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EPRG Working Paper 2507

Cambridge Working Paper in Economics 2525

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Keywords Incomplete markets, Market distortion, Bi-level programming, Stochastic equilibrium models, Optimal regulation, Power markets.

JEL Classification D81, C72, C73, Q41

Contact	andreas.ehrenmann@engie.com
Publication	April 2025

www.jbs.cam.ac.uk/eprg

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March 25, 2025

Abstract

Risk-mitigation instruments are essential for fostering investments in renewable electricity-production assets and their role is all the more important in the case of market incompleteness. At the same time, such instruments may induce distortions of competition, thereby limiting the effectiveness of spot markets. An example of such an effect is the dramatic increase in negative prices observed in many power markets. Some mechanisms that protect investors from risk decouple operating incentives from spot prices, leading to inefficient trading. At the same time, those negative prices incentivize investments in storage. Such distortions have so far been overlooked in most quantitative research focused on market incompleteness. Using a bi-level programming approach, this paper proposes a framework within which to integrate market distortions when analyzing incompleteness. The lower level of the framework models the power economy via an equilibrium formulation of the two-stage investment problem under risk aversion, where agents invest in the first stage before operating in the stochastic second stage. A central planner offers a set of risk-mitigation schemes in the form of Contracts for Difference and price markups to foster investments, but these schemes can distort competitive bidding. On the upper level, the central planner tunes the design of contracts optimally so that social welfare is maximized. We provide an existence result and undertake a thorough numerical simulation inspired by the French power system, which demonstrates the potential for optimally adjusting the risk-mitigation instruments offered to electricity producers to enhance welfare and limit the prevalence of negative prices.

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1 Introduction and literature survey

1.1 Context: Risk mitigation and market incompleteness in power markets

The creation of spot markets for electricity trading marked the beginning of the liberalization of the European power systems era of the nineties. Following the seminal work of Marcel Boiteux (Boiteux [1960]), the logic of that time was to let markets send the right price signals for investments according to the fundamental principle that short-term and long-term marginal costs should be equal in a perfectly competitive market and when production capacities are adapted to demand. At that time, alas, policymakers did not anticipate the detrimental role that the many market failures that limit sound functioning of the markets play. Among these failures, risk aversion and market incompleteness (Staum [2007]) are now recognized by many economists as serious obstacles to investments because power-producing technologies are, on the one hand, CAPEX-intensive,[1] while many short- and long-term risk drivers, on the other hand, affect spot markets and, in turn, the revenues of investments: the operations research (OR) and energy economics literatures are now replete with studies, including Bichuch et al. [2023], Philpott et al. [2016], and Ehrenmann and Smeers [2011], that quantify the impact of these failures.

Incompleteness in electricity markets stems from the existence of long-term risk drivers, such as regulatory and technological risks, for which there exist no hedging instruments today. Therefore, it is now acknowledged that risk-sharing and risk-mitigating instruments are crucial to ensuring the adequacy of the system by providing financial security to investors and reducing their exposure to spot-market risks (see, for instance, de Maere d Aertrycke et al. [2017] and Abada et al. [2019]). Crucially, in the context of the energy transition and the urgent need to reduce greenhouse gas emissions of the power sector in many countries, such instruments are of paramount importance in fostering investment in renewable energy assets, such as farms of solar panels and wind turbines, which must simultaneously bear both price and production volume risks (Ferris and Philpott [2024], Weiss and Sarro [2013], and Chacon [2012]). Regulators and policymakers have also acknowledged the issue of market incompleteness, as is highlighted in a series of white papers published recently by the Council of European Energy Regulators and the European Agency for the Cooperation of Energy Regulators. These papers discuss the lack of long-term risk-mitigation instruments in Europe and its impact on investments in presence of risk aversion.[2] This explains, in part, why all recent investments in production have been subsidized by contracts of some form, such as Contracts for Difference (hereafter CfDs) signed with States for nuclear production and Power Purchase Agreements (PPAs) signed with large industrial consumers for renewable production (see Joskow [2006] for a thorough analysis of the phenomenon).

1.2 Market distortions and the rise of negative spot prices

Negative prices sometimes appear in electricity spot markets. Such prices are not necessarily a result of malfunctioning markets; they are simply a natural consequence of unit-commitment constraints on power plants combined with renewable oversupply in hours of low demand. They become problematic, however, when they occur frequently, as they signal a lack of adaptation of capacity to demand and

[1] CAPEX stands for Capital Expenditure Cost.

[2] The reports are available at: https://www.ceer.eu/wp-content/uploads/2024/04/C21-FP-49-03_Paper-on-LT-investment-signals.pdf and at https://www.acer.europa.eu/sites/default/files/documents/Publications/Final_Assessment_EU_Wholesale_Electricity_Market_Design.pdf.

many economists point to risk-mitigating State subsidies, particularly fixed feed-in-tariffs (FITs), as a source of such inefficiency.[3] In recent years the presence or duration of those prices has been increasing very rapidly. In Germany, for instance, negative electricity prices occurred for 457 hours in 2024, up from 301 hours in 2023. Similar figures have been reported for France (320 hours in 2024), the Netherlands (458 hours), and Belgium (401 hours)—only countries like Italy that do not allow negative prices to occur have been spared. And the phenomenon is not restricted to Europe: for example, the Australian NEM Market reported more than 1300 half-hour periods of negative prices in the first nine months of 2024 alone.

FITs, two-sided CfDs and the practice of floating premia to renewable developers to facilitate rapid deployment and low capital costs often trigger this phenomenon. Indeed, one of the side effects of these tactics is that most renewable installations become fully protected from market prices and continue operating even if prices are negative. For example, German research center FfE finds that more than 72.4 GW (or 74.5%) of all photovoltaic PV installations in Germany have no or limited incentives to adjust their production schedules.[4] In response to negative power prices, the European Commission has called for more robust investments in flexible assets. In this context, the Commission's Regulation 2024/1747 mandates an assessment of the need for non-fossil flexibility—through Demand Side Management and batteries—driven by the integration of renewable production, which should ultimately translate into indicative country targets for storage. Paradoxically, specific support or hedging contracts for investments in batteries do not exist today in Europe, but storage assets have become the main beneficiary of negative prices (Zhou et al. [2016]).

But what is the relationship between risk-mitigating instruments and negative prices? The answer lies in market distortions. A risk-mitigation scheme is, in fact, a double-edged sword. Consider, for instance, a fixed FIT contract secured by a power producer. Such a design protects the producer against spot-price fluctuations, reducing the investment risk. At the same time, the FIT makes it, in theory, always profitable to sell to the market, irrespective of the spot-market price, which might constitute an instance of market distortion. We regard any short-term action taken by an agent that is not in line with perfectly competitive behavior in response to a price signal as a market distortion: in our case, this includes, for instance, producing at hours when the spot price is below the production cost or withholding capacity in the opposite case. The former could be an instance of moral hazard where the producer is no longer exposed to the market price, whereas the latter might be a consequence of market power abuse. In the present paper, we abstract away from market power and focus on the first issue, where distortion is caused by an absence or lack of price exposure. Such a phenomenon might prompt overproduction of renewables in low-demand hours, ultimately leading to negative prices.

Interestingly, some economists and management scholars have studied the relationship between risk-mitigating contracts, market distortions, and negative prices. Peura and Bunn [2021] underscore how hedging strategies deployed by wind-power producers affect short-term electricity prices. In particular, the paper demonstrates how forward-market hedging strategies could reduce prices for a moderate

[3]See, for instance, *The Economist*: Europe faces an unusual problem: ultra-cheap energy, June 20th 2024.
[4]See: *https://www.ffe.de/en/publications/negative-electricity-prices-how-many-renewable-energy-systems-will-run-through/*.

portion of the hedged capacity. Newbery et al. [2018] analyze some market distortions induced by risk-mitigation schemes associated with renewable production and Meus et al. [2021] develop an equilibrium market representation to quantify the extent of market distortions of offshore wind-support schemes, including FITs and capacity-based subsidies. Newbery [2023] and Huntington et al. [2017] propose remedies such as a market-compatible financial CfD to foster investments while simultaneously limiting distortions, which involves remuneration that depends on an hourly contracted volume. Billimoria and Simshauser [2023a] do the same with storage assets. Naturally, this stream of research has become particularly relevant with the recent increase in the number of hours during which negative prices for electricity appear, as highlighted above. As a result, many European countries are progressively removing or replacing Fixed-Price contracts with spot-indexed instruments with the objective of making contracted production more reactive to market signals, as implemented in the UK[5] and Spain[6]. To the best of our knowledge, the existing literature has not identified an optimal contract design that balances risk-hedging incentives with efficient spot trading in the context of market incompleteness while considering the entire system's perspective. Therefore, from the perspective of policymakers, a balance must be found when elaborating risk-mitigating instruments between i) fostering investments in the context of risk aversion and market incompleteness and ii) limiting market distortions by producers when trading in the spot market, thereby also mitigating negative prices.

1.3 The research question

To the best of our knowledge, there is a research gap in the OR and management literature that assesses the impact of risk-mitigation schemes on market surplus and investments in the context of market incompleteness from the whole power system's perspective, inasmuch as market distortions have been overlooked so far in most of the related models. Indeed, we observe that almost all existing articles assume that agents react perfectly to price signals once contracts have been secured (as in Ralph and Smeers [2011], Ehrenmann and Smeers [2011], Philpott et al. [2016] and related articles), with the notable exceptions of de Maere d'Aertrycke et al. [2017b], Abada and Ehrenmann [2023], and Bichuch et al. [2023], who account for the possibility of exercising market power in short-term trading after the investment and contracting stage. In that respect, by performing a stylized simulation of the French market with risk-averse agents, Abada and Ehrenmann [2023] show that welfare can be worse off after contracts are introduced when an incumbent leverages market power. The present paper follows suit by undertaking a similar effort, but here we focus on market distortions caused by a lack of price exposure instead of market power. We insist on the need to account for these distortions, as they have recently proved potentially substantial in European power markets, as illustrated above with the current crisis involving negative prices. Therefore, our research question can be summarized as follows: How can a set of risk-sharing and risk-mitigating instruments be designed to reap their full benefits for investments, particularly in renewable production, while limiting market distortions and negative prices?

