Discounting along the merit order, with an application to the electricity market

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Abstract

Within the same sector, technologies yielding larger variable costs are more sensitive to disruptions during a recession. For this reason, assets lower in the merit order should be valued using a larger risk-adjusted discount rate. We characterize the efficient discount rates along the technological merit order in a standard CCAPM framework, and we link them to their option values. We apply our results to the electricity sector in France, showing that the CCAPM beta of fossil electricity is more than twice that of renewable or nuclear electricity. This fossil beta is increasing with the carbon price. We also propose a methodology to measure the value creation of different generation technologies in a given electricity mix by comparing their levelized costs and prices of electricity that take risks and intermittency into account.

Keywords: Energy transition, CCAPM beta, option pricing, carbon price, cost-benefit analysis.

JEL codes: G12, H43, Q48.

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1 Introduction

In public economics, the traditional method of Benefit-Cost Analysis (CBA) consists of estimating the Net Present Value (NPV) of an investment by discounting the flow of its expected net benefits at a risk-adjusted rate. This is supported by the normative version of the Consumption-based Capital Asset Pricing Model (CCAPM), which is itself derived from Discounted Expected Utility (DEU) theory.[1] By discounting expected net benefits at a risk-adjusted discount rate, the CBA transfers the risk premium associated with a risky investment to the investment-specific discount rate. Another traditional approach to BCA comes from the toolbox of Option Pricing Theory (OPT) pioneered by Black and Scholes (1973). OPT offers simple operational rules to value an option-like payoff, such as $\max(0, x)$, where x is the return of an underlying asset. But the well-known Black-Scholes formula does not fit the CCAPM framework based on a risk-adjusted discounting of the expected payoff. One of the objectives of this paper is to contribute to the reconciliation between the CCAPM and the OPT approaches for asset valuation, as initiated by Cochrane (2001) and Duffie (2001). In particular, we will characterize the CCAPM risk-adjusted discount rates that are compatible with the correct OPT valuation of option-like payoffs.

The electricity market is the perfect playing field for applying such analysis. The energy transition is capital-intensive, as assets associated with renewable and nuclear electricity generation plants face high capital expenditures and low variable costs. The instantaneous payoff of an electricity unit is equal to the difference between the spot price of electricity and its variable cost of production if this difference is positive, and zero otherwise, which is illustrative of an option-like payoff. The level of the variable cost of a generation technology determines its ranking in the merit order. Moreover, the value of electricity is positively linked to economic growth through the positive income-elasticity of electricity demand. So, instantaneous payoffs are sensitive to aggregate income, which implies that risks in electricity investments are not diversifiable. These risks must therefore be priced.

The main message of this paper is that production strategies lower in the merit order, i.e., strategies yielding higher variable costs, are more sensitive to changes in aggregate income. In the case of a normal good such as electricity, their production revenues will be more negatively affected by a recession. Therefore, the evaluation of their social value creation should be based on a larger risk-adjusted discount rate. To illustrate, solar and wind electricity yield almost zero variable costs. Their production will not be affected by a recession; their revenue will only be impacted by the lower equilibrium price. On the contrary, fossil electricity faces a much larger variable cost, particularly in countries with an ambitious carbon pricing mechanism. A recession will reduce both the equilibrium production and the price at which it is sold. This means that, in the case of fossil electricity, a quantity effect must be added to the price effect prevailing for renewables. Investments in fossil electricity generation are thus riskier than renewable investments, thereby yielding a larger risk-adjusted discount rate.

Our results go against the tradition of evaluating different technologies of electricity generation using a single discount rate. For example, in order to compare the relative merits of different French electricity mixes in 2050, RTE (2021) uses a single discount rate of 4%. IEA (2020) examines the same issue at the global level by using a single discount rate of 7%

[1] The seminal contributions for the CCAPM are from Lucas (1978), Breeden (1979), and Rubinstein (1976). For a normative interpretation, see Gollier and Hammitt (2014).

in the benchmark calibration. Our results also state that a mono-product corporation with different production units facing different variable costs should not use the same discount rate to value these units, contrary to tradition (Krueger, Landier and Thesmar, 2015).

The lifetime of energy infrastructures is typically rather long, over 50 years for nuclear power plants in some countries. Moreover, wind and solar infrastructures are capital-intensive and do not require fuel or extensive maintenance services. Their levelized costs come mostly from upfront capital expenditures, contrary to coal and gas power plants where fuel costs dominate lifetime expenditures (Steffen et al., 2025). This implies that the choice of differentiated discount rates could be critical for the outcome of the cost-benefit analysis of these technologies and, therefore, for the characterization of the optimal electricity mix. But the electricity market is only one example of the issue examined in this paper. More generally, we value any investment in any market where different production strategies yield different marginal production costs, thereby generating a merit order among these strategies in the corresponding market. International oil, gas, and coal markets, together with other natural resources, share the same characteristics as the electricity market examined in this paper (Coulomb, Henriet and Reitzmann, 2026). They are obvious fields of application for our insights.

This paper is related to Breeden (1980), which has linked the CCAPM beta of an asset to the characteristics of supply and demand for the underlying good or service generated by that asset. More precisely, Cherbonnier and Gollier (2022) shows that in the absence of production risk, the CCAPM beta of an asset should be equal to the income-elasticity of demand for the underlying good, which measures the price risk.[2] This paper extends this analysis to the case in which different technologies to produce the same good face different production risks in addition to the same price risk.

This paper is also related to Joskow (2011), who argued that the comparison of expected levelized costs of electricity (LCOE) across different technologies of electricity generation is misleading for evaluating their relative merits. This is because non-dispatchable renewable technologies may generate electricity when its social value is relatively low compared to thermal electricity, which will exercise its option to produce only when the electricity price is large enough. In a model with a risk-neutral representative agent, Ambec, Crampes and Lamp (2025) have recently proposed an adaptation of the LCOE to take into account the intermittency of renewable electricity. We propose a valuation methodology that is compatible with both the CCAPM and the OPT. It requires comparing the technology-specific levelized cost and price of electricity (LPOE), using risk-adjusted discount rates to value cost and price flows.

The paper is structured as follows. In Section 2, we explore a simple theoretical model of a good market whose price uncertainty is exogenous. We value an investment yielding the option to produce a single unit of the good at a predetermined variable cost. We show how to adjust the discount rate to the level of this variable cost. This duplicates the outcome generated by the Black-Scholes formula but under the CCAPM framework. Section 3 is devoted to the valuation of solar, wind, hydraulic, gas and nuclear power plants in the French electricity mix. A numerical solution for the efficient risk-adjusted discount rates specific to each generation technology is obtained with an endogenous electricity price formation with

[2] Breeden, Gibbons and Litzenberger (1989) empirically shows that goods with high income elasticities of demand have a high consumption beta.

three sources of uncertainty: economic growth, idiosyncratic demand shocks, and generation intermittency of renewable technologies. Some concluding remarks are presented in Section 4.

2 Adding a merit order into the standard asset pricing model

2.1 A general result

We consider a good market whose supply side is composed of different technologies or infrastructures with heterogeneous variable costs. The merit order within this family of technologies is determined by the rank of their variable cost c. To make the problem as simple as possible, we assume that each infrastructure generates a single unit of the good at some future date t. This yields a net future benefit equal to the difference between the price v_t of the output and the variable cost c if it is positive, and zero otherwise.

Aggregate income C_t in the economy is uncertain, and this uncertainty is transferred to the equilibrium price of the good through its income-elasticity. We assume here that income growth is the only source of uncertainty surrounding the equilibrium price. More specifically, the price v_t occurring at t has an income-elasticity b, so that v_t equals $\exp(bx_t)$, with $x_t = \ln(C_t/C_0)$. Breeden (1980) and Cherbonnier and Gollier (2022) link b to the income and price-elasticities of demand and supply, and to the CCAPM beta of the underlying asset. Notice that we normalize the price of the output at date 0 to unity. The net operational cash flow is the option-like payoff $(v_t - c)^+ = \max(0, v_t - c)$.

We assume a representative agent with a rate of pure preference for the present δ and relative risk aversion γ. This yields a price kernel (or stochastic discount factor) $m_t = e^{-\delta t} u'(C_t)/u'(C_0) = \exp(-\delta t - \gamma x_t)$. The present value PV of the project is

$$PV = E_0 \left[e^{-\delta t - \gamma x_t} \left(e^{bx_t} - c \right)^+ \right] = E_0 \left[e^{-\delta t - \gamma x_t} \left(e^{bx_t} - c \right) Ind \left(e^{bx_t} \geq c \right) \right]. \quad (1)$$

The theory of option pricing initiated by Black and Scholes (Black and Scholes, 1973) provides an analytical solution to this expectation. Obviously, the value of this call option is decreasing in its strike price c.

