventional producers' revenue risk}}+\sum_{i=1}^{N_I}\underbrace{Cov\left(\tilde{S}\times\frac{\widetilde{Q}_I}{N_I},\tilde{S}\right)}_{\text{Intermittent producers' revenue risk}}$$

$$=N_R\left(\underbrace{-Cov\left(\tilde{S}\times\frac{\widetilde{Q}_D}{N_R},\tilde{S}\right)}_{\text{Retailers' cost risk}}\right)+N_N\underbrace{Cov\left(\tilde{S}\times\frac{\widetilde{Q}_{RD}}{N_N},\tilde{S}\right)}_{\text{Conventional producers' revenue risk}}+N_I\underbrace{Cov\left(\tilde{S}\times\frac{\widetilde{Q}_I}{N_I},\tilde{S}\right)}_{\text{Intermittent producers' revenue risk}}$$

$$=0,$$

given that $\widetilde{Q}_{RD}=\widetilde{Q}_D-\widetilde{Q}_I$.

C.3 A note of the identification of the cost parameters

Recall that from (12), the aggregate supply curve depends on these cost parameters as follows:

$$S(Q_{RD})=\begin{cases} c^L\exp(\frac{\gamma^L}{N_N}Q_{RD}) & \text{if } Q_{RD}<\underline{Q} \\ \\ \frac{c^M}{N_N}Q_{RD} & \text{if } \underline{Q}<Q_{RD}<\overline{Q} \\ \\ c^R\exp(\frac{\gamma^R}{N_N}Q_{RD}) & \text{if } \overline{Q}<Q_{RD} \end{cases},$$

where Q_{RD}, the residual load, is defined as the difference between total load Q_D and the volume of intermittent power generation Q_I, both defined in section 2.1.

The data we observe correspond to the quantity Q^S conventional and green producers are willing to sell on the spot market after having committed to selling a quantity Q^F on the futures market, i.e., $Q^S=g(S)$, where $g(.)$ is the aggregate quantity supplied on the spot market at price S that we observe. From this observed supply curve, one would like to infer the (aggregate) marginal costs of conventional producers, which are such that the aggregate quantity Q_B that they are willing to supply at price S respects the zero profit condition $MC(Q_N)=S$.

To fix ideas, let us define g such that $g^{-1}(Q^S-c)=g_0e^{g_1Q^S}$. Again fixing ideas, let us assume that marginal costs of conventional producers take the following form: $MC(Q_N)=\gamma_0e^{\gamma_1Q_N}$. This requires some adjustment to identify γ_0 and γ_1 from the estimation of g_0 and g_1.

First, if producers of type i have already committed to selling a quantity $Q_i^F\equiv(1-\alpha_i)Q_i$

on the futures market, they trade on the spot market the remaining quantity, i.e., $Q_i^S = \alpha_i Q_i$. Under the assumption that $\alpha_I = \alpha_N = \alpha$ where $\alpha \equiv \frac{Q^S}{Q_D}$, the conventional producers' zero profit condition yields

$$S = \gamma_0 e^{\gamma_1 Q_N} \iff \frac{Q_N^S}{\alpha} = \frac{1}{\gamma_1} \ln\left(\frac{S}{\gamma_0}\right) \tag{30}$$

Second, the data we observe correspond to the quantity Q^S conventional and green producers are willing to sell on the spot market after having committed to selling a quantity Q^F on the futures market, i.e.,

$$Q_N^S + Q_I^S - c = \frac{1}{g_1} \ln\left(\frac{S}{g_0}\right) \iff Q_N^S = \frac{1}{g_1} \ln\left(\frac{S}{g_0}\right) - \alpha Q_I + c \tag{31}$$

Combining the conditions provided in (30) and (31), this implies that

$$Q_N^S = \alpha \frac{1}{\gamma_1} \ln\left(\frac{S}{\gamma_0}\right) = \frac{1}{g_1} \ln\left(\frac{S}{g_0}\right) - \alpha Q_I + c \tag{32}$$

By appropriately choosing to shift the supply curve by an amount $c = \alpha Q_i$, parameters γ_0 and γ_1 can thus be identified as follows:

$$\gamma_0 = g_0 \tag{33}$$

$$\gamma_1 = \alpha g_1 \tag{34}$$

Now, we observe in the data the following kinks: $\underline{q}$ and $\overline{q}$, from which we want to infer the kinks in the conventional cost function $\underline{Q}$ and $\overline{Q}$.