To answer this question, we construct a methodological framework that captures the following features of European spot markets: i) some market drivers (such as demand, plant availability, and fuel costs) are random; ii) producers are risk-averse when they invest and contract before operating their

[5]https://www.ofgem.gov.uk/environmental-and-social-schemes/feed-tariffs-fit/scheme-closure.
[6]https://iea-pvps.org/wp-content/uploads/2021/09/NSR_Spain_2020_b.pdf.

plants; iii) the financial market is incomplete in the sense that risk cannot be perfectly exchanged between market participants; iv) producers do not necessarily react to spot prices and might distort competition depending on how contracts affect their exposure to those prices; and v) the State, anticipating the potential for contracts to induce market distortions, can calibrate the design of the hedging instruments to arbitrage optimally between risk mitigation and market distortion. Items i) through iv) can be captured by adapting standard two-stage stochastic equilibrium models of risk-averse agents with incompleteness, as developed in Ehrenmann and Smeers [2011], Philpott et al. [2016], de Maere d Aertrycke et al. [2017], and similar studies. The present paper follows suit and deploys coherent risk measures (Artzner et al. [1999]) to model risk aversion with the objective of obtaining convexity properties. Accounting for item v) constitutes this study's main methodological novelty: we embed our two-stage equilibrium model of the power economy into an optimization problem that models the objective of the State, whose decision variables are features of the contracts it offers to producers on behalf of consumers. This strategy leads naturally to a bi-level problem where the upper level models the behavior of the State and the lower level represents the power economy. We formulate our model as a Mathematical Programming problem with Equilibrium Constraints (MPEC), a class of problems known for their non-convexity and susceptibility to multiple equilibria.

1.4 Contributions and structure of the paper

The present study offers multiple noteworthy contributions to the literature. First, motivated by the recent surge in negative prices in Europe caused in part by renewable production to which we have alluded, our paper is, to the best of our knowledge, the first to extend models of power markets in incompleteness to capture some unintended consequences of risk-hedging contracts in the form of market distortions. Second, our model is also the first to incorporate an automatic procedure for optimizing the design of (some of) risk-sharing contracts, namely CfDs and price markups, which are currently debated by policymakers for green assets, to optimize welfare. In doing so, we had to extend the mathematical framework of incompleteness to an MPEC formulation where contracts are optimized on the upper level. In that respect, our model is close in flavor to the recent work of Dimanchev et al. [2024], which also analyzes the optimization of some instruments—a CO_2 tax and some technology-specific tax credits for renewable investments —to foster investments in renewables via a bi-level approach. This approach, however, falls short of fully addressing market distortions, as it still leaves producers significantly exposed to the price risk. This is the first difference between theirs and our approach. The second pertains to the algorithm we develop specifically to solve the bi-level model: Dimanchev et al. [2024] were able to reformulate the MPEC problem as a Mixed Integer Linear Problem (MILP) using a linear reformulation because they model risk aversion via Conditional Value at Risk (CVaR), which can, on the one hand, be reformulated linearly (Rockafellar and Uryasev [2000]), and most importantly, on the other hand, the instruments they optimize on the upper level induce a linear objective function. Our model, however, which adjusts parameters of CfDs and markups, involves non-linear terms, making it impossible to reformulate our MPEC as an MILP. Therefore, we had to write a specific algorithm to solve our model within a reasonable timeframe. This algorithm leverages an efficient method for solving the lower level (i.e. the two-stage stochastic investment problem in equilibrium under market incompleteness) developed in Abada and Ehrenmann [2023]. The elaboration of this specific algorithm constitutes our third contribution.

With its fourth contribution, this study addresses policymakers: by developing a realistic representation of the French market that incorporates all production technologies as well as storage (keeping in mind the subtle synergies that exist between renewable production and storage, as underscored in Kaps et al. [2023]), we can quantify the substantial impact that optimizing contract design should have on welfare with respect to some instruments that are currently implemented. We also find that this optimization can bring the system relatively close to the complete market benchmark, which is the benchmark of an efficient, smoothly functioning market where the spot market is perfectly competitive and the financial market offers sufficient instruments with which to hedge or exchange any risk. Crucially, we also demonstrate the efficiency of our approach in limiting the occurrence of negative prices by providing the right incentives for investment in sustainable assets and batteries, as well as efficient operations in the spot market. More broadly, our research represents an initial step toward identifying optimal instruments for the power system that balance risk-hedging opportunities and efficient market trading in the transition to low-emission technologies. Our model of the power economy when the financial market is incomplete is deliberately simple, as our purpose is to propose a proof of concept, demonstrating that bi-level methods can effectively support policymakers in their effort to enhance welfare while supporting the installation of renewables in the context of the energy transition.

The remainder of the paper is structured as follows. Section 2 presents our bi-level model. The lower level is outlined in Section 2.1 along with a formalization of the contracts and risk-hedging instruments we consider and Section 2.2 presents the upper-level problem of the optimal contract design. We provide an existence result in Section 3 as well as a heuristic that facilitates solving the MPEC. In Section 4, we conduct a thorough numerical application of our models to the French context and demonstrate the importance of carefully adjusting the set of risk-mitigating contracts offered to producers with respect to welfare, production, and storage capacity. Finally, Section 5 provides some policy recommendations and concluding remarks.

2 Risk and optimal contracts in the power economy

In this section we develop our bi-level approach to optimizing contracts. The stochastic investment problem under risk and incompleteness in the power economy is exposed in Section 2.1, which models the lower level. In particular, we detail in this section which kinds of contracts are offered to market participants and how we model the market distortions they might generate. Section 2.2 displays the problem of the State, which operates on the upper level and strives to maximize system welfare by adjusting contract design optimally.

2.1 The lower level: a stochastic equilibrium model of the power economy under market incompleteness

Our starting point is the model of the power economy constructed in Abada and Ehrenmann [2023], to which we add electricity storage and market distortions. Because such a model is now standard in the OR literature, we present it only briefly for the sake of completeness. To facilitate reference to the model, we deliberately retain some of the symbolic notation used by Abada and Ehrenmann [2023].

2.1.1 Generalities

Consider a power economy with n producers indexed by $i \in I = \{1, 2, ..., n\}$. Each producer invests to build capacity before operating and trading in the spot market. Without loss of generality, investors are differentiated by the production technology they own, but we still consider that the exchanged good (electricity) is homogeneous. The invested capacity of producer i is K_i (expressed in MW). The investment decision is undertaken in the first stage and the optimal operations and trading occur in the second stage. Time is indexed by $t \in T = \{1, 2, ..., \tau\}$ and we assume an hourly granularity for ease of exposition. The time set T allows us to span, for instance, an entire year of production (meaning that we set, in this case, τ to 8760 hours) or any other characteristic period (a day, a week, a month, etc.). The second stage comprises stochastic events which we model via a discrete set of scenarios Ω weighted by a probability measure $\theta(\omega)$, $\omega \in \Omega$. Agent i faces a constant marginal investment cost CI_i (or CAPEX, expressed in €/MW/year) and a constant marginal operational cost $CO_i^t(\omega)$ (or OPEX, expressed in €/MWh). The marginal operational cost is made time- and scenario-dependent as it reflects fluctuating fuel prices (natural gas, uranium, coal, etc.). Plant i's normalized availability is denoted by $g_i^t(\omega) \in [0, 1]$, and we make it stochastic to account for random outages or fluctuating meteorological conditions affecting wind and solar assets. The production of i's plant is $x_i^t(\omega)$ (expressed in MWh) and, when the producer sells it to the spot market, it receives the spot price $p^t(\omega)$ (expressed in €/MWh). For ease of exposition and to ensure that the optimization programs of market agents are convex, we abstract away from unit-commitment constraints, as we are interested primarily in long-term investment decisions and market distortions, although we are aware that these constraints constitute some main drivers of negative prices in Europe. Therefore, we model the linear version of the plants' production constraints.

We also consider storage (or battery) assets operated by a single storage operator; this feature is added to the model of Abada and Ehrenmann [2023]. The invested capacity in storage is K_s and the battery-generated volume traded is $x_s^t(\omega) \in \mathbb{R}$ (expressed in MWh): a positive (respectively, negative) value models a withdrawal (respectively, an injection) of power from (respectively, into) the battery. We linearize the battery's operational constraints; in particular, the Energy-to-Power ratio is denoted by γ (expressed in hours). In other words, the injected/withdrawn volumes are bounded by K_s and the volume of electricity stored at each moment, which we denote by $lev^t(\omega)$, should never exceed $K_s\gamma$. The marginal investment cost is taken as constant and denoted by CI_s (expressed in €/MW/year), and we overlook operational battery costs, as they are negligible with respect to the capital cost. We neglect storage losses but this can easily be relaxed in our model.

Consumers are aggregated into a single representative agent. The consumer responds to the price via the following linear inverse-demand function

$$p^t(\omega) = a^t(\omega) - b^t(\omega)d^t(\omega), \quad \forall (t, \omega) \in T \times \Omega, \tag{1}$$

with $b^t(\omega) \geq 0$. We assume linearity to ensure numerical tractability. Externalities pertaining to carbon emissions are modeled via a hard constraint whose dual variable $p_{CO_2}(\omega)$ represents the CO_2 price (expressed in €/tons). In other words, we assume that the price of CO_2 emissions is always calculated to meet the exact environmental objectives for the economy under scrutiny within the time horizon of interest. The total level of tolerated emissions between $t = 1$ and $t = \tau$ is denoted by L_{CO_2} (expressed in tons of equivalent CO_2 per year) and, naturally, we make this bound independent of the scenarios we use in the second stage. Finally, the CO_2 content of technology i is denoted by $\delta_i > 0$ (expressed in tons/GWh).