The consumption-based CAPM pioneered by Lucas (1978), Breeden (1979) and Rubinstein (1976) provides an alternative tradition by characterizing the present value of the asset as its expected future value (EFV) discounted at a risk-adjusted discount rate ρ_t:

$$PV = \exp(-\rho_t t) EFV$$

with

$$EFV = E_0 \left[\left(e^{bx_t} - c \right)^+ \right]. \quad (2)$$

Combining these two equations yields

$$\rho_t = -\frac{1}{t} \ln \left(\frac{PV}{EFV} \right). \quad (3)$$

We now establish that the efficient discount rate ρ_t is increasing in c when b is positive. Proposition 1 is proven in Appendix A.

Proposition 1. *The efficient discount rate ρ_t is increasing (resp. decreasing) in the variable cost c when the income-elasticity of demand b is positive (resp. negative).*

Thus, assuming a normal good, technologies that are worse in the merit order, i.e., those with a larger variable cost, should be discounted at a larger rate. The quantification of this effect requires specifying the demand risk. In the remainder of this section, we consider the special case in which aggregate income follows a geometric brownian motion with trend μ_x and volatility σ_x, so that x_t is $N(\mu_x t, \sigma_x^2 t)$.

2.2 Option pricing under the CCAPM

The standard results that are useful to solve standard asset pricing problems in this framework can easily be derived from the following simple lemma. This Lemma will also be useful later on to characterize the efficient discount rate along the merit order.

Lemma 1. *Suppose that z is normally distributed with mean m and standard deviation s. Then, for any set $Z \subset \mathcal{R}$ and any $k \in \mathcal{R}$, we have that*

$$E[\exp(kz)Ind(z \in Z)] = \exp(km + 0.5k^2s^2)P\left[\hat{z} \subset Z \mid \hat{z} \sim N(m + ks^2, s^2)\right],$$

where F is the CDF of z, and P is the probability operator.

Proof: This lemma is proven as follows:

$$\begin{aligned}\int_{z \subset Z} \exp(kz)dF(z) &= \frac{1}{\sqrt{2\pi}s}\int_{z \subset Z} \exp(kz)\exp\left(-\frac{(z-m)^2}{2s^2}\right)dz \\ &= \frac{1}{\sqrt{2\pi}s}\int_{z \subset Z} \exp(km + 0.5k^2s^2)\exp\left(-\frac{(z-(m+ks^2))^2}{2s^2}\right)dz \\ &= \exp(km + 0.5k^2s^2)P\left[\hat{z} \subset Z \mid \hat{z} \sim N(m + ks^2, s^2)\right]. \blacksquare\end{aligned}$$

Observe that we recover from this lemma the cumulant-generating function in the gaussian case. Indeed, for $Z = \mathcal{R}$, this lemma yields $\ln(E\exp(kz)) = km + 0.5k^2s^2$. When $Z \neq \mathcal{R}$, this formula needs to be multiplied by a risk-adjusted probability that z is in Z. This risk-adjustment is due to the fact that $\exp(kz)$ and $Ind(z \in Z)$ are statistically linked, so the expectation of their product is generally not equal to the product of their expectations, with $E[Ind(z \in Z)]$ being the probability of $z \in Z$. This risk-adjustment takes the form of measuring the probability that $\hat{z} \sim N(m + ks^2, s^2)$ – not $z \sim N(m, s^2)$ – is in Z.

As is well-known (Cochrane, 2017), the equilibrium risk-free interest rate r_f in this economy is constant. It equals

$$r_f = \delta - \frac{1}{t}\ln(E_0\exp(-\gamma x_t)) = \delta + \gamma\mu_x - 0.5\gamma^2\sigma_x^2. \tag{4}$$

This equation complements the Ramsey rule $r_f = \delta + \gamma\mu_x$ under certainty with a negative precautionary term $-0.5\gamma^2\sigma_x^2$ (Gollier, 2001). Similarly, the price of the asset that yields payoff $C_t^b = e^{bx_t}$ at date t follows a geometric brownian motion with trend $\mu = \gamma\mu_x - 0.5(b - \gamma)^2\sigma_x^2$ and volatility $b\sigma_x$. In this framework, Black and Scholes (1973), and later on Duffie

(2001) in the CCAPM equivalent context, characterize the price of the European call option with payoff $(e^{bx_t} - c)^+$. Assuming $b > 0$, equation (1) can be rewritten as follows:

$$e^{\delta t} PV = E_0[\exp((b-\gamma)x_t) Ind(x_t \geq b^{-1}\ln(c))] - cE_0[\exp(-\gamma x_t) Ind(x_t \geq b^{-1}\ln(c))].$$

The present value of technology c equals the difference between the present values of two risky assets: one that generates v_t when the option is in the money, and the other that costs c under the same condition, with the two assets generating 0 otherwise. Using Lemma 1 twice, this yields the following result:

$$PV = \exp(-(r_f + b\gamma\sigma_x^2)t)E_0[C_t^b]\Phi(d_1) - c\exp(-r_f t)\Phi(d_2), \tag{5}$$

where Φ is the standard normal cumulative distribution function,

$$d_1 = \frac{(\mu_x + (b-\gamma)\sigma_x^2)t - b^{-1}\ln(c)}{\sigma_x\sqrt{t}},$$

$$d_2 = \frac{(\mu_x - \gamma\sigma_x^2)t - b^{-1}\ln(c)}{\sigma_x\sqrt{t}},$$

and

$$E_0[C_t^b] = \exp((b\mu_x + 0.5b^2\sigma_x^2)t).$$

Equation (5) is the celebrated Black-Scholes formula (Black and Scholes, 1973) adapted to the equilibrium dynamic pricing of the underlying asset yielding C_t^b at date t (Cochrane, 2001; Duffie, 2001). This equation shows that the value of the call option $(C_t^b - c)^+$ is the difference between, on one side, the value of the future payoff C_t^b adjusted for its own risk and for the risk-adjusted probability $\Phi(d_1)$ of being in the money, and on the other side, the value of the cost c discounted at the risk-free rate multiplied by its own risk-adjusted probability $\Phi(d_2)$ of being in the money.

2.3 Efficient discounting for options

Similarly, using Lemma 1 twice, we also have that the expected future value of the option equals

$$EFV = E_0[C_t^b]\Phi(d_3) - c\Phi(d_4), \tag{6}$$

with

$$d_3 = \frac{(\mu_x + b\sigma_x^2)t - b^{-1}\ln(c)}{\sigma_x\sqrt{t}},$$

$$d_4 = \frac{\mu_x t - b^{-1}\ln(c)}{\sigma_x\sqrt{t}}.$$

Combining these equations directly yields Proposition 2 for $b > 0$. A symmetric proof for case $b < 0$ is straightforward. Our Proposition 2 restates the Black-Scholes formula in the CCAPM language of a risk-adjusted discount rate for option values. It characterizes the efficient risk-adjusted discount rate as a function of variable cost c in that case.

Proposition 2. *Suppose that consumption follows a geometric brownian motion with trend μ_x and volatility σ_x. We consider a project that yields a single benefit* $\max(0, \exp(bx_t) - c)$ *at date t, where x_t is the change in log consumption between 0 and t. When b is positive, the risk-adjusted discount rate ρ_t to be used to value this project is characterized as follows:*

$$\rho_t = r_f - \frac{1}{t} \ln \left(\frac{e^{(b\mu_x + 0.5b^2\sigma_x^2 - b\gamma\sigma_x^2)t}\Phi(d_1) - c\Phi(d_2)}{e^{(b\mu_x + 0.5b^2\sigma_x^2)t}\Phi(d_3) - c\Phi(d_4)} \right), \tag{7}$$

When b is negative, the same rules hold, with Φ being the standard-normal decumulative distribution function. When $b = 0$, we have $\rho_t = r_f$.