$$Q_{RD} < \overline{Q} \iff Q_N < \overline{Q} \iff Q_N^S < \alpha\overline{Q} \iff Q^S < \alpha\overline{Q} + \alpha Q_I,$$

thus we identify $\underline{Q}$ and $\overline{Q}$ as follows:

$$\overline{q} = \alpha\overline{Q} + \alpha Q_I \tag{35}$$

$$\underline{q} = \alpha\underline{Q} + \alpha Q_I \tag{36}$$

To sum up, we identify the model's parameters from our estimates using the supply curve on the spot market as follows:

$$
\begin{aligned}
\alpha &= \frac{Q^S}{Q^D} \\
\text{Shift} &= -\alpha Q_I \\
c^L &= \hat{c}^L \text{ and } c^R = \hat{c}^R \\
c^M &= \alpha \hat{c}^M \\
\gamma^L &= \alpha \hat{\gamma}^L \text{ and } \gamma^R = \alpha \hat{\gamma}^R \\
\underline{Q} &= \frac{\underline{\hat{Q}}}{\alpha} - \alpha Q_I \\
\overline{Q} &= \frac{\overline{\hat{Q}}}{\alpha} - \alpha Q_I
\end{aligned}
\tag{37}
$$

D Appendix: Additional material on the structural analysis

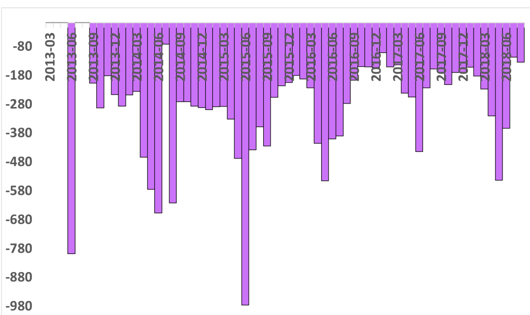
D.1 Estimates

D.1.1 Estimation of c^L and c^R

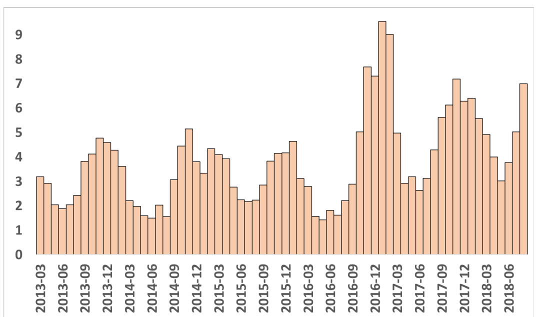
Figure D.1: **Monthly estimates of cost parameters:** c^L **and** c^R

Figure D.1 shows the average monthly estimates of parameters c^L and c^R, following the approach described in section 4.1.1. Having identified the parameters $\underline{\hat{Q}}$ and $\overline{\hat{Q}}$, we fit the first concave (i.e., where $Q < \underline{\hat{Q}}$) and the last convex (i.e., where $Q > \overline{\hat{Q}}$) segments of the piecewise function (17) using nonlinear least squares. For each hourly fitted curve, we obtain values of the parameters $\hat{c}^L, \hat{c}^R$ and the Adjusted R-Squared. We recover the model parameters c^L and c^R from equation (37) in Appendix C.3. We compute the monthly weighted averages after windsorizing at 90%. In panel (a), the purple bars represent the parameter c^L. The orange bars in panel (b) represent the parameter c^R.

(a) c^L



(b) c^R



D.1.2 Diversifiable Risks Estimation

Figure D.2: **Time series of diversifiable risks**

Figure D.2 plots the time series of diversifiable risks. For readability, we plot correlations instead of covariances. The conventional producers' revenue risk, in brown, is computed here as $Corr\left(\tilde{S} \times \widetilde{Q}_{RD}, \tilde{S}\right)$. The intermittent power producers' revenue risk, in green, is computed here as $Corr\left(\tilde{S} \times \widetilde{Q}_{I}, \tilde{S}\right)$. The retailers' cost risk, in grey, is computed here as $Corr\left(\tilde{S} \times \widetilde{Q}_{D}, \tilde{S}\right)$. Parameters c^L, γ^L, c^M, c^R, γ^R, $\alpha_{j\in\{1,2,3\}}$ are estimated as described in sections 4.1 and 4.2.2, and used to compute time series of theoretical spot prices.