2.1.2 Generalized Contracts for Difference, price markups, and market distortions

We turn now to delineating contracts of the kind on which we focus and describing how they could be designed by the State when acting on behalf of consumers. Consider a scenario $\omega \in \Omega$ and time $t \in T$ in the second stage. If producer i sells its electricity $x_i^t(\omega)$ to the market without hedging, it receives the market price $p^t(\omega)$ and earns revenue of $p^t(\omega)x_i^t(\omega)$. If the producer secures a Fixed-Price CfD (FP-CfD) at strike price s_i, it receives the market price $p^t(\omega)$ from the market and exchanges $p^t(\omega) - s_i$ with the State outside the market (side payments). More precisely, the producer pays to the State the difference between the spot price and the strike price multiplied by production whenever $p^t(\omega) \geq s_i$; otherwise, the producer receives compensation from the State. We assume that the State passes its revenues and costs entirely on to consumers. Therefore, under a FP-CfD, the producer (respectively, the consumer) receives (respectively, pays) revenue (respectively, a cost) of:

$$R_{FP-CfD} = p^t(\omega)x_i^t(\omega) + \left(s_i - p^t(\omega)\right) x_i^t(\omega) = \Big(p^t(\omega) + s_i - p^t(\omega)\Big)x_i^t(\omega) = s_i x_i^t(\omega). \qquad (2)$$

In other words, FP-CfDs completely eliminate the price risk associated with production. These contracts have been secured by producers in Europe to undertake capital-intensive investments, mainly for nuclear technology. For example, the French nuclear operator EDF secured an FP-CfD prior to developing the Hinkley Point C 3.2 GW nuclear reactor in the UK at a strike price of 92 £/MWh (2012 prices). The so-called *as-produced* PPAs for solar and wind production yield a similar effect, as they eliminate the price risk and leave the producer with only the volume risk to manage. In practice, the strike price is calculated to reflect the technology's total production cost following an LCOE calculation (Levelized Cost Of Electricity; see Obi et al. [2017]).

To limit market distortions, it is necessary to leave the producer exposed to a portion of the spot-price risk. Therefore, our study analyzes interest in signing *Generalized* CfDs (G-CfD) that provide the following revenue to the producer,

$$R_{G-CfD} = p^t(\omega)x_i^t(\omega) + (1 - \lambda_i)\left(s_i - p^t(\omega)\right) x_i^t(\omega), \qquad (3)$$

with $\lambda_i \in [0, 1]$ representing a *technology-specific* parameter that can be adjusted by the State. Naturally, FP-CfDs represent a particular instance of G-CfDs whereby $\lambda_i = 0$ and the producer is no longer exposed to the price risk. In contrast, when λ_i is set to 1, the contract will expose the producer fully to the price risk. In other words, the higher is λ_i, the greater the risk the producer bears. This can easily be observed by rewriting expression (3) as follows:

$$R_{G-CfD} = \Big[\lambda_i p^t(\omega) + (1 - \lambda_i)\, s_i\Big] x_i^t(\omega). \qquad (4)$$

Markups offer another alternative way to subsidize investments. They can take the form of a direct subsidy of an investment (such as the one treated in Dimanchev et al. [2024]) or a markup on the revenue accrued from the amount of electricity produced. In the latter case, we can model this markup by modifying the expression of the producer's revenue (4) as follows,

$$R_{G-CfD-Markup} = \Big[\lambda_i p^t(\omega) + (1-\lambda_i)\, s_i + \beta_i\Big] x_i^t(\omega), \tag{5}$$

where $\beta_i \geq 0$ (expressed in €/MWh) is the technology-specific price markup we consider.

Of course, many other risk-mitigating instruments and subsidies exist or have been proposed by energy economists. For ease of exposition, we restrict our analysis to G-CfDs and price markups, as shown in equation (5), but our model is general enough to accommodate many other schemes, including subsidies of capacity, spot-indexed strike prices such as those implemented in some European countries where a producer which benefits from a CfD does not receive the strike price if the spot market price is negative (as simulated in our numerical application of Section 4), etc. In particular, because consumers are aggregated into a single agent, PPAs can be regarded as a particular instance of G-CfDs in our framework. In addition, a technology-dependent reference production profile for the contracts can also be specified in our model, such as the financial CfD advocated by Newbery [2023]. Needless to say, a technology i that one does not want to subsidize will be assigned values $\lambda_i = 1$ and $\beta_i = 0$. Finally, in line with current European proposals, storage assets are not subsidized in our model, but this limitation can easily be relaxed.

2.1.3 Risk aversion, risk measures, market incompleteness, and financial contracts

We turn to coherent risk measures to model risk aversion on the part of agents in the economy.[7] There are today two approaches to modeling aversion to risk. The first, widely used in economics, relies on expected concave utility functions to rank risk preferences. In contrast, the present paper adopts the second approach, which is more prevalent in finance and operations research, by employing *risk measures*. Several factors motivate this choice. First, utility functions are often challenging to estimate. Second, risk measures provide a straightforward way to incorporate hedging instruments such as contracts and options. Third, they can be formulated via optimization theory, often benefiting from favorable convexity properties. Fourth, *coherent* risk measures, as defined below, recast risk in terms of equivalent risk-adjusted expectations of loss, easing economic and financial interpretations. Since their introduction by Artzner et al. [1999], risk measures have become a standard tool for modeling risk aversion.[8] In many related studies, coherent risk measures have been used extensively to model aversion to risk related to energy-market incompleteness; these studies include Ehrenmann and Smeers [2011], Philpott et al. [2016], Abada et al. [2024], Ferris and Philpott [2022], and Mays and Jenkins [2022] to cite but a few. In practice, it is well known that many companies and financial institutions, including power-producing firms, assess risk via the so-called Conditional Value at Risk, also known as Expected Shortfall (Sarykalin et al. [2008], Sutter et al. [2011], and Filippi et al. [2020]). In fact, as argued in Wang and Zitikis [2021],

[7] The notions developed in this section are now standard in the OR and finance literature, and the editing is inspired by Abada and Ehrenmann [2023].

[8] For a comprehensive discussion of the application of risk measures in stochastic programming, we refer the reader to Shapiro et al. [2021].

the Basel Accords now adopt the CVaR as the standard method to assess market risk, making it the most widely used measure of risk in finance. As we show below, the CVaR risk measure is a particular case of a coherent risk measure.

When the financial market is complete, sufficiently many risk-hedging instruments are available, but expecting that availability is unrealistic, as this would require the existence of a set of instruments rich enough to hedge *any* stochastic payoff. Therefore, we consider the general and more realistic case of market incompleteness in which there is no unique way to value risk.[9] We then must model varying individual risk preferences, leading to an equilibrium formulation (Ralph and Smeers [2015], Gaur et al. [2011]). Faced with a stochastic payoff $Z \in \mathbb{R}^{|\Omega|}$, a market agent a values its risk $\rho_a(Z)$ using a coherent risk measure as follows,

$$\forall Z \in \mathcal{Z}, \quad \rho_a(Z) = \text{Max}_{\zeta \in \mathcal{M}_a} \left(-\mathbb{E}_\zeta[Z]\right), \tag{6}$$

where $\mathcal{M}_a \subset \mathbb{R}^{|\Omega|}$ is its risk set, which is a convex and compact set of probability measures. In other words, the risk of a stochastic payoff is the worst expected loss, evaluated with a probability measure that belongs to the risk set. Therefore, a risk-averse agent distorts the weighting of scenarios to assign greater weight to those with low or negative profits. When problem (6) has a unique solution ζ_a^*, we call it the risk-adjusted probability. With the envelope theorem, we can show that the risk measure is differentiable almost everywhere on $\mathbb{R}^{|\Omega|}$ and we can write that

$$\partial \rho_{a_Z}(Z) = -\zeta_a^* = -\text{Argmax}_{\zeta \in \mathcal{M}_a} \left(-\mathbb{E}_\zeta[Z]\right). \tag{7}$$

In the remainder of this paper, we assume that risk measures are differentiable, possibly after an infinitesimal perturbation of the data. It is well known that any *financial* agreement exchanged by agent a can be incorporated into the expression of its risk set $\mathcal{M}_a$ by writing an absence-of-arbitrage condition between the first and second stages indicating that the risk-adjusted expectation of the payoff on the agreement should equal its cost. Therefore, we do not model *financial* instruments explicitly, focusing instead on the *physical* risk-mitigation instruments presented in Section 2.1.2. Finally, we define the risk-adjusted profit of agent a as $\mathbb{E}_{\zeta_a^*}[Z]$, which is also the opposite of its risk $\rho_a(Z)$.

The most popular example of a coherent risk measures is certainly the Conditional Value at Risk (CVaR) or the Expected Shortfall, which can be expressed in the form of (6) as (Rockafellar and Uryasev [2000]):

$$\begin{aligned} \rho_a^{CVaR}(Z) = \quad & \text{Max} \quad \left(-\textstyle\sum_\omega \zeta(\omega) Z(\omega)\right) \\ & \text{s.t.} \quad 0 \le \zeta(\omega) \le \tfrac{\theta(\omega)}{1-\xi_a} \qquad \forall \omega \in \Omega \\ & \qquad\quad \textstyle\sum_\omega \zeta(\omega) = 1, \end{aligned} \tag{8}$$

where $\xi_a \in [0,1]$ is agent a's level of risk aversion. As ξ_a approaches 0, the CVaR assesses risk in a risk-neutral manner, equivalent to computing the expected loss under distribution θ (which is the natural distribution of scenarios). Conversely, as ξ_a approaches 1, the risk measure adopts a robust approach, considering only the worst-case scenario with the highest loss. We will leverage this risk measure in our

[9] Indeed, it can be demonstrated that when the financial market is complete, any stochastic payoff can be valued in a unique manner by a risk-averse agent resorting to a risk measure (Ralph and Smeers [2011]).

numerical application of Section 4.