The second term on the right-hand side of equation (7), i.e., $\rho_t - r_f$, can thus be interpreted as the risk premium specific to the project. In the CCAPM, where the future payoff is assumed to have a constant income-elasticity β (Cherbonnier and Gollier, 2022), this risk premium is equal to $\beta\pi$, where π is the aggregate risk premium $\pi = \gamma\sigma_x^2$. In our framework, the payoff to be evaluated has a non-constant income-elasticity due to the constant variable cost and to the option not to produce. We can derive the implicit beta of the technology from its efficient discount rate characterized in Proposition 2:

$$\beta_t = \frac{\rho_t - r_f}{\gamma\sigma_x^2}. \tag{8}$$

In the special case when c tends to zero, the optional nature of the payoff disappears. In this case, equation (7) simplifies to

$$\lim_{c \to 0} \rho_t = r_f + b\gamma\sigma_x^2. \tag{9}$$

In this special case, b is the CCAPM-beta of the operational revenue. On the contrary, when c tends to infinity, the fraction on the right-hand side of equation (7) behaves like $h(\gamma)/h(0)$, which tends to zero. It implies that

$$\lim_{c \to +\infty} \rho_t = +\infty. \tag{10}$$

Technologies very far out of the money should be discounted at a very high rate.

We illustrate Proposition 2 by calibrating the model as follows. We consider a maturity of $t = 50$ years. I assume an income-elasticity of the equilibrium price of $b = 0.75$ (see next section). We calibrate the asset pricing model to fit an equilibrium risk-free rate of 3% and an aggregate risk premium of 2%. We assume $\delta = 1\%$ and $\gamma = 2$. This is a consensual estimation of risk aversion in public economics (Gollier and Hammitt, 2014). We follow Christensen, Gillingham and Nordhaus (2018), who used a survey of growth experts to calibrate the long-run consumption growth model. In 2010, these authors used 13 probabilistic expert forecasts to aggregate beliefs about the growth of global real per-capita GDP between 2010 and 2100. From these expert beliefs, they estimate the parameters of $x_t \sim N(\mu_x t, \sigma_x^2 t)$. They obtain $\mu_x = 2.06\%$ and $\sigma_x = 10.62\%$. To keep it simple, We hereafter use $\mu_x = 2\%$ and $\sigma_x = 10\%$. It is noteworthy that this annual volatility of growth is much larger than the historical standard deviation of annual growth rates of western economies.

Figure 1 describes the efficient discount rate as a function of the variable cost c of the project maturing in t =50 years. As anticipated above, when c tends to zero, it approaches 4.5%, which corresponds to a CCAPM beta equal to $b = 0.75$. This discount rate increases

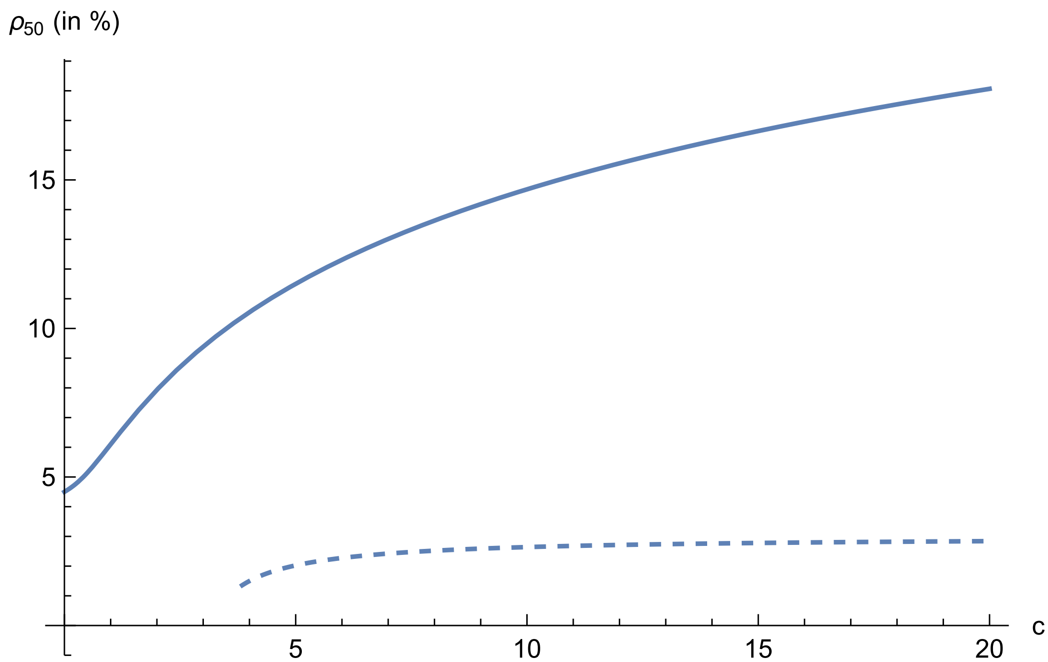

Figure 1: Efficient discount rate for an option-like payoff as a function of the variable cost c, as described in Proposition 2, with $t = 50$, $\gamma = 2$, $\delta = 1\%$, $\mu_x = 2\%$, $\sigma_x = 10\%$, and $b = 0.75$. The risk-free rate and the aggregate risk premium are equal to 3% and 2%, respectively. The dashed curve corresponds to the efficient discount rate for risky (but option-free) future benefit $e^{bx_{50}} - c$.

variable cost c	production probability $P[e^{bx_{50}} \geq c]$	Present value PV	Expected future value EFV	efficient discount rate ρ_{50}	implicit CCAPM beta β_{50}
0.00	1.00	0.2568	2.437	4.50	0.75
0.62	0.99	0.1250	1.821	5.36	1.18
0.88	0.95	0.0827	1.560	5.87	1.44
1.48	0.75	0.0312	1.048	7.03	2.01
2.12	0.5	0.0112	0.652	8.12	2.56
3.03	0.25	0.0029	0.322	9.42	3.21
5.06	0.05	0.0002	0.070	11.60	4.28
7.27	0.01	0.0000	0.016	13.20	5.09

Table 1: Efficient discount rates ρ_{50} for different technologies as a function of their probability to be profitable at $t = 50$, under the calibration summarized in the caption of Figure 1.

with the variable cost c, illustrating the fact that technologies lower in the merit order are riskier. In Table 1, the efficient discount rates corresponding to different technologies are computed as a function of their probability of being productive in 50 years, i.e., the probability that the option will be in the money at the exercise date. Interestingly, introducing a 1% out-of-the-money probability raises the implicit β_{50} from 0.75 to 1.18, representing a 57% increase in the risk-adjustment of the investment project. Raising this probability to 25% increases the risk premium to 2.01, a 168% increase with respect to the zero variable cost benchmark.

It is useful to compare the rate ρ_t, which is efficient for discounting $(e^{bx_t} - c)^+$, with the rate R_t, which is efficient for discounting $e^{bx_t} - c$. This is the payoff of a portfolio with two assets. The first asset is risky with a CCAPM beta equaling b. The portfolio is short on the safe asset, whose payoff c should be discounted at the risk-free rate r_f. The value of that portfolio is equal to

$$e^{-R_t t} E[e^{bx_t} - c] = e^{-(r_f + b\pi)t} E[e^{bx_t}] - e^{-r_f t} c. \tag{11}$$

It is easy to show that the efficient discount rate R_t is increasing with c whenever this portfolio has a positive value, i.e., whenever Ee^{bx_t} is larger than c. When c tends to infinity, r_f tends to the risk-free discount rate r_f. The dashed curve in Figure 1 corresponds to this r_f. So, both R_t and ρ_t are increasing in t, but the risk profile of the option-like payoff $(e^{bx_t} - c)^+$ makes ρ_t much larger, particularly for technologies that are far out of the money.

3 Discounting along the merit order in electricity generation

In the previous section, we have shown that the risk-adjusted discount rate is increasing in the variable cost in a simple model in which the output price is exogenous, log-normally distributed, and depends only on aggregate income. In reality, the output price is sensitive to other (idiosyncratic) factors. The equilibrium price depends on the distribution of variable costs in the market. Non-atomic production capacities with the same variable cost generate clusters of state equilibria yielding the same price. In this section, we illustrate the fundamental insight from the previous section in the context of the French electricity sector. We make the model realistic by endogenizing the electricity price process to balance demand and supply, introducing carbon pricing, and adding two sources of uncertainty that arise from renewable intermittency and idiosyncratic electricity demand shocks.

3.1 The model

In each state of nature characterized by the triplet (x, z, p), consumers choose their electricity consumption q to maximize their ex post utility:

$$\max_q e^{z+bx} \frac{q^{1-\alpha}}{1-\alpha} - pq, \tag{12}$$

where x is aggregate income growth, b is the income-elasticity of the value of electricity, z is an idiosyncratic shock to consumers' utility, and p is the instantaneous electricity price. Parameter $\alpha > 0$ measures the intensity of decreasing marginal utility of electricity. This characterizes the demand function $q(p)$:

$$p = e^{z+bx} q^{-\alpha}. \tag{13}$$

This means that the price-elasticity and the income-elasticity of the demand for electricity correspond, respectively, to $-1/\alpha$ and b/α.