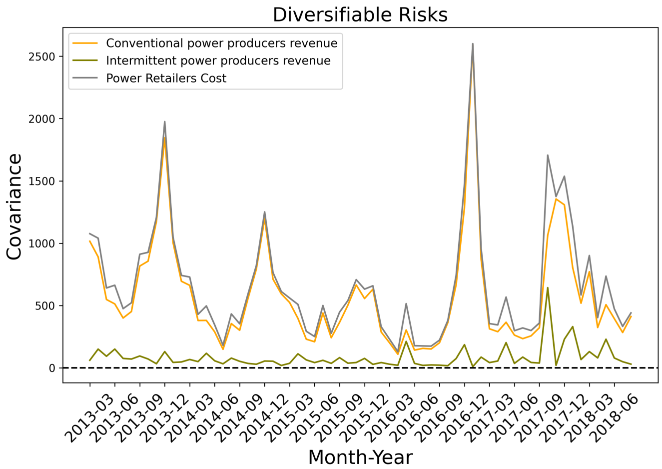


Figure D.2 depicts diversifiable risks that impact hedging strategies but not the risk premium. We convert the covariances into correlation coefficients to compare the relationship between these risks and the spot price. As the figure exhibits, given their high correlation with the spot price, the retailers' cost and the conventional producers' revenue risks are a hedging priority. The intermittent power producers' revenue risk is lower, more seasonal, and more volatile. Since the correlation coefficients are positive, producers' revenue risk points towards selling electricity forwards (long position), while retailers' cost risk points towards a need to buy forwards (short position).

Note that correlations between revenues and the spot price for producers are higher in summer than in winter. In particular, revenue risks are close to zero for intermittent power producers in winter. In summer, both producer types' hedging needs are more critical because electricity prices are usually lower this season, representing a higher risk to their revenues. Conversely, the correlation between retailers' production costs and spot prices is higher in winter, as during this season, the spot prices are higher and, therefore, production costs rise.

D.2 Robustness

D.2.1 Goodness of fit: supply curves and marginal costs

To interpret the results of these parameters, we perform the following linear regressions:

$$\gamma_t^R = \beta_1 \times GSRMC_t + \beta_2 \times CSRMC_t + \beta_3 \times OSRMC_t + \beta_4 \times RL_t + Season_t + \varepsilon_t \quad (38)$$

$$\gamma_t^L = \beta_1 \times GSRMC_t + \beta_2 \times CSRMC_t + \beta_3 \times OSRMC_t + \beta_4 \times RL_t + Season_t + \varepsilon_t \quad (39)$$

where the dependent variables γ_t^L and γ_t^R are the determinants of the concavity and convexity of the conventional producers' cost function, respectively. GSRMC, CSRMC, and OSRMC are the monthly electricity short-run marginal gas, carbon, and oil costs in Eur/MWh, respectively, defined in section 2.1. RL is the residual load in GWh, and $Season_t$ are dummy variables to control for seasonality.

Table D.1 presents the outcomes of regression (38). The data from this table indicate that a rise in the marginal cost of coal reduces the convex curvature. While this outcome may initially appear counter-intuitive, it signals a substitution effect between gas and coal as energy sources. As the marginal cost of coal escalates, producers shift from coal to gas. This transition could rearrange their positions on the merit order curve, decreasing its convexity.

Furthermore, given that oil is the most expensive and least used electricity source, any increase in its marginal cost directly increases the convex curvature. Lastly, an increase in residual demand decreases the convexity. This implies that a rise in residual demand prompts a short-term expansion in the production capacity of conventional producers, thereby reducing convexity.

Table D.1 also shows the results for regression (39). Only the marginal cost of gas is relevant in determining the γ^L 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 D.1: **Cost Parameters regression on SRMCs**

Table reports coefficients (z-statistics) from regressions of cost parameters on SRMC. Control variables include seasons. t-stats are reported in parenthesis. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