2.1.4 Modeling the producers and market distortions

We now turn to modeling the behavior of producers. We proceed by backward induction. Given invested capacity K_i, in each scenario $\omega \in \Omega$ in the second stage, producer i maximizes its profit by adjusting its production $x_i^t(\omega)$,

$$
\begin{aligned}
Z_i(\omega, K_i) = \text{Max} \quad & \sum_{t=1}^{\tau} \Big[\lambda_i p^t(\omega) + (1-\lambda_i)\, s_i + \beta_i - CO_i^t(\omega) - \delta_i p_{CO_2}(\omega)\Big] x_i^t(\omega) \\
\text{s.t} \quad & x_i^t(\omega) \geq 0 && \forall t \in T \\
& x_i^t(\omega) \leq K_i g_i^t(\omega) && (\mu_i^t(\omega)), \quad \forall t \in T.
\end{aligned}
\tag{9}
$$

where some relevant dual variables are written next to their constraints. Moral hazard in the form of market distortions is reflected explicitly in the formulation of the objective function, as producers respond not only to the spot-market price $p^t(\omega)$ but also to risk-mitigation instruments and subsidies. This sensitivity is often overlooked in the existing literature, which typically focuses solely on the impact of these instruments and subsidies on investment decisions, neglecting their influence on short-term physical trading. Optimization program (9) is convex; it exhibits the following KKT conditions:

$$
\begin{aligned}
0 \leq x_i^t(\omega) \perp \quad & \mu_i^t(\omega) + CO_i^t(\omega) - \beta_i + \delta_i p_{CO_2}(\omega) - \lambda_i p^t(\omega) - (1-\lambda_i)\, s_i \geq 0 && \forall t \in T \\
0 \leq \mu_i^t(\omega) \perp \quad & K_i g_i^t(\omega) - x_i^t(\omega) \geq 0 && \forall t \in T.
\end{aligned}
\tag{10}
$$

Dual variables $\mu_i^t(\omega)$ represent the so-called scarcity rents: they quantify the margins accrued from the spot market as indicated in the first line of (10). Producer i values its stochastic second-stage payoff $Z_i(\omega, K_i)$ via its risk measure ρ_i that is associated with risk set $\mathcal{M}_i$ as specified in (6),

$$
\rho_i(K_i) = \text{Max}_{\zeta_i \in \mathcal{M}_i} \left(- \sum_{\omega \in \Omega} \zeta_i(\omega) Z_i(\omega, K_i) \right), \tag{11}
$$

which provides an expression of the second-stage risk-adjusted profit from the investment $-\rho_i(K_i)$. Moving to the first stage, the producer estimates its invested capacity K_i that maximizes its risk-adjusted profit net of the investment cost, as in

$$
\text{Max}_{K_i \geq 0} \ \Big[-\rho_i(K_i) - CI_i K_i \Big]. \tag{12}
$$

This optimization problem is of the Max Min Max form. Leveraging the envelope theorem, it can be shown that it is nevertheless convex (thanks to the use of a coherent risk measure) and that it can be tackled via its KKT conditions, which we can write as follows (we refer for instance to Abada and Ehrenmann [2023] for the full derivation of the following equations):

$$
\begin{aligned}
0 \leq x_i^t(\omega) \perp \quad & \mu_i^t(\omega) + CO_i^t(\omega) - \beta_i + \delta_i p_{CO_2}(\omega) - \lambda_i p^t(\omega) - (1-\lambda_i)\, s_i \geq 0 \quad && \forall(\omega, t) \in \Omega \times T \\
0 \leq \mu_i^t(\omega) \perp \quad & K_i g_i^t(\omega) - x_i^t(\omega) \geq 0 \quad && \forall(\omega, t) \in \Omega \times T \\
0 \leq K_i \perp \quad & CI_i - \sum_{\omega \in \Omega} \zeta_i^*(\omega) \left(\sum_{t=1}^{T} \mu_i^t(\omega) g_i^t(\omega) \right) \geq 0 \\
\zeta_i^* = \quad & \text{Argmax}_{\zeta_i \in \mathcal{M}_i} \left(- \sum_{\omega \in \Omega} \zeta_i(\omega) \sum_{t=1}^{T} \mu_i^t(\omega) g_i^t(\omega) \right).
\end{aligned} \tag{13}
$$

Variables $\zeta_i^*(\omega)$ constitute the risk-adjusted probability of producer i. The third line of (13) conveys an interesting economic interpretation of our model. It states that the producer invests if only it trusts that it recoups the investment cost through the risk-adjusted expectation of second-stage scarcity rents multiplied by the availability of the producer's plant. Finally, at optimality, we define the industry's risk-adjusted profit as producers' total risk-adjusted profit:

$$RAP = \sum_{i=1}^{n} \Big[\sum_{\omega \in \Omega} \zeta_i^*(\omega) Z_i(\omega, K_i) - CI_i K_i \Big]. \tag{14}$$

2.1.5 Modeling storage

In scenario $\omega \in \Omega$, the storage operator manages its batteries to maximize profit while respecting its technical constraints. Here again, we reason by backward induction assuming that storage capacity K_s has already been set in the first stage and we remind readers that battery operators do not receive any subsidy from the State and that they do not pay the CO_2 price inasmuch as they only transport energy through time:

$$
\begin{aligned}
Z_s(\omega, K_s) = \text{Max} \quad & \sum_{t=1}^{\tau} p^t(\omega) x_s^t(\omega) \\
\text{s.t} \quad & x_s^t(\omega) \geq -K_s && (\nu_s^t(\omega)), \quad \forall t \in T \\
& x_s^t(\omega) \leq K_s && (\mu_s^t(\omega)), \quad \forall t \in T \\
& lev^t(\omega) = lev^{t-1}(\omega) - x_s^t(\omega) && (\sigma_s^t(\omega)), \quad \forall t \in \{2, ..., \tau\} \\
& 0 \leq lev^t(\omega) \leq \gamma K_s && (v_s^t(\omega)), \quad \forall t \in T \\
& lev^{t=1}(\omega) = 0.
\end{aligned} \tag{15}
$$

The first and second constraints limit the volume of power that can be stored and withdrawn from the battery by the invested capacity. The third constraint models the state equation and the fourth constraint limits the volume of electricity stored in the battery by the invested capacity multiplied by the number of hours of storage γ. Furthermore, we control for edge effects by imposing the final condition that the battery is always empty at $t = 1$. Here again, the storage operator values its second-stage profit through the prism of a risk measure ρ_s associated with risk set $\mathcal{M}_s$,

$$\rho_s(K_s) = \text{Max}_{\zeta_s \in \mathcal{M}_s} \left(- \sum_{\omega \in \Omega} \zeta_s(\omega) Z_s(\omega, K_s) \right), \tag{16}$$

and in the first stage the operator maximizes its risk-adjusted revenue net of the investment cost:

$$\text{Max}_{K_s \geq 0} \ \Big[- \rho_s(K_s) - CI_s K_s \Big]. \tag{17}$$

We can demonstrate that optimization problem (17) is convex and resort to the envelope theorem to derive the KKT conditions of the storage operator's investment problem as follows:[10]

$$\begin{aligned}
x_s^t(\omega) \perp & \quad \mu_s^t(\omega) - \nu_s^t(\omega) + \sigma_s^t(\omega) - p^t(\omega) = 0 & \forall(\omega, t) \in \Omega \times T \\
0 \leq lev^t(\omega) \perp & \quad \sigma_s^t(\omega) - \sigma_s^{t+1}(\omega) + v_s^t(\omega) \geq 0 & \forall(\omega, t) \in \Omega \times T - \{\tau\} \\
0 \leq \mu_s^t(\omega) \perp & \quad K_s - x_s^t(\omega) \geq 0 & \forall(\omega, t) \in \Omega \times T \\
0 \leq \nu_s^t(\omega) \perp & \quad K_s + x_s^t(\omega) \geq 0 & \forall(\omega, t) \in \Omega \times T \\
\sigma_s^t(\omega) \perp & \quad lev^t(\omega) - lev^{t-1}(\omega) + x_s^t(\omega) = 0 & \forall(\omega, t) \in \Omega \times T - \{1\} \\
0 \leq v_s^t(\omega) \perp & \quad \gamma K_s - lev^t(\omega) \geq 0 & \forall(\omega, t) \in \Omega \times T \\
0 \leq K_s \perp & \quad CI_s - \sum_{\omega \in \Omega} \zeta_s^*(\omega) \sum_{t=1}^{T} \big(v_s^t(\omega)\gamma + \mu_s^t(\omega) + \nu_s^t(\omega) \big) \geq 0 & \\
\zeta_s^* = & \quad \text{Argmax}_{\zeta_s \in \mathcal{M}_s} \left(- \sum_{\omega \in \Omega} \zeta_s(\omega) \sum_{t=1}^{T} p^t(\omega) x_s^t(\omega) \right). &
\end{aligned} \tag{18}$$

The seventh equation in (18) gives the investment criterion: the storage operator invests only if it trusts that it recovers the CAPEX cost via its risk-adjusted second-stage margins. Finally, we define the storage operator's risk-adjusted profit at optimality as

$$RAPS = \sum_{\omega \in \Omega} \zeta_s^*(\omega) Z_s(\omega, K_s) - CI_s K_s. \tag{19}$$

2.1.6 Modeling consumers

In scenario ω in the second stage, consumers adjust their consumption $d^t(\omega)$ to maximize their surplus as follows:

$$\begin{aligned}
CS(\omega) = \text{Max} \quad & \sum_{t=1}^{\tau} \left(a^t(\omega) d^t(\omega) - b^t(\omega) \frac{d^t(\omega)^2}{2} - p^t(\omega) d^t(\omega) \right) \\
& - \sum_{t=1}^{\tau} \left(\sum_{i \in I} \Big[(1 - \lambda_i)(s_i - p^t(\omega)) + \beta_i \Big] x_i^t(\omega) \right) \\
\text{s.t} \quad & d^t(\omega) \geq 0 \qquad \forall t \in T.
\end{aligned} \tag{20}$$

The consumer surplus is composed of two terms: the first is the utility accrued from consumption net of the cost incurred from buying electricity at the market price. The second term is the side payment the State exchanges with producers for their G-CfDs and markups, which, we remind the reader, is assumed to be transferred to consumers. Because this second term is, in fact, independent of the consumers' decision variable (their consumption), it does not intervene in the formation of the KKT conditions of

[10] In the remainder of the present paper, when A and B are two sets, we use $A - B$ to denote $A \cap \bar{B}$.

optimization problem (20):

$$0 \leq d^t(\omega) \perp \left(p^t(\omega) - a^t(\omega) + b^t(\omega)d^t(\omega)\right) \geq 0 \quad \forall t \in T. \tag{21}$$

Side payments appear, however, when one calculates risk-adjusted probabilities $\zeta_d^*(\omega)$, which are obtained as follows,

$$\zeta_d^* = \text{Argmax}_{\zeta_d \in \mathcal{M}_d} \left(- \sum_{\omega \in \Omega} \zeta_d(\omega) CS(\omega) \right), \tag{22}$$

where $\mathcal{M}_d$ is consumers' risk set. They also appear in the expression of the risk-adjusted consumer surplus, which we define as:

$$RACS = \sum_{\omega \in \Omega} \zeta_d^*(\omega) CS(\omega). \tag{23}$$

2.1.7 The Nash equilibrium

Given that the financial market is incomplete, we must model the power economy as a partial equilibrium model where each agent optimizes its profit given the output of the other agents. We undertake this task by concatenating the KKT conditions for all market agents—(13) with $i \in I$ for producers, (18) for the storage operator, and (21) for consumers—to which we add i) a spot-market-clearing constraint whose dual variable models the market price, and ii) a constraint on carbon emissions whose dual variable represents the CO_2 price, as written below:

$$\begin{aligned} p^t(\omega)\perp \qquad & d^t(\omega) - \sum_{i=1}^{n} x_i^t(\omega) - x_s^t(\omega) = 0 \qquad && \forall (\omega, t) \in \Omega \times T \\ 0 \leq p_{CO_2}(\omega)\perp \qquad & \sum_{i=1}^{n}\sum_{t=1}^{\tau} \delta_i x_i^t(\omega) \leq L_{CO_2} && \forall \omega \in \Omega. \end{aligned} \tag{24}$$