We consider three types of technologies for electricity generation: renewables, nuclear and fossils, i.e., natural gas. We assume that nuclear power plants can adjust their operations to the renewable output fluctuations in real time, as is the case in France (Astier and Wolack, 2026).[3] Technology $i \in \{ren, nuc, fos\}$ is characterized by a capacity q_i, expressed in MW, and a variable cost c_i, expressed in EUR/MW, along with fixed (mostly capital) costs that we will describe later in this section. The merit order is given by the observation that $c_{ren} < c_{nuc} < c_{fos}$. This yields the marginal cost curve $Cm(q)$ described in Figure 2. The instantaneous renewable capacity q_{ren} is a random variable that describes the intermittency of the associated technologies. The supply curve is characterized by the optimality condition $p = Cm(q)$. Combining this optimality condition with equation (13) yields the instantaneous equilibrium in the electricity market. The equilibrium price p^* and quantities q^* are functions of the instantaneous state of nature characterized by the triplet $y = (z, x, q_{ren})$. Variable $y = y(t)$ represents the uncertainty surrounding the market conditions of any randomly selected hour in t years.

Let K_i denote the sum of the overnight capital cost of the infrastructure and the present value of its fixed maintenance cost for technology i, expressed in EUR/MW. The risk-free discount rate is used to estimate this fixed cost, as the maintenance costs are assumed hereafter to be certain. If n_i denotes the lifetime of the infrastructure associated with technology i, the present value of the net benefit of one MW of capacity using technology i installed at date 0 equals

$$NPV_i = -K_i + 8766 \sum_{t=1}^{n_i} E_0 \left[e^{-\delta t - \gamma x(t)} \left(p^*(y(t), t) - c_i(t) \right)^+ \right], \tag{14}$$

[3] Astier and Wolack (2026) show that an additional MWh of renewable generation in France predicts a 0.66 MWh decrease in nuclear output during the hour.

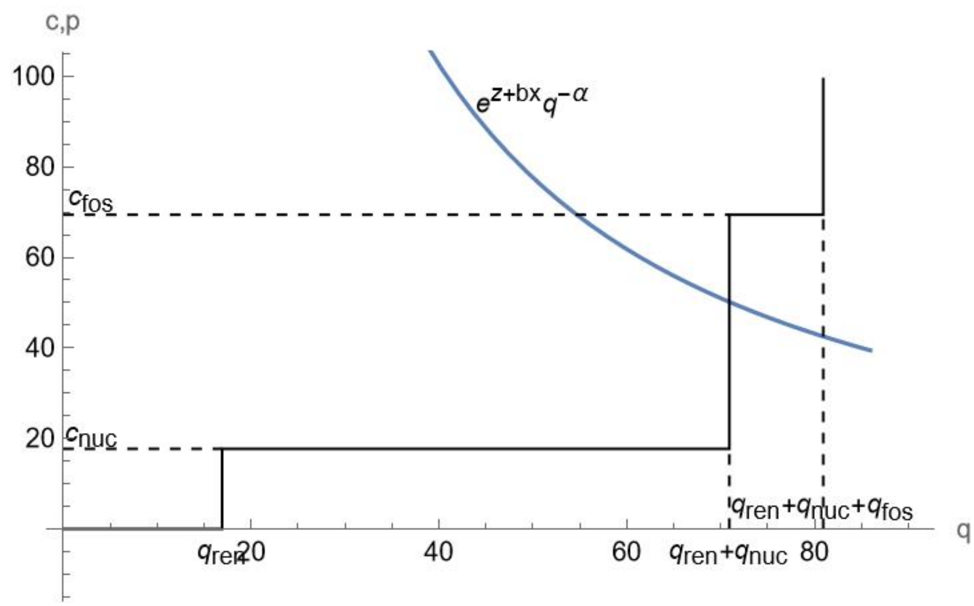

Figure 2: Instantaneous electricity market equilibrium. This graph represents the market at date 0 when using the expected values of the parameters used in the calibration of Section 3.

where δ and γ are respectively the rate of impatience and the relative risk aversion of the representative consumer. Coefficient 8766 corresponds to the number of hours in an average year. This equation characterizes the term structure of the risk-adjusted discount rates ρ_{it} to be used at date $t = 0$ for technology i:

$$e^{-\rho_i(t)t} = \frac{E_0\left[e^{-\delta t+\gamma x(t)}\left(p^*(y(t),t) - c_i(t)\right)^+\right]}{E_0\left[\left(p^*(y(t),t) - c_i(t)\right)^+\right]}. \tag{15}$$

These discount rates $\rho_i(t)$ are used to compute the NPV_i of each technology i:

$$NPV_i = -K_i + 8766\sum_{t=1}^{n_i} e^{-\rho_i(t)t} E_0\left[\left(p^*(y(t),t) - c_i(t)\right)^+\right]. \tag{16}$$

A marginal expansion of generation capacity using technology i is socially desirable if and only if NPV_i is positive.

3.2 Calibration of the model

The benchmark calibration of the parameters of our model is summarized in Table 2. The first four parameters in this table have already been justified in the previous section. Remember that in such an economy, the equilibrium risk-free rate is 3%, and the equilibrium aggregate risk premium is 2%.

Demand parameters α and b are calibrated to fit the observed price and income elasticities of the demand for electricity. The income-elasticity of electricity demand in the developed world is usually estimated to be around 0.6 (Kamerschen and Porter, 2004), whereas its price-elasticity in France is estimated to be around -0.8 (Auray, Caponi and Ravel, 2018). This is compatible with $\alpha = 1.25$ and an income-elasticity of the electricity value of $b = 0.6/0.8 = 0.75$.

We follow Percebois and Pommeret (2024) to calibrate the costs of electricity. They are assumed to be constant over time in this benchmark calibration. The variable cost of renewables is zero. The variable cost of nuclear electricity includes the fuel cost (7.2 EUR/MWh), the variable maintenance cost (3.8 EUR/MWh), and the cost of nuclear waste management (6.7 EUR/MWh), yielding c_{nuc}=17.7 EUR/MWh. The variable cost of fossil electricity is calibrated on gas, as coal is mostly fully eliminated from the French electricity mix. It includes the fuel cost (40.7 EUR/MWh), the variable maintenance cost (3.5 EUR/MWh), and a carbon price. I assume a carbon price of 70 EUR/tCO_2, which corresponds to the average price of the ETS permit between 2023 and 2025. Following the Swiss Federal Office of the Environment, we assume a carbon intensity of gas generation of 0.36 tCO2/MWh. Thus, the ETS adds 25.2 EUR/MWh to the variable cost of fossil electricity. In total, we thus have c_{fos}=69.4 EUR/MWh.

Nominal capacities $(q_{solar}(t), q_{wind}(t), q_{hydro}(t), q_{nuc}(t), q_{fos}(t))$ evolve over time under different investment scenarios. To calibrate capacity at the time of the investment, we extract maximal generation observed in the data of hourly generation by technology and spot price data between January 2023 and October 2025, made publicly available by the electricity transport operator RTE.[4] Total initial generation capacity is 112 GW, with an allocation $q_j(0)$ that is described in Table 2.[5] This must be compared to the average electricity demand in France of around 50 GW between 2023 and 2025, with peaks of around 85 GW during short periods in the winter season. In our benchmark calibration, we assume that generation capacities for solar, wind and nuclear electricity grow at a constant annual growth rate g:

$$q_j(t) = \begin{cases} q_j(0)e^{gt}, & \text{if } j \in \{solar, wind, nuclear\} \\ q_j(t) = q_j(0), & \text{if } j \in \{hydro, fossil\}, \end{cases}$$

for all t. We assume that the mean and variance of renewable generation increase at the same rate. In other words, we assume no impact of climate change on solar and wind dynamics. We assume that the fossil capacity remains constant. At a constant price of electricity, its demand grows proportionally to aggregate income with an income-elasticity of 0.6. Therefore, the expected demand for electricity grows at a rate that is equal to $0.6\mu_x + 0.5(0.6)^2\sigma_x^2 = 1.38\%$. We select $g = 1.38\%$ in order to keep the mean price of electricity approximately constant over time.