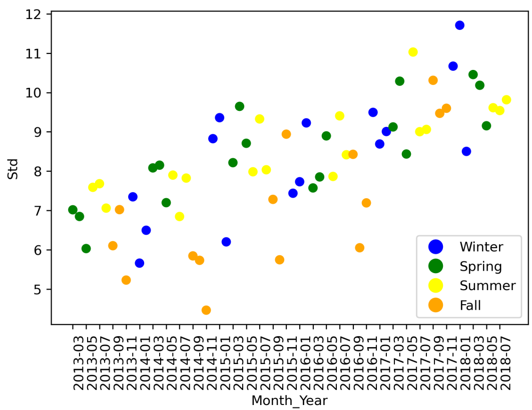
	Right Parameters		Left Parameters	
	γ^R	c^R	γ^L	c^L
Coal Marginal Cost	-8.648***	0.214***	-4.346	11.08***
	(-4.68)	(10.25)	(-0.47)	(2.73)
Gas Marginal Cost	-2.061	0.00913	21.81**	1.453
	(-1.20)	(0.47)	(2.56)	(0.38)
Oil Marginal Cost	2.907***	-0.0270***	-4.594	-2.579
	(4.11)	(-3.39)	(-1.31)	(-1.65)
Residual Load in GWh	-9.085**	0.107***	3.501	18.13**
	(-2.65)	(2.77)	(0.21)	(2.41)
Constant	1,321***	-5.564***	-1,346*	-1,282***
	(8.48)	(-3.17)	(-1.74)	(-3.74)
Observations	66	66	66	66
R-squared	0.773	0.802	0.267	0.248
Seasonal FE	Yes	Yes	Yes	Yes

D.3 Electricity mix and the variance-covariances of intermittent power generation

Figure D.3: **Time series of the moments of intermittent power generation**

Figure D.3 plots time series of the standard deviation of the intermittent renewable energy generation (σ_I) in panel (a) (resp. the correlation between intermittent power generation and demand ($r_{D,I}$) in panel (b)) over the period 2013-2018. Each dot represents the monthly standard deviation (resp. correlation with load demand) computed from hourly power generation data. We split months of observation by season. Blue (resp. green, yellow, orange) dots show the standard deviation (resp. correlation) for the months in Winter (resp. Spring, Summer, Fall) season.

(a) Monthly $\sigma_{\widetilde{Q}_I}$



(b) Monthly $Corr(\widetilde{Q}_D, \widetilde{Q}_I)$

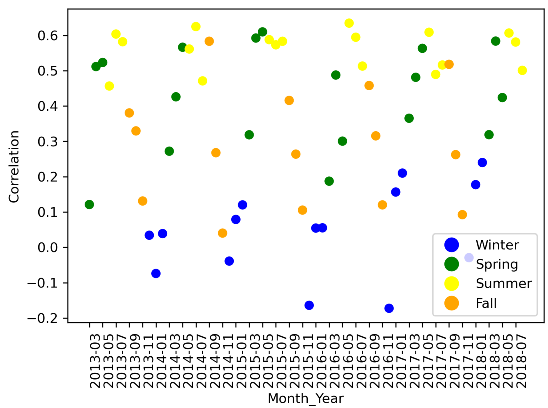


Table D.2: **Regression of intermittent power distribution's characteristics and the share of intermittent power**

Table D.2 reports the estimates from the following OLS regression: $Y = a_0 + a_k \frac{Q_I}{Q_D} + \varepsilon$. In Column (1), coefficients are estimated over the sample period. In Columns (2) and (3), we focus on one source of intermittent power generation: solar or wind in Summer and Winter.
In panel (a), the dependent variable is the volatility of intermittent power generation, σ_I. The dependent variable in panel (b) is the correlation between intermittent power generation and load demand, $r_{D,I}$. t-stats are reported in parenthesis. ***, **, and * denote significance levels of 1%, 5%, and 0%, respectively.

	All	**Summer**	**Winter**
	(1)	(2)	(3)
(a) Dependent variable: σ_I			
	σ_I	σ_I	σ_I
Renewables share (%)	0.2198***		
	(13.94)		
Wind share (%)		0.186***	0.200***
		(6.68)	(4.06)
Solar share (%)		0.376***	-0.0784
		(4.21)	(-0.26)
Cons	3.248***	2.425*	4.167*
	(8.87)	(16.33)	(2.87)
(b) Dependent variable: $r_{D,I}$			
	$r_{D,I}$	$r_{D,I}$	$r_{D,I}$
Renewables share (%)	0.00132		
	(0.28)		
Wind share (%)		-0.00692	0.000279
		(-1.90)	(0.05)
Solar share (%)		0.0255 *	0.0616
		(2.18)	(1.89)
Cons	0.314**	0.361**	-0.0879
	(2.86)	(3.24)	(-0.57)
N	66	18	15