Several studies have demonstrated that our problem always has a solution provided that the interior of the intersection of market agents' risk sets, $\cap_{i\in}\mathcal{M}_i \cap \mathcal{M}_s \cap \mathcal{M}_d$, is not empty. To make our notation more precise, we concatenate all our primal and dual variables,

$x_i^t(\omega), K_i, x_s^t(\omega), lev^t(\omega), K_s, d^t(\omega), \mu_i^t(\omega), \zeta_i^*(\omega), \mu_s^t(\omega), \nu_s^t(\omega), \sigma_s^t(\omega), \upsilon_s^t(\omega), \zeta_s^*(\omega), \zeta_d^*(\omega), p^t(\omega)$, and $p_{CO_2}(\omega)$,

into a single vector $\boldsymbol{X} \in \mathbb{R}^{\left[|\Omega|(T(2n+8)+n+3)+n+1\right]}$. We also concatenate variables λ_i and β_i, where $i \in I$, into a vector $(\boldsymbol{\lambda}, \boldsymbol{\beta}) \in \mathbb{R}^{2n}$ and denote by $Sol\,(\boldsymbol{\lambda}, \boldsymbol{\beta})$, the solution set for our equilibrium problem of the power economy (13), (18), (21), and (24). We make the dependence of this solution set with respect to variables $\boldsymbol{\lambda}, \boldsymbol{\beta}$ explicit in the notation. Additionally, we also amend the notation for the risk-adjusted profits of producers (14), the storage operator (19), and the consumer surplus (23) by making them depend explicitly on $\boldsymbol{X}$. For example, the risk-adjusted consumer surplus will henceforth be denoted as $RACS(\boldsymbol{X})$.

Proposition 1. *If the interior of set* $\left(\cap_{i\in}\mathcal{M}_i \cap \mathcal{M}_s \cap \mathcal{M}_d\right)$ *is not empty, then* $\forall\,(\boldsymbol{\lambda}, \boldsymbol{\beta}) \in \mathbb{R}^{2n}$, $Sol\,(\boldsymbol{\lambda}, \boldsymbol{\beta})$ *is not empty.*

Proof. This results from a fixed-point argument. We refer to de Maere d Aertrycke and Smeers [2013], Theorem 3.14, for a general proof of the proposition.

2.2 The upper level: optimizing contracts

On the upper level, the State, acting as a benevolent agent, adjusts the design of the contracts $\boldsymbol{\lambda}$ and price markups $\boldsymbol{\beta}$ to maximize the risk-adjusted system's welfare. We define the latter as the sum of the risk-adjusted profits of the industry (producers), the storage operator, and the risk-adjusted consumer surplus:

$$RASW(\boldsymbol{X}) = RAP(\boldsymbol{X}) + RAPS(\boldsymbol{X}) + RACS(\boldsymbol{X}). \tag{25}$$

In other words, we assume that the State anticipates the outcome of the power economy resulting from the set and design of risk-mitigating schemes and the subsidies it offers to market participants investing in a context of market incompleteness. In doing so, the State also anticipates that producers can be subject to moral hazard by bidding non-competitively in spot markets, as discussed in Section 2.1.4. The optimization problem for the State is the following:

$$\begin{aligned}
\text{Max} \quad & RASW(\boldsymbol{X}) & \\
\text{s.t} \quad & \boldsymbol{X} \in Sol\,(\boldsymbol{\lambda}, \boldsymbol{\beta}) & \\
& 0 \leq \lambda_i \leq 1 & \forall i \in I \\
& 0 \leq \beta_i & \forall i \in I \\
& \lambda_i = 1 \text{ and } \beta_i = 0 & \forall i \in I'.
\end{aligned} \tag{26}$$

We denote by $I' \subset I$ the set of technologies that the State does not want to subsidize or promote, either because they are already profitable or because, like coal-fired power plants, they are not aligned with energy transition objectives.

Problem (26) is expressed as a Mathematical Programming problem with Equilibrium Constraints, or MPEC. MPEC problems, which are a particular instances of bi-level problems (Colson et al. [2007]), are famously difficult to solve because they are non-convex most of the time (see, for instance, the seminal work of Luo et al. [1996]). In our case, non-convexity stems from two key factors. On the one hand, the complementarity conditions on the lower level that are embedded in the formulation of set $Sol\,(\boldsymbol{\lambda}, \boldsymbol{\beta})$ involve non-convex products of variables. On the other hand, the objective function of the MPEC also comprises products of variables: for instance, the risk-adjusted producers' profit includes the products of such variables as $\lambda_i p^t(\omega)$. We present in the next section a strategy for tackling this issue.

3 Some theoretical results and a heuristic with which to solve the problem

In this section we demonstrate that our bi-level problem (26) has at least one solution and we propose a heuristic to find one numerically.

3.1 An existence result

To prove the existence of a solution, we must make an assumption pertaining to the formation of investors' risk-neutral probabilities, as follows:

Assumption H1. *Risk measures ρ_i, $i \in I$ and ρ_s always assign positive values to risk-adjusted probabilities:*

$$\forall i \in I,\ \forall Z \in \mathbb{R}^{|\Omega|}, \forall \zeta^* \in Argmax_{\zeta^* \in \mathcal{M}_i} \left(- \sum_{\omega \in \Omega} \zeta^*(\omega) Z(\omega) \right),\ \forall \omega \in \Omega,\ \zeta^*(\omega) > 0, \tag{27}$$

$$\forall Z \in \mathbb{R}^{|\Omega|}, \forall \zeta^* \in Argmax_{\zeta^* \in \mathcal{M}_s} \left(- \sum_{\omega \in \Omega} \zeta^*(\omega) Z(\omega) \right),\ \forall \omega \in \Omega,\ \zeta^*(\omega) > 0. \tag{28}$$

Economically, Assumption H1 ensures that the producers and storage operator account for all scenarios when they value their investment decisions. This prevents some scarcity rents $\mu_i^t(\omega)$, $\mu_s^t(\omega)$, $\nu_s^t(\omega)$, and $v_s^t(\omega)$ from being degenerate. Assumption H1 is, in fact, not new as it has already been invoked in theoretical articles that analyze investment decisions in an incomplete market (see, for instance, Abada et al. [2017a]). Practically speaking, the assumption always holds for some specific risk measures such as entropic or good-deal risk measures (provided that risk aversion is not excessive in this case; see Cochrane and Saa-Requejo [2000]). Most importantly, the assumption always applies when one values risk via a coherent risk measure $\tilde{\rho}$ built from a convex combination of the expectation under the natural probability measure θ and a coherent risk measure ρ of the form

$$\forall Z \in \mathbb{R}^{|\Omega|},\ \tilde{\rho}(Z) = -\phi \mathbb{E}_\theta(Z) + (1-\phi)\rho(Z) \tag{29}$$

with $\phi \in (0,1)$. This approach, similar in spirit to the mean-variance portfolio optimization of Markowitz [2014], has been used by several authors when modeling risk aversion on the part of electricity agents, as in Downward et al. [2012].

Theorem 1. *Under Assumption H1, Problem* (26) *has at least one solution.*

The proof relies on a continuity argument. Schematically, optimization problem (26) can be reformulated as follows,

$$\begin{aligned} \text{Max} \quad & f(\boldsymbol{X}, \boldsymbol{\lambda}, \boldsymbol{\beta}) \\ \text{s.t} \quad & (\boldsymbol{X}, \boldsymbol{\lambda}, \boldsymbol{\beta}) \in \mathcal{H}, \end{aligned} \tag{30}$$

where

$$f(\boldsymbol{X}, \boldsymbol{\lambda}, \boldsymbol{\beta}) = RASW(\boldsymbol{X}) \tag{31}$$

and

$$\mathcal{H} = \left\{ (\boldsymbol{X}, \boldsymbol{\lambda}, \boldsymbol{\beta}) \in \mathbb{R}^{m+2n} \text{ s.t. } \boldsymbol{X} \in Sol(\boldsymbol{\lambda}, \boldsymbol{\beta}) \text{ and } (\boldsymbol{\lambda}, \boldsymbol{\beta}) \in \mathcal{F} \right\}, \tag{32}$$

and where, for ease of notation, integer m is defined as the dimension of vector $\boldsymbol{X}$,

$$m = |\Omega| \left(T(2n+8) + n + 3 \right) + n + 1, \tag{33}$$

and set $\mathcal{F}$ is the feasibility set of the upper-level problem:

$$\mathcal{F} = \left\{ (\boldsymbol{\lambda}, \boldsymbol{\beta}) \in \mathbb{R}^{2n} \text{ s.t. } \forall i \in I,\ \lambda_i \in [0,1] \text{ and } \beta_i \geq 0 \text{ and } \forall i' \in I',\ \lambda_{i'} = 1 \text{ and } \beta_{i'} = 0 \right\}. \tag{34}$$

Function f is continuous because the risk-adjusted profits of producers and the storage operator as well as the risk-adjusted consumer surplus involve continuous expressions of the lower-level variable $\boldsymbol{X}$. Furthermore, set $\mathcal{H}$ is clearly not empty (by Proposition 1). It remains to demonstrate that set $\mathcal{H}$ can be cast into a compact set, which we undertake in Appendix A. Therefore, Problem (30) is designed to optimize a continuous function on a compact set, which guarantees the existence of a solution.