Renewable generation is intermittent. In practice, it means that the actual generation $q_j^a(t)$ from technology $j \in \{solar, wind, hydro\}$ is given by

$$q_j^a(t) = \ell_j q_j(t), \tag{17}$$

where ℓ_j is a random variable measuring the instantaneous load factor of technology j. To estimate its distribution, we observe in 2024 (the last full year of generation data) a mean

[4]https://www.rte-france.com/donnees-publications/eco2mix-donnees-temps-reel/telecharger-indicateurs

[5]In 2025, the official combined nominal capacities in renewables (solar, wind, and hydraulic) and nuclear operations were 46 GW and 63 GW, respectively. However, in practice, maintenance activities in nuclear operations limit the actual capacity over the last three years to around $q_{nuc}(0) = 56$ GW, which corresponds to the maximum generation observed during the period.

parameter	value	interpretation
δ	1%	rate of pure preference for the present
γ	2	relative risk aversion
μ_x	2%	annual trend of growth of aggregate consumption
σ_x	10%	volatility of growth of aggregate consumption
μ_z	9.242	mean idiosyncratic shock on demand
σ_z	0.72	idiosyncratic volatility on demand
b	0.75	income-elasticity of electricity value
α	1.25	inverse of the price-elasticity of demand
c_{ren}	0 EUR/MWh	variable cost of renewable electricity
c_{nuc}	17.7 EUR/MWh	variable cost of nuclear electricity
c_{fos}	69.4 EUR/MWh	variable cost of fossil electricity
$q_{solar}(0)$	17 GW	initial solar capacity
$q_{wind}(0)$	20 GW	initial wind capacity
$q_{hydro}(0)$	18 GW	initial hydraulic capacity
$q_{nuc}(0)$	56 GW	initial nuclear capacity
$q_{fos}(0)$	10 GW	initial fossil capacity
$\mu_{\ell_{solar}}$	0.17	mean solar load factor
$\sigma_{\ell_{solar}}$	0.23	volatility of solar load factor
$\mu_{\ell_{wind}}$	0.27	mean wind load factor
$\sigma_{\ell_{wind}}$	0.22	volatility of wind load factor
$\mu_{\ell_{hydro}}$	0.48	mean hydro load factor
$\sigma_{\ell_{hydro}}$	0.15	volatility of hydro load factor
g_{solar}	1.38%	growth rate of solar capacity
g_{wind}	1.38%	growth rate of wind capacity
g_{hydro}	0.00%	growth rate of hydraulic capacity
g_{nuc}	1.38%	growth rate of nuclear capacity
g_{fos}	0.00%	growth rate of fossil capacity

Table 2: Benchmark calibration of the parameters of the pricing model

generation of renewable electricity of 16.6 GW, along with a standard deviation of 5.0 GW. Given the symmetric nature of the histogram of renewable generation, as shown in Figure 3 in the Appendix, we assume that the load factors ℓ_j are normally distributed, and we calibrate their mean and standard deviations on their intermittency observed in 2024 in France. We define total renewable generation

$$q_{ren}(t) = \max\left(\sum_j \ell_j q_j(t), q_{min}\right)$$

We need to put a lower bound q_{min}= 1 GW to renewable generation to keep it non-negative with probability one.

Finally, we calibrate the idiosyncratic shock z on electricity demand. We use this degree of freedom to fit the mean (60 EUR/MWh) and the standard deviation (44 EUR/MWh) of the equilibrium price in the spot electricity market from January 2024 to December 2025, given

Technology	Lifetime (years)	Overnight cost (EUR/kW)	Maintenance cost (EUR/(kW year))	Fixed cost (K_i) (EUR/kW)
Solar	25	969	10.65	1 699
Wind	25	1 421	36.95	3 059
Hydro	50	2 063	33.01	2 937
Nuclear	50	5 003	95.06	7 522
Gas	25	770	13.09	1 474

Table 3: Estimation of the fixed cost over 50 years of the different electricity technologies in France, based on Percebois and Pommeret (2024) from which we extracted the overnight and maintenance costs in USD. We assume an exchange rate of 0.84 EUR/USD and a risk-free discount rate of 3%. The fixed cost has three components: The immediate overnight cost, the of the present value overnight cost incurred in the 26th year for technologies with a lifetime of 25 years, and the present value of the flow of maintenance costs over 50 years.

that 2023 was particularly affected by the boycott of Russian gas. Our numerical analysis indicates that this is compatible with $\mu_z = 9.242$ and $\sigma_z = 0.72$.

The calibration of the parameters in Table 2 is sufficient to price the flow of operational revenues of the different technologies. In order to evaluate the relative merits of the different technologies in the French electricity mix, the capital expenses need to be included in the picture. This is done in Table 3. We again rely on the cost estimations provided by Percebois and Pommeret (2024). As stated earlier, we estimate the CAPEX K_i by combining the overnight capital investment in EUR/kW and the present value of the flow of recurrent fixed maintenance costs, discounted at the risk free rate, which is 3% in this economy. We assume a lifetime of 50 years for nuclear and hydraulic power installations and a lifetime of 25 years for the other technologies. Our evaluation procedure covers 50 years of electricity generation. We assume that, for electricity infrastructures whose lifetime is limited to 25 years, an additional overnight cost (unchanged with respect to current overnight costs) is incurred at the beginning of the 26th year to renew it.

3.3 Results

We numerically estimate the expectations that appear in equations (15) and (16) by truncating the normal distributions of the triplet (z, q_{ren}, x) around their expected value, plus and minus $k = 3.3$ times their standard deviation. Our results are described in Table 4. In Figure 4, we draw the cumulative distribution function of spot prices in the year $t = 25$. With a probability of 28.74%, all available electricity generation units are active, and the price is determined to equalize demand to this total supply. With a probability of 55.48%, total supply is limited to renewable and nuclear units. The dashed curve in this figure corresponds to the CDF of equilibrium prices when diversifiable risks (idiosyncratic demand risk and intermittency) are eliminated. These risks cannot be ignored in the model because of the option-like nature of the non-renewable payoffs. By increasing the risk on prices, they raise their option values.

Figures 5 and 6 show the evolution of the average equilibrium spot price of electricity and its volatility over the 50-year lifetime of the infrastructure. The mean price is mostly constant at around 60 EUR/MWh but is slightly hump-shaped, with a maximum of around 62.50 EUR/MWh in 35 years. The volatility of the spot price increases over time, from 44 to 62 EUR/MWh. In Figure 7, we illustrate the cannibalization impact of the development of renewables on the load factor of nuclear capacity, which goes down from 92% initially to less than 83% in year $t = 50$.

Keep in mind that an unconstrained 1 MW capacity would be able to generate operational revenue equal to the difference between the mean spot electricity price of around 60 EUR/MWh and the variable cost c_i of the corresponding technology. Solar panels have an average load charge of $\mu_{\ell_{solar}} = 17\%$ and no variable cost. Thus, we should expect an operational revenue of $0.17\times$ 60= 10.2 EUR/MW, which is what the model predicts for the first year. Wind and hydro generate larger operational revenues because of their larger load factors. Because expected spot electricity prices are higher in 50 years, operational revenues of renewables will be greater at that time than today. In Figure 8, we present the term structure of the expected operational revenue for each technology.

A similar observation can be made for nuclear electricity, with the difference that the operational revenue is reduced by the variable cost $c_{nuc} = 17.7$ EUR/MWh. Moreover, nuclear generation is reduced by renewable generation when the demand is low. Accordingly, the model predicts that the nuclear load factor will decrease from 92% today to 83% in five decades.

But the marginal technology is most often gas generation. In spite of a mean price around 60 EUR/MWh and a variable cost of $c_{fos} = 69.4$ EUR/MWh, this technology is able to generate an hourly operational revenue of 11.50 EUR/MW in the first year, with a load charge of 25.4%. This is explained by the ability of this dispatchable technology to produce more electricity when its price is higher, either because demand is high or because renewable generation is low. Because of the growing volatility of equilibrium prices, this bonus increases over time, with an hourly operational revenue reaching 17.80 EUR/MW in fifty years.

	Operational revenue		Discount rate	
	$t = 1$	$t = 50$	$t = 1$	$t = 50$
Solar	10.20	14.20	4.34	4.17
Wind	19.30	26.60	4.34	4.17
Hydro	30.40	21.40	4.34	4.17
Nuclear	42.30	45.30	4.89	4.87
Fossil	11.50	17.80	6.77	6.07

Table 4: Expected hourly operational revenue (in EUR/MW) and the efficient risk-adjusted discount rate (in %) for a one-year maturity and a fifty-year maturity.

Let us now turn to the choice of the risk-adjusted rate at which these flows of expected operational revenues should be discounted. Cherbonnier and Gollier (2022) has linked the CCAPM beta of productive capital to the price and income elasticities of supply and demand in the corresponding market. In the special case in which variable costs are insensitive to economic growth, they show that the CCAPM beta of the investment is equal to the income-elasticity of demand, i.e., to $b/\alpha = 0.6$ when the supply curve is horizontal. On the contrary, when the supply curve is vertical, the CCAPM beta of the investment is equal to $b = 0.75$. In our calibration, the efficient risk-free interest rate and the efficient aggregate risk premium are equal to 3% and 2%, respectively, with flat term structures. Thus, these two CCAPM betas would yield two discount rates ρ, corresponding respectively to 4.2% and 4.5%.

In our benchmark model, the supply curve is stepwise, and different technologies vary in their ranking within the merit order. The right side of Table 4 illustrates our main insight from Section 2 that technologies lower in the merit order should be discounted at a larger rate. To discount operational cash flows, a discount rate within the range of the reference window of 4.2-4.5% holds for renewable technologies, with $\rho_{ren}(t) \simeq 4.3\%$. Because of its lower merit, nuclear technology is associated with a larger efficient discount rate $\rho_{nuc}(t) \simeq 4.9\%$. As for fossil technology, it suffers from the fact that its operational revenue is, on average, larger when aggregate consumption is greater. For fossil technology, this justifies using a much larger discount rate ($\rho_{fos}(1) = 6.77\%$), at least for small maturities. Its term structure is decreasing, down to $\rho_{fos}(50) = 6.07\%$.

We can infer the implicit CCAPM betas of the three technologies as follows:

$$\beta_i(t) = \frac{\rho_i(t) - r_f}{\pi}, \tag{18}$$

with $r_f = 3\%$ and $\pi = 2\%$, the efficient risk-free discount rate and aggregate risk premium under this calibration. Our results are summarized in Table 5. Observe that in this benchmark calibration, the fossil beta is typically three times larger than the renewable beta.

	CCAPM beta	
	t=1	t=50
Renewables	0.67	0.58
Nuclear	0.95	0.94
Gas	1.89	1.54

Table 5: CCAPM beta per technology and maturity in the benchmark model.

In Table 6, we document our findings concerning the profitability of different technologies under this benchmark scenario, as measured by the net present value per kW of generation capacity. In this discussion, we ignore hydro technology due to the absence of any investment opportunities in this technology in France. Solar and gas technologies break even under this benchmark scenario. Nuclear and wind generations do not. What is the role of differentiated risk-adjustments of the discount rate for this outcome? To answer that question, we also estimated the present value of the flow of operational revenues using a single discount rate of 4.5%, based on a single CCAPM beta of $b = 0.75$. Using this ineffective valuation method would reduce the renewable bonus arising from its lower CCAPM beta, whereas it would sufficiently reduce the nuclear disadvantage for it to generate a positive nuclear NPV. The real winner of such a discounting methodology would be fossil generation because it ignores the fact that much of the value creation of fossil generation takes place in high economic growth scenarios.

Technology	Fixed cost K_i	PV operational revenues	NPV_i	
			efficient	4.5%
Solar	1699	1867	168	89
Wind	3059	2966	-92	-216
Hydro	2937	5274	2336	2116
Nuclear	7522	7074	-447	17
Gas	1474	1760	286	946

Table 6: Present value of operational revenues and net present value (NPV_i) for different technologies in the benchmark model calibrated as described in Table 2. The last column corresponds to the NPV if a uniform discount rate of 4.5% would be used to value the flow of operational revenues. Units are in kEUR/MW.

3.4 Levelized cost of electricity

Experts in electricity markets typically prefer using the concept of Levelized Cost of Electricity (LCOE) of different technologies to evaluate their relative profitability. To perform this transformation, let us first observe that, using equation (14), NPV_i is positive if and only if

$$\sum_{t=1}^{n_i} E_0\left[e^{-\delta t+\gamma x(t)}p^*(y(t),t)f_i(y(t),t)\right] \geq K_i + 8766c_i \sum_{t=1}^{n_i} E_0\left[e^{-\delta t+\gamma x(t)}f_i(y(t),t)\right], \tag{19}$$

where $f_i \equiv \mu_{\ell_i}$ for $i \in \{solar, wind, hydro\}$,

$$f_{nuc}(y,t) = \begin{cases} 0, & \text{if } p^*(y,t) < c_{nuc}(t) \\ (c_{nuc}^{-1/\alpha}\exp((z+bx)/\alpha) - q_{ren})/q_{nuc}(t), & \text{if } p^*(y,t) = c_{nuc}(t), \\ 1, & \text{if } p^*(y,t) > c_{nuc}(t), \end{cases} \tag{20}$$

and

$$f_{fos}(y,t) = \begin{cases} 0, & \text{if } p^*(y,t) < c_{fos}(t) \\ (c_{fos}^{-1/\alpha}\exp((z+bx)/\alpha) - q_{ren} - q_{nuc}(t))/q_{fos}(t), & \text{if } p^*(y,t) = c_{fos}(t), \\ 1, & \text{if } p^*(y,t) > c_{fos}(t). \end{cases} \tag{21}$$

Function $f_i(y,t)$ represents the load factor of technology i in state y on date t. For nuclear and fossil technologies, it is the load factor. Then, the two sides of the inequality (19) represent the values of the flow of revenues and costs, respectively, associated with a one-MW capacity of technology i. Following tradition, we can rewrite the above inequality expressed in energy units rather than in capacity units. In order to do this, we divide both sides of this inequality by a discounted value of the flow of production over the lifetime of this 1-MW infrastructure. Let us define the LCOE of technology i as follows:

$$LCOE_i = \frac{K_i + 8766c_i \sum_{t=1}^{n_i} E_0\left[e^{-\delta t+\gamma x(t)}f_i(y(t),t)\right]}{8766\sum_{t=1}^{n_i} E_0\left[e^{-\delta t+\gamma x(t)}f_i(y(t),t)\right]}. \tag{22}$$

Technology	LCOE	LPOE
Solar	44.72	49.14
Wind	50.68	49.14
Hydro	27.37	49.14
Nuclear	54.03	51.87
Gas	102.46	108.87

Table 7: Levelized cost (LCOE) and levelized price (LPOE) of electricity for different technologies in the benchmark case. Units are in EUR/MWh.

Similarly, let us define the Levelized Price of Electricity (LPOE) as follows:

$$LPOE_i = \frac{\sum_{t=1}^{n_i} E_0 \left[e^{-\delta t + \gamma x(t)} p^*(y(t), t) f_i(y(t), t) \right]}{\sum_{t=1}^{n_i} E_0 \left[e^{-\delta t + \gamma x(t)} f_i(y(t), t) \right]}. \tag{23}$$

Observe that $LPOE_i$ is a mean price since $LPOE_i = p$ whenever the price at which electricity from technology i is a constant p. In order to obtain this property, we discount the flow of production f_i in each state and date by its corresponding Ramsey factor $\exp(-\delta t + \gamma x_t)$. For example, in the case of renewable electricity, $f_{ren} \equiv 1$ with certainty, so the flow of production is discounted at the risk-free rate r_f. Thus, the social value creation of a marginal investment in a technology is equal to the difference between its levelized price and its levelized cost of electricity over its lifetime. By definition, NPV_i is positive if and only if $LPOE_i$ is larger than $LCOE_i$. This decomposition of the NPV into a LPOE and a LCOE using their respective risk profiles, discount rates, and in-the-money probabilities is reminiscent of the Black-Scholes formula (5) as described in Section 2.2.

In Table 7, we show that under the benchmark calibration, a marginal investment in electricity generation creates social value at the margin using solar and gas infrastructures, but it destroys value at the margin for wind and nuclear ones. The fossil technology has the largest LCOE, but its ability to generate electricity in high-price states makes it socially valuable.

3.5 Sensitivity analysis

In this section, we explore alternative calibrations of the model, as summarized in Table 8. Notice that most of these alternative calibrations do not significantly affect the structure of risks in the initial years of the infrastructures, so they have no impact on the short-term technology-specific discount rates. This is why we only report on the long-term discount rates $\rho_i(50)$.