3.2 Finding a solution

In this section, we propose a heuristic with which to seek a solution to our bi-level problem. In that respect, numerous numerical methods for solving an MPEC have been proposed in the OR literature for various applications, including electricity systems. A non-exhaustive list includes Scholtes and Stöhr [1999], Facchinei et al. [1999], Giallombardo and Ralph [2008], Gabriel and Leuthold [2010], Siddiqui and Gabriel [2013], and Guo et al. [2015]. Addressing a problem that is similar to ours, Dimanchev et al. [2024] use an MILP reformulation of the problem by transforming complementarity conditions on the lower level into linear equations involving integer variables. Such an approach would not work in our case because the upper-level objective involves products of variables, as explained in Section 2.2. In that vein, we found that an MINLP (Mixed Integer Non-Linear Problem) reformulation of our problem, following the philosophy of Dimanchev et al. [2024], did not provide satisfactory results when implemented for large models involving multiple producers, scenarios, and hours. More broadly, we also tried to solve our model using standard NLP (Non-Linear Problems) commercial solvers such as IPOPT without success. Furthermore, an iterative relaxation of complementarity constraints $x.equation = 0$ of the form $|x.equation| =\leq \epsilon$ with decreasing ϵ proved efficient for large values of ϵ but quickly became intractable when ϵ was reduced.

We believe that these approaches cannot resolve our MPEC problem because of the challenges associated with solving the lower-level problem in its complementarity form, even when employing polyhedral risk measures such as the Conditional Value at Risk (CVaR) to model risk aversion; CVaR is a measure that can be expressed in a linearized form (Rockafellar and Uryasev [2000]). This issue has been reported repeatedly in the literature (Abada and Ehrenmann [2023], Abada et al. [2017b]) and some heuristics have been proposed to tackle the lower-level problem numerically and also efficiently. This observation is the starting point of the procedure we propose for solving the MPEC. Given that the literature provides an efficient means of solving the lower level, we can easily calculate, for a given set of contracts and subsidy parameters $(\boldsymbol{\lambda}, \boldsymbol{\beta})$, risk-adjusted social welfare. In other words, we have an efficient heuristic to estimate the objective function of Problem (26). Therefore, it is natural to develop a gradient-based approach to solve the MPEC, as we now explain.

Algorithm A: solving the lower level. Given upper-level variables $(\boldsymbol{\lambda}, \boldsymbol{\beta})$, we solve the lower level following the heuristic of Abada and Ehrenmann [2023], which we generalize by adding the storage operator problem and the CO_2 emissions constraint. Given upper-level variables $(\boldsymbol{\lambda}, \boldsymbol{\beta})$, we split the lower-level problem into two sub-problems and denote by $q \in \mathbb{N}$ the iteration of the present algorithm. The first sub-problem focuses on physical trade and investment decisions for given risk-adjusted probabilities $\zeta_i^{q-1}(\omega)$, $i \in I$, $\zeta_s^{q-1}(\omega)$, and $\zeta_d^{q-1}(\omega)$ obtained at iteration $q-1$. We denote this sub-problem as Sub-problem $P^q(\zeta_i^{q-1}, \zeta_s^{q-1} \zeta_d^{q-1})$ and express it as a complementarity problem that has the same complexity as a standard two-stage stochastic equilibrium problem of capacity expansion with spot trade. In practice, this problem can be tackled efficiently by standard complementarity solvers.

Sub-problem $P^q(\zeta_i^{q-1}, \zeta_s^{q-1}\zeta_d^{q-1})$ is:

$$
\begin{aligned}
0 \le x_i^t(\omega) \perp \quad & \mu_i^t(\omega) + CO_i^t(\omega) - \beta_i + \delta_i p_{CO_2}(\omega) - \lambda_i p^t(\omega) - (1-\lambda_i)\, s_i \ge 0 && \forall(\omega,t) \in \Omega \times T \\
0 \le \mu_i^t(\omega) \perp \quad & K_i g_i^t(\omega) - x_i^t(\omega) \ge 0 && \forall(\omega,t) \in \Omega \times T \\
0 \le K_i \perp \quad & CI_i - \sum_{\omega\in\Omega} \zeta_i^{q-1}(\omega) \left(\sum_{t=1}^{T} \mu_i^t(\omega) g_i^t(\omega) \right) \ge 0 && \\
x_s^t(\omega) \perp \quad & \mu_s^t(\omega) - \nu_s^t(\omega) + \sigma_s^t(\omega) - p^t(\omega) = 0 && \forall(\omega,t) \in \Omega \times T \\
0 \le lev^t(\omega) \perp \quad & \sigma_s^t(\omega) - \sigma_s^{t+1}(\omega) + v_s^t(\omega) \ge 0 && \forall(\omega,t) \in \Omega \times T - \{\tau\} \\
0 \le \mu_s^t(\omega) \perp \quad & K_s - x_s^t(\omega) \ge 0 && \forall(\omega,t) \in \Omega \times T \\
0 \le \nu_s^t(\omega) \perp \quad & K_s + x_s^t(\omega) \ge 0 && \forall(\omega,t) \in \Omega \times T \\
\sigma_s^t(\omega) \perp \quad & lev^t(\omega) - lev^{t-1}(\omega) + x_s^t(\omega) = 0 && \forall(\omega,t) \in \Omega \times T - \{1\} \\
0 \le v_s^t(\omega) \perp \quad & \gamma K_s - lev^t(\omega) \ge 0 && \forall(\omega,t) \in \Omega \times T \\
0 \le K_s \perp \quad & CI_s - \sum_{\omega\in\Omega} \zeta_s^{q-1}(\omega) \sum_{t=1}^{T} \left(v_s^t(\omega)\gamma + \mu_s^t(\omega) + \nu_s^t(\omega) \right) \ge 0 && \\
0 \le d^t(\omega) \perp \quad & \left(p^t(\omega) - a^t(\omega) + b^t(\omega) d^t(\omega) \right) \ge 0 && \forall t \in T \\
p^t(\omega) \perp \quad & d^t(\omega) - \sum_{i=1}^{n} x_i^t(\omega) - x_s^t(\omega) = 0 && \forall(\omega,t) \in \Omega \times T \\
0 \le p_{CO_2}(\omega) \perp \quad & \sum_{i=1}^{n} \sum_{t=1}^{\tau} \delta_i x_i^t(\omega) \le L_{CO_2} && \forall \omega \in \Omega.
\end{aligned}
\tag{35}
$$

From Sub-problem $P^q(\zeta_i^{q-1}, \zeta_s^{q-1}\zeta_d^{q-1})$, we extract, at equilibrium, the expressions of the stochastic profits of producers $Z_i^q(\omega)$, $i \in I$, the storage operator $Z_s^q(\omega)$, and the consumer surplus $CS^q(\omega)$ by leveraging equations (9), (15), and (20), respectively. We also keep track of investment decisions K_i and K_s, which we concatenate into a vector, $\mathbf{K}^q \in \mathbb{R}^{n+1}$. We then use agents' profits and the surplus to compute risk-adjusted probabilities $\zeta_i^q(\omega)$, $i \in I$, $\zeta_s^q(\omega)$, and $\zeta_d^q(\omega)$ at iteration q from the financial Sub-problem $F^q(Z_i^q, Z_s^q, CS^q)$, as follows:

Sub-problem $F^q(Z_i^q, Z_s^q, CS^q)$ is:

$$
\begin{aligned}
\zeta_i^q &= \operatorname{Argmax}_{\zeta_i \in \mathcal{M}_i} \left(- \sum_{\omega\in\Omega} \zeta_i(\omega) Z_i^q(\omega) \right) \\
\zeta_s^q &= \operatorname{Argmax}_{\zeta_s \in \mathcal{M}_s} \left(- \sum_{\omega\in\Omega} \zeta_s(\omega) Z_s^q(\omega) \right) \\
\zeta_d^q &= \operatorname{Argmax}_{\zeta_s \in \mathcal{M}_d} \left(- \sum_{\omega\in\Omega} \zeta_s(\omega) CS^q(\omega) \right).
\end{aligned}
\tag{36}
$$

Financial Problem $F^q(Z_i^q, Z_s^q, CS^q)$ is summable and is equivalent to

$$
\operatorname*{Max}_{\substack{\zeta_i^q \in \mathcal{M}_i, \quad i \in I \\ \zeta_s^q \in \mathcal{M}_s \\ \zeta_d^q \in \mathcal{M}_d}} \left[- \sum_{\omega\in\Omega} \left(\sum_{i\in I} \zeta_i^q(\omega) Z_i^q(\omega) + \zeta_s^q(\omega) Z_s^q(\omega) + \zeta_d^q(\omega) CS^q(\omega), \right) \right], \tag{37}
$$

implying that it can be solved efficiently. We now have collected all the building blocks we need to express Algorithm A:

- **Initialization.** We initialize the risk-adjusted probabilities as follows:

$$\begin{aligned} \zeta_i^0(\omega) &= \theta(\omega) \quad \forall (i,\omega) \in I \times \Omega \\ \zeta_s^0(\omega) &= \theta(\omega) \quad \forall \omega \in \Omega \\ \zeta_d^0(\omega) &= \theta(\omega) \quad \forall \omega \in \Omega. \end{aligned} \tag{38}$$

- **Iteration.** At iteration $q \geq 1$, we solve physical Sub-problem $P^q(\zeta_i^{q-1}, \zeta_s^{q-1}\zeta_d^{q-1})$ and compute Z_i^q, $i \in I$, Z_s^q, and CS^q. We then solve financial Sub-problem $F^q(Z_i^q, Z_s^q, CS^q)$ to obtain solution ζ_i^*, ζ_s^*, and ζ_d^* at optimality. At iteration q, ζ_i^q, ζ_s^q, and ζ_d^q are computed as

$$\begin{aligned} \zeta_i^q(\omega) &= (1-\iota)\zeta_i^{q-1}(\omega) + \iota\zeta_i^*(\omega) \quad \forall (i,\omega) \in I \times \Omega \\ \zeta_s^q(\omega) &= (1-\iota)\zeta_s^{q-1}(\omega) + \iota\zeta_s^*(\omega) \quad \forall \omega \in \Omega, \\ \zeta_d^q(\omega) &= (1-\iota)\zeta_d^{q-1}(\omega) + \iota\zeta_d^*(\omega) \quad \forall \omega \in \Omega, \end{aligned} \tag{39}$$

  with $\iota \in (0, 1]$ being the *memory rate*.