In column "carbon", we examine the impact of doubling the carbon price to 140 EUR/tCO_2. This pushes fossil technology further down the merit order, thereby increasing its long-term discount rate from 6.07% in the benchmark scenario to 6.40%.[6] Because increasing the carbon price raises the equilibrium spot price of electricity (Reguant, 2019), it increases the NPV of all technologies except gas.

[6]Notice that this doubling of the carbon price also increases the short-term fossil discount rate from 6.77% to 7.37%.

	benchmark	carbon	fix capacity	nuclear	no-intermittency
$\rho_{ren}(50)$	4.17%	4.17%	4.26%	4.17%	4.17%
$\rho_{nuc}(50)$	4.87%	4.86%	4.55%	4.87%	4.87%
$\rho_{fos}(50)$	6.07%	6.40%	5.41%	6.08%	6.08%
NPV^{solar}	168	228	677	166	158
NPV^{wind}	-92	3	715	-96	-107
NPV^{nuc}	-447	-133	2546	-460	-503
NPV^{fos}	286	-433	1790	274	237

Table 8: Sensitivity analysis. In the "carbon" scenario, the price of carbon is doubled to 140 EUR/tCO_2. In the "fix capacity" scenario, we assume that all technologies have a constant capacity ($g_i = 0 \quad \forall i$). In the "nuclear scenario", renewable capacities remain constant ($g_{solar} = g_{wind} = 0$), and are replaced by nuclear capacity growth ($q_{nuc}(t) = 62.29e^{g_{nuc}t} - 8.29$). In the "no-intermittency" scenario, we eliminate the variability of renewable generation ($\sigma_{\ell i} = 0 \quad \forall i$).

Table 8 also documents a scenario in which the electricity mix and capacities remain constant over time, i.e., $g_i = 0$ for all i. In this case, equilibrium electricity prices go up dramatically over time, reaching a mean price of around 125 EUR/MWh in 50 years. This increases the frequency of nuclear and fossil technologies being in the money, thereby reducing their efficient discount rates. It also increases the NPV of all technologies, thereby demonstrating the social necessity to expand electricity investments under this status quo scenario.

We also examine the case in which investments are limited to nuclear electricity. This is assumed by switching renewable capacity growth entirely to nuclear capacity growth: $g_{solar} = g_{wind} = 0$ and $q_{nuc}(t) = 54\exp(g_{nuc}t) + 8.29(\exp(g_{nuc}t) - 1)$, given the 8.29 GW of actual initial solar and wind generation. Because of the low variable cost of nuclear technology, this switch does not significantly modify the variability of electricity prices in the market. Thus, this does not significantly affect the efficient discount rates and the profitability of the different power plants.

Finally, we solved the model with a scenario in which the intermittency of renewable power plants is eliminated ($\sigma_i = 0$ for all i). There is not enough convexity in the market pricing mechanism for the elimination of intermittency to significantly reduce the mean electricity price (conditional to x_t). In other words, the non-diversifiable risk component of electricity prices is mostly unaffected, and so are the technology-specific discount rates. NPVs are marginally deteriorated by the reduction of mean prices.

4 Conclusion

The value of an incremental investment in production capacity is equal to the difference in the NPVs of the flow of revenues and costs. Different discount rates should be used in this process. In this paper, we show that these rates are sensitive to the variable cost associated to the production technology. In sectors with widely heterogeneous variable costs, there is no such thing as a sectoral discount rate.

We have calibrated a pricing model for the French electricity sector. In the case of renewable electricity with zero variable cost, there is no quantity risk, as our model excludes the possibility of a negative spot price at equilibrium. In that case, renewable investments should be valued with a beta equal to the income-elasticity of electricity for revenues and equal to zero for costs. On the contrary, for gas power plants that are last in the merit order, the corresponding betas are much larger because of the quantity risk that those plants face. Under our benchmark calibration, these plants should be valued using a gas-beta that is three times larger than the renewable-beta. The recognition that generation technologies lower in the merit order should be discounted at a larger rate has a non-marginal impact on the measurement of value creation of these different technologies. For example, under our benchmark calibration, the true value creation of a marginal investment in nuclear generation is negative. A positive value creation would be measured if a single discount rate of 4.5% were used.

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APPENDIX

A Proof of Proposition 1

We hereafter prove Proposition 1 in the case with $b > 0$, so that $e^{bx_t} - c$ is positive if and only if x_t is larger than $y = b^{-1}\ln(c)$. The other case with $b < 0$ is proven symmetrically. Equation (3) implies that ρ_t is increasing in c if and only if

$$\int_y e^{-\gamma x}(e^{bx} - c)dF_t(x) \leq \int_y e^{-\gamma x}dF_t(x)\frac{\int_y (e^{bx} - c)dF_t(x)}{1 - F_t(y)},$$

where F_t is the CDF of x_t. Let z_t denote the truncated version of random variable x_t. It has a CDF G_t which is such that, for all z, $dG_t(z) = dF_t(z)/(1 - F_t(y))$ if $z \geq y$, and 0 otherwise. The above inequality can be rewritten as follows:

$$E[e^{-\gamma z_t}(e^{bz_t} - c)] \leq E[e^{-\gamma z_t}]E[e^{bz_t} - c].$$

This inequality holds by the covariance rule, as $e^{-\gamma z_t}$ and $e^{bz_t} - c$ covary negatively. ■

B Figures

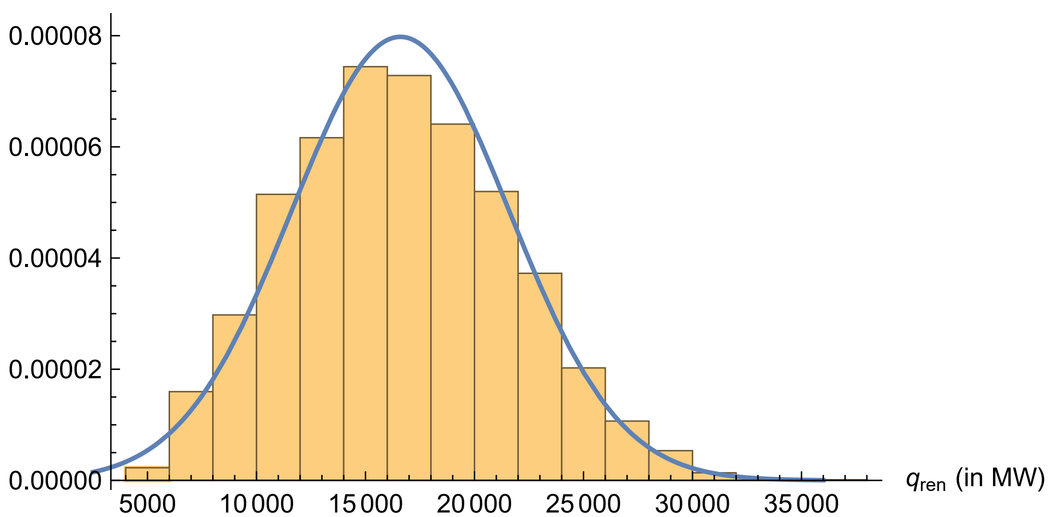

Figure 3: Histogram of the renewable generation q_{ren} in 2024 and its fitted distribution $N(\mu_{qren}, \sigma^2_{qren})$.

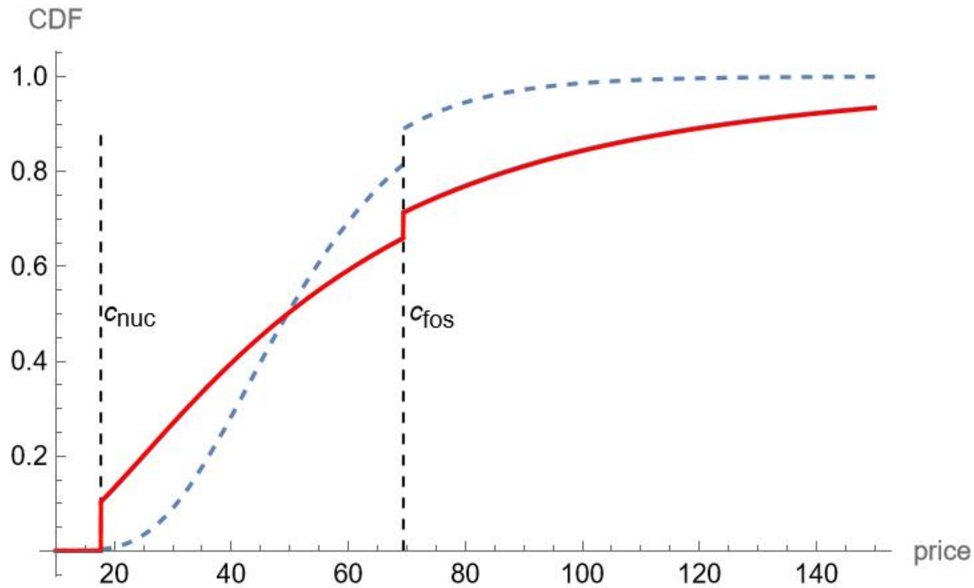

Figure 4: Cumulative distribution function of the equilibrium price in 25 years. The dashed curve corresponds to the CDF when switching off intermittency ($\sigma_{\ell i} = 0 \quad \forall i$) and the idiosyncratic demand uncertainty ($\sigma_z = 0$). $P[price < c_{nuc}] = 0.00\%$; $P[price = c_{nuc}] = 10.35\%$; $P[c_{nuc} < price < c_{fos}] = 55.48\%$; $P[price = c_{fos}] = 5.38\%$; $P[price > c_{fos}] = 28.74\%$.