- **Stopping criterion.** Carry on the iteration phase until convergence,

$$\|\mathbf{K}^q - \mathbf{K}^{q-1}\| \leq \text{tolerance}_A, \tag{40}$$

  where $\text{tolerance}_A > 0$ is the convergence tolerance level and $\|.\|$ is a norm defined over the space $\mathbb{R}^{n+1}$.

By design, when it converges, Algorithm A always finds an element of $Sol\,(\boldsymbol{\lambda}, \boldsymbol{\beta})$, i.e., an equilibrium solution to the lower-level problem given the State's policy $(\boldsymbol{\lambda}, \boldsymbol{\beta})$. Practically speaking, we found that the algorithm finds a solution systematically, even though we are aware that it might miss others, as shown in Gérard et al. [2018]. We also observed that convergence is facilitated by the introduction of some memory, modeled by parameter ι, during the iteration process. Needless to say, after convergence we can calculate system welfare and other indicators at the reached solution straightforwardly.

Algorithm B: solving the upper level (MPEC). We now outline our heuristic for solving Problem (26), following a gradient-ascent procedure. Gradient-based methods have recently garnered heightened interest with the advent of machine learning, as they are used routinely to calibrate weights of neural networks. They are, however, hardly general enough to accommodate large classes of problems, as they should be tailored to the numerical characteristics of a given problem to be solved, as shown by the variety of methods proposed for adjusting the algorithm's learning rate optimally (see, for instance, Baydin et al. [2017], Smith [2017], Nacson et al. [2019], Zhang [2019], and Smith and Topin [2019] for some recent articles on the topic; we also refer the reader to Ruder [2016] for a review). The gradient method is iterative: $(\boldsymbol{\lambda}^q, \boldsymbol{\beta}^q)$ is the upper-level variable at iteration $q \in \mathbb{N}$.

- **Initialization.** We initialize the upper-level decision variables as follows (no subsidies):

$$\begin{aligned} \beta_i^0(\omega) &= 0 \quad \forall i \in I \\ \lambda_i^0(\omega) &= 1 \quad \forall i \in I. \end{aligned} \tag{41}$$

- **Iteration.** At iteration $q \geq 1$, we estimate the gradient of the State's objective function by perturbing point $\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right)$ along all dimensions corresponding to the power plants one wants to subsidize $I - I'$ and by estimating risk-adjusted welfare via Algorithm A. More precisely, we approximate the gradient of risk-adjusted system welfare at $\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right)$ as follows:

  1. For any $i \in I - I'$, use Algorithm A to calculate risk-adjusted welfare at some perturbed points (in what follows, by abuse of notation, we make explicit the dependence of $RASW$ with respect to upper-level decision variables),

  $$\begin{aligned} RASW_{\lambda_i,-} &= RASW\left(\lambda_1^{q-1}, \lambda_2^{q-1}, ..., \lambda_i^{q-1} - \epsilon, ..., \lambda_n^{q-1}, \boldsymbol{\beta}^{q-1}\right) \quad \forall i \in I - I' \\ RASW_{\lambda_i,+} &= RASW\left(\lambda_1^{q-1}, \lambda_2^{q-1}, ..., \lambda_i^{q-1} + \epsilon, ..., \lambda_n^{q-1}, \boldsymbol{\beta}^{q}\right) \quad \forall i \in I - I' \\ RASW_{\beta_i,-} &= RASW\left(\boldsymbol{\lambda}^{q-1}, \beta_1^{q-1}, \beta_2^{q-1}, ..., \beta_i^{q-1} - \epsilon, ..., \beta_n^{q-1}\right) \quad \forall i \in I - I' \\ RASW_{\beta_i,+} &= RASW\left(\boldsymbol{\lambda}^{q-1}, \beta_1^{q-1}, \beta_2^{q-1}, ..., \beta_i^{q-1} + \epsilon, ..., \beta_n^{q-1}\right) \quad \forall i \in I - I', \end{aligned} \tag{42}$$

  where $\epsilon > 0$ is an arbitrary small parameter.

  2. We approximate the gradient of $RASW$ at point $\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right)$ numerically as follows:

  $$\begin{aligned} \frac{\partial RASW}{\partial \lambda_i}\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right) &\approx \frac{RASW_{\lambda_i,+} - RASW_{\lambda_i,-}}{2\epsilon} && \forall i \in I - I' \\ \frac{\partial RASW}{\partial \beta_i}\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right) &\approx \frac{RASW_{\beta_i,+} - RASW_{\beta_i,-}}{2\epsilon} && \forall i \in I - I', \\ \frac{\partial RASW}{\partial \lambda_i}\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right) &= 0 && \forall i \in I' \\ \frac{\partial RASW}{\partial \beta_i}\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right) &= 0 && \forall i \in I'. \end{aligned} \tag{43}$$

We keep track of our approximation of the gradient of $RASW$ in vector $\boldsymbol{\nabla} RASW^q \in \mathbb{R}^{2n}$. We then update point $\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right)$ as follows: we first define the new target points according to the gradient-ascent philosophy

$$\begin{aligned} \lambda_i^* &= \lambda_i^{q-1} + \alpha^q \frac{\partial RASW}{\partial \lambda_i}\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right) \quad \forall i \in I - I' \\ \beta_i^* &= \beta_i^{q-1} + \alpha^q \frac{\partial RASW}{\partial \beta_i}\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right) \quad \forall i \in I - I' \\ \lambda_i^* &= 1 \quad \forall i \in I' \\ \beta_i^* &= 0 \quad \forall i \in I', \end{aligned} \tag{44}$$

where $\alpha^q > 0$ is an iteration-dependent *learning rate*. Second, we define the new variable $(\boldsymbol{\lambda}^q, \boldsymbol{\beta}^q)$ as the projection $\mathbf{P}_{\mathcal{F}}$ of $(\boldsymbol{\lambda}^*, \boldsymbol{\beta}^*)$ onto the upper level's feasibility set $\mathcal{F}$ defined in (34) (a set that is convex and that can be cast into a compact set):

$$(\boldsymbol{\lambda}^q, \boldsymbol{\beta}^q) = \mathbf{P}_{\mathcal{F}}(\boldsymbol{\lambda}^*, \boldsymbol{\beta}^*). \tag{45}$$

For our problem, a high learning rate can speed up convergence but risks overshooting the optimal solution. Conversely, a low learning rate may become trapped in a local optimum. To address this challenge, we propose the following heuristic approach for adjusting the learning rate in our problem: we increase the learning rate if, indeed, the gradient step led to an increase in welfare between iterations $q-1$ and q; otherwise we reduce it to ensure that we do not overshoot the optimal solution.

$$\begin{aligned} \alpha^{q+1} &= \psi\, \alpha^q \quad \text{if } RASW(\boldsymbol{\lambda}^q, \boldsymbol{\beta}^q) > RASW\left(\boldsymbol{\lambda}^{q-1}, \boldsymbol{\beta}^{q-1}\right) \\ \alpha^{q+1} &= \psi'\, \alpha^q \qquad\qquad \text{otherwise} \qquad\qquad \forall q \geq 1, \end{aligned} \tag{46}$$

where $0 < \psi' < 1 < \psi$.

- **Stopping criterion.** Carry on the iteration phase until convergence,

$$\|\boldsymbol{\nabla} RASW^q\| \leq \text{tolerance}_B, \tag{47}$$

where $\text{tolerance}_B > 0$ is the convergence tolerance level and $\|.\|$ is a norm defined over the space $\mathbb{R}^{2n}$.

4 A numerical application

4.1 The French economic context in brief

In this section we demonstrate the efficiency and estimate the welfare gains derived from optimizing the risk-mitigating instruments. To do so, we focus on the French power economy, chosen for two key reasons. First, France has developed high-capacity nuclear production of 62 GW covering approximately 70% of demand. Most French nuclear reactors were built, however, before the 1980s, meaning they are approaching their expected lifetimes. Combined with lofty ambitions for electrification of demand, aimed at achieving France's emissions targets, this conjuncture necessitates substantial investments in new capacity in the coming years. The French State has repeatedly expressed its commitment to nuclear technology—as is reflected in all official scenarios forecasting the evolution of the country's power mix (see RTE [2022])—and the will to develop adequate risk-sharing schemes to do so. Second, France harbors significant potential for wind and photo-voltaic (PV hereafter) electricity production thanks to favorable solar irradiation in the south and a relatively long coastline in the west and north. Coupled with declining capital costs for these technologies, this context makes investments in renewable production economically viable and, indeed, we observe that all official forecasts for French power capacity include investments in wind and PV. (Henceforth we refer to Wind and PV technologies as Renewable Energy Sources, or RES.) Therefore, French authorities and energy economists emphasize the need to strongly and jointly foster investments in nuclear and renewable production associated with flexibility in the form of batteries via risk-sharing schemes involving consumers.

The variety of means for achieving this goal include designing adequate risk-mitigating contracts such as CfDs and PPAs, which are being vividly debated in the country (see Percebois [2023] for a summary). These debates address not only the nature of the instruments themselves but also their characteristics (duration, strikes, etc.). Of course, these debates have increased in intensity with the recent crisis inherent to the strong increase in the occurrence of negative prices in Europe. In this context, although we are aware that decisions pertaining to investments in nuclear and renewable technologies can be political, reflecting concerns over the security of supply, we still believe that an economic analysis of the proper design of risk-mitigating schemes to foster investments with the objective of optimizing welfare may constitute a valuable contribution to the ongoing debate. To do so, we propose building a simple representation of the French power economy inspired by our model in Section 2, as we explain in the next section. Because MPEC problems can rapidly become computationally intractable, we had to keep the size of our models reasonable. In particular, we achieved this by assuming that power plants of the same technology are symmetric and by limiting the dynamics of the second stage to a single representative day.

4.2 Data collection, additional assumptions, and benchmarks

In this section we outline our procedure for building the dataset with which we ran our model in Section 2.