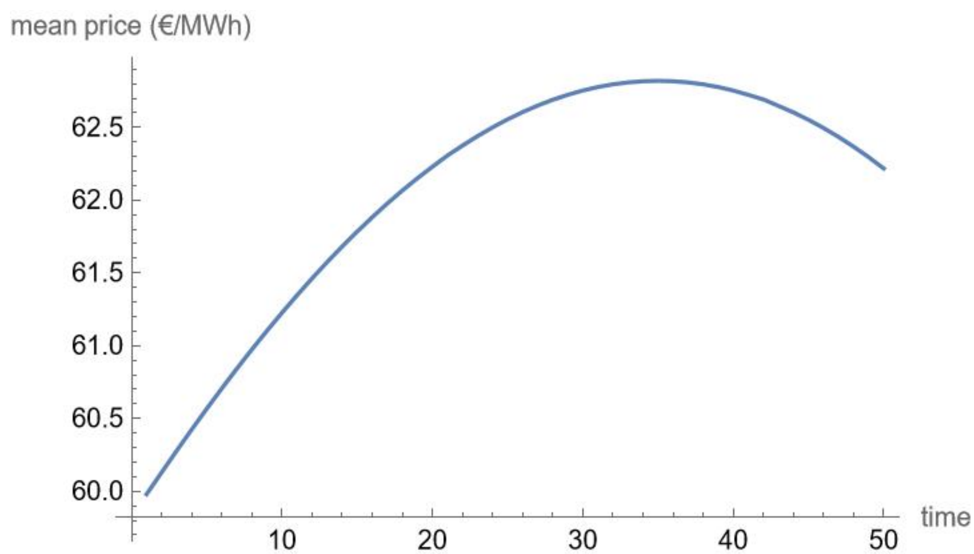

Figure 5: Mean spot price (in EUR/MWh) over 50 years in the benchmark calibration.

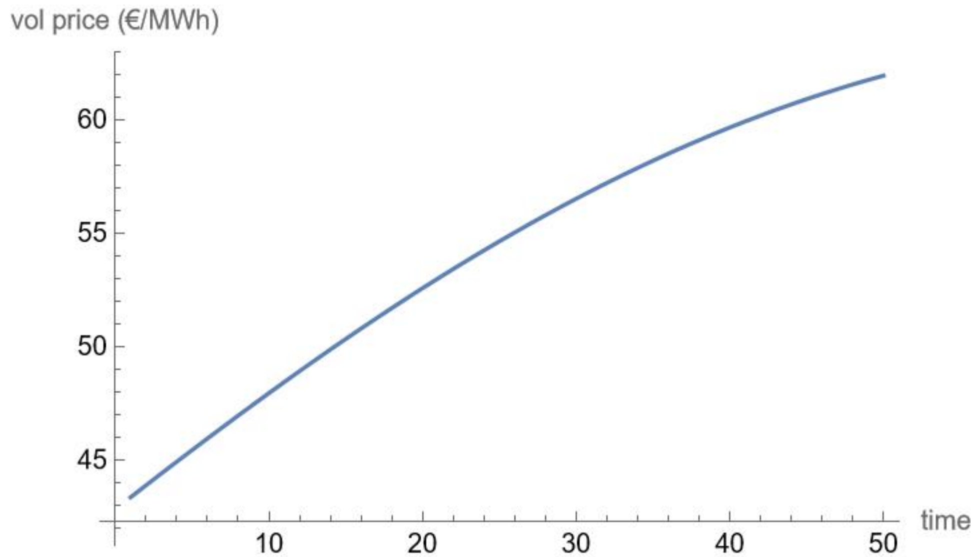

Figure 6: Volatility of spot prices (in EUR/MWh) over 50 years in the benchmark calibration.

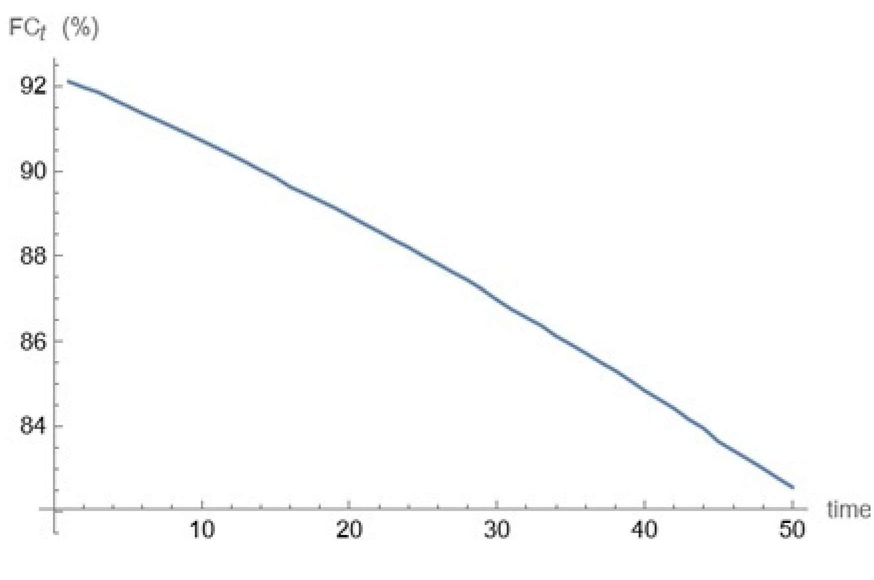

Figure 7: Annual load factor of nuclear electricity over 50 years in the benchmark calibration.

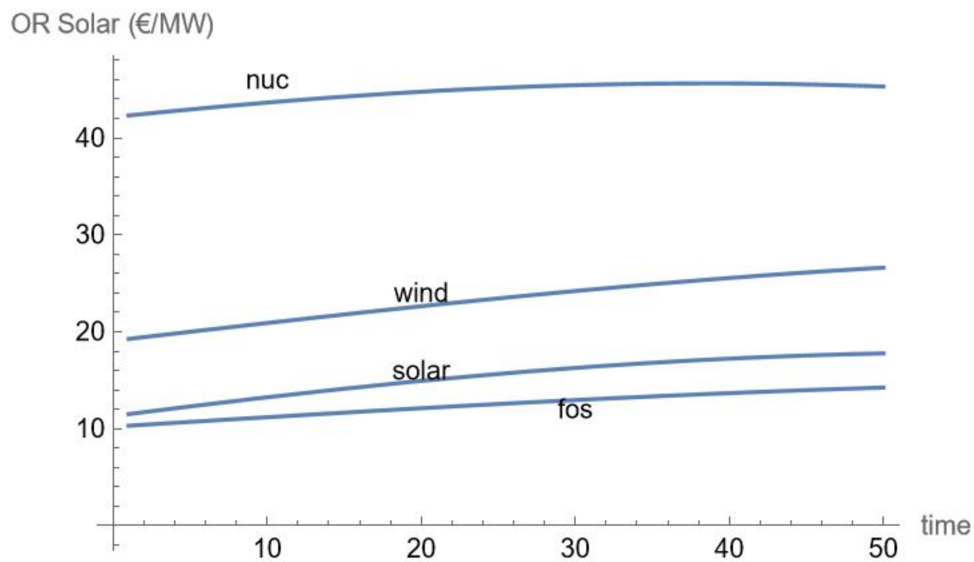

Figure 8: Expected hourly operational revenue (in EUR/MW) per technology over 50 years in the benchmark calibration.