4.2.1 Data calibrated using public sources

We account for the main production technologies in France: PV, wind, nuclear, gas-fired (typically combined-cycle gas turbines, CCGT, which are used during mid-load hours, or gas turbines, GT, used for peak production), coal-fired power plants, fuel-fired power plants, as well as hydropower production. All plants of the same technology are assumed to be symmetric in terms of cost and efficiency, which is a reasonable assumption for long-term investment models. Moreover, a plant's production profile is assumed to remain unchanged throughout the lifetime of the asset. We also account for large-scale energy storage batteries (the most important of which rely on lithium-ion technology) having an Energy-to-Power ratio of 4 hours. We calibrate our model using public data for the year 2019. We chose that year as it was the last year when power markets followed a standard regime in Europe.[11] Hence, this choice allows us to derive general enough results and recommendations. Fuel costs are taken from the French energy transparency platform ODRÉ.[12] Hourly demand for electricity and power plants availability is extracted from publications of the French Transmission System Operator RTE.[13] Hourly day-ahead power prices are taken from the EPEX spot database. Investment costs and CO_2 content factors are taken from the ADEME database.[14] CAPEX costs are translated into annuities using a discount rate of 5% for all technologies and expected lifetimes extracted from Statista [2024]. The CO_2 constraint level is derived from production data for the year 2019. We focus our modeling of time on one representative day obtained with a clustering technique for market data comprising demand, fuel costs, and available capacity. We abstract away from congestion costs, as they are, on the one hand, negligible in France, and,

[11] Indeed, starting in 2020, European power markets entered a crisis regime in response to the COVID pandemic that drastically decreased demand and prices to abnormal levels, followed by the Russo-Ukrainian war that led to natural gas disruptions causing a regime of extremely high prices, before entering a regime of extremely low and often negative prices, as argued in the introduction.

[12] See https://opendata.reseaux-energies.fr/.

[13] RTE [2022].

[14] Agence de la transition écologique, see https://www.ademe.fr/.

on the other hand, producers are subject to zonal pricing.[15] We use a bootstrapping technique with the market data to generate 20 equally weighted scenarios depicting consumption, prices, plant availability, and fuel costs. We deliberately choose only one representative day to model plants' operations to allow numerical tractability, given the fundamental property in virtue of which MPEC problems are extremely challenging to solve and are subject to the curse of dimensionality. This shortcoming is, however, compensated by the variety of the scenarios we consider. The linear inverse demand function parameters are calculated from reference consumption and prices, assuming an elasticity of consumption with respect to the price of -0.01 (see Zhu et al. [2018]).[16] These reference prices are only used to construct the inverse demand functions and we remind readers that spot prices are endogenous to our models.

Given that hydroelectric production is geographically constrained, we cap its capacity at the installed level of 27.7 GW. Additionally, we deliberately limit the capacity of nuclear technology to 30 GW, a value that lies in the mid-range of capacities forecast in official scenarios for the evolution of the French power energy mix between the present day and 2050.[17] This choice is driven by several factors: (i) our aim to provide long-term policy recommendations for optimal subsidies for the energy transition and (ii) our interest in examining synergies between renewable subsidies, investment in flexibility, welfare, and negative market prices. Coupled with our CO_2 constraint, this choice increases the need for renewable technologies with flexibility, necessitating a thorough evaluation of optimal contracts and subsidies.

Regarding CfDs, the French (and European) policy is to subsidize nuclear, wind, and PV production because these energy sources align with the objectives of the transition to low-emission electricity production. Therefore, these are the technologies that benefit from contracts and markups in our model. We calibrate the strike price for nuclear technology to reflect that of the Hinkley Point C reactor that the French producer EDF secured in 2016: 110 €/MWh.[18] The strike prices for PV and wind production are calibrated on average PPA prices in 2019: 104 €/MWh for PV[19] and 95 €/MWh for wind.[20] Finally, as argued above, in alignment with France and other European countries' subsidy schemes for the energy transition, storage assets do not receive centralized support today. This approach likely reflects the European Commission's belief that supporting wind and solar PV production is sufficient to foster investments in flexibility, thereby reducing the transaction costs associated with contracting and subsidizing. This choice is, however, a matter of debate among energy economists (Billimoria and Simshauser [2023b] and Winzer et al. [2024]).

We conduct our analysis under the assumption that capacity is built from scratch, with the objec-

[15]See the French Transmission System's Operator's publication, available at `https://www.rte-france.com/analyses-tendances-et-prospectives/le-schema-decennal-de-developpement-du-reseau`.

[16]If $p^t_{ref}(\omega)$ denotes the reference price and $q^t_{ref}(\omega)$ the reference consumption at time t and scenario ω, and if $elas \leq 0$ denotes the elasticity of consumption with respect to the price, we compute the inverse demand function parameters as:

$$a^t(\omega) = p^t_{ref}(\omega)\left(1 - \frac{1}{elas}\right), \quad b^t(\omega) = -\frac{p^t_{ref}(\omega)}{elas\ q^t_{ref}(\omega)}.$$

[17]See RTE's publications at `https://rte-futursenergetiques2050.com/scenarios/m1/v2`.

[18]See official communication at `https://www.gov.uk/government/collections/hinkley-point-c`.

[19]See `https://www.pv-magazine.fr/2023/02/10/les-prix-des-ppa-solaires-europeens-ont-augmente-de-114-au-t4-2022/`.

[20]See `https://windeurope.org/wp-content/uploads/files/about-wind/campaigns/2020-successes/levelten/products/LevelTen-Energy-European-Q42020-PPA-Price-Index.pdf`.

tive of providing a long-term perspective of the power system under various risk-mitigating schemes. Therefore, our models are not intended to replicate the current mix of the French power system.

4.2.2 Assumptions pertaining to risk aversion

Experimental and behavioral economics offer a range of methods with which to elicit individuals' risk preferences (we refer to Charness et al. [2013] for a general review). Unfortunately, to the best of our knowledge, this task has not been carried out with power producers facing both short-term and long-term risk. Therefore, we must rely on standard assumptions in the literature to estimate producers' attitudes when facing risk. As is now standard in the OR literature when it is applied to energy, we model market agents' risk aversion with the CVaR, which is a coherent measure of risk as explained in Section 2.1.3 (for applications of the CVaR, see Downward et al. [2016], de Maere d Aertrycke et al. [2017], Ferris and Philpott [2022], Mays and Jenkins [2022], and Dimanchev et al. [2024] to cite only a few). This choice is motivated by the fact that, as argued in Section 2.1.3, companies often rely on this risk measure to assess risk, as it has become the standard approach to do so in finance. More precisely, as in Downward et al. [2012], we assume that agents strive to maximize a mean-risk formulation of their stochastic profit of the form presented in equation (29) with parameter ϕ taken at 0.4. This choice has the advantage of ensuring that Assumption H1 always holds and therefore, that the MPEC has a solution according to Theorem 1. Levels of risk aversion under the CVaR are the same for all agents (reflecting the point that, notwithstanding differences in hedging strategies, they all have the same exposure to market risk), but this does not necessarily imply they face the same risk exposure. Here again there exist some elicitation methods for levels of risk aversion for the CVaR (see, for instance, Fissler and Ziegel [2021]), but we are not aware of any application in the context of investment decisions related to electricity. Therefore, we set the level of risk aversion to 0.75, a value that is standard in the OR literature. This means that, when valuing an investment, agents focus on scenarios where the profits fall below the 25% quantile of the profit distribution. We verified that our results remain qualitatively the same with other (close) values of the level of risk aversion.

4.2.3 Hyper-parameters

We use the following values for Algorithm A's hyper-parameters. The memory rate ι is set to 0.2. Convergence is measured with tolerance$_A$ equal to 5.10^{-2} for the $\mathcal{L}_1$ norm. Algorithm B's hyper-parameters are the following. The initial learning rate is 0.02, $\psi' = 0.5$, and $\psi = 1.1$. Convergence is measured with the $\mathcal{L}_1$ norm and with a tolerance of 10^{-4}. Finally, parameter ϵ, which we use to approximate the gradient of the upper level's objective function, is taken at 10^{-2}.

4.3 Economic benchmarks

We analyze five benchmarks for the French power economy.

1. **The complete market.** When the financial market is complete, risk can be swiftly exchanged between participants. In other words, the set of financial securities spans the entire space of random variables, meaning that any stochastic profit can be replicated by a portfolio of financial contracts (Cochrane [2009]). It is well known that, when the market is complete, risk-adjusted welfare is maximal and there is no need to further subsidize investments, as agents can trade risk perfectly

in the market (Ralph and Smeers [2015]). In this case, the lower level can be solved by optimizing risk-adjusted social welfare instead of its equilibrium formulation.

2. **The fully incomplete market.** When the financial market is fully incomplete, there are no risk-sharing instruments in the economy. Agents cannot trade risk and the set of financial contracts that could be exchanged is empty. There are also no subsidies or CfDs: $\forall i \in I$, $\lambda_i = 1$ and $\beta_i = 0$.

3. **Current regulation.** For this benchmark, we model the economy in its current logic in the country: producers receive a CfD that guarantees a fixed price irrespective of the spot-market price. This removes the price risk for nuclear, PV, and wind production and naturally induces incentives for market distortions. Using our notation, this means that $\lambda_{nuclear} = \lambda_{PV} = \lambda_{wind} = 0$, $\forall i \in I'$, $\lambda_i = 1$, and $\forall i \in I$, $\beta_i = 0$.

4. **Current regulation^{+}.** For this benchmark, we model how some European countries have modified the functioning of CfDs by making contract payments conditional on a non-negative market price. More precisely, we assume for this benchmark that the producer receives the strike price only if it is non-negative; otherwise, it receives the spot price. This adaptation of the CfD has the advantage of limiting the incentives for market distortions and aligning renewable production with the system's market needs in case of oversupply.

5. **Optimal regulation.** For this benchmark, the State optimizes its G-CfDs and markups to maximize social welfare, as presented in Section 2. We remind readers that these contracts and subsidies are provided to nuclear, wind, and solar production and no subvention is offered to storage assets.

We note that the first two benchmarks are unrealistic as a complete market for risk is only a theoretical chimera and there exists today a small number of contracts that could be exchanged in the economy. The main interest of these cases is that they serve as theoretical benchmarks for an optimal system for the complete market case, and for an inefficient power economy for the fully incomplete case.

4.4 Results for welfare

Figure 1 shows risk-adjusted social welfare expressed in Billions €/year (B €/year hereafter). Naturally, risk-adjusted social welfare is highest when the financial market is complete. This result is reassuring and coincides with what one finds in the literature. In particular, it implies that, no matter how the State adjusts its subsidies and risk-hedging instruments, it can never reach the case where agents can fully trade risk between themselves. Of course, as mentioned before, this benchmark is, in fact, a utopia as it assumes that any random payoff can be replicated by a set of contracts (or, in other words, that any risk can be hedged), which requires the elaboration of more hedging instruments than the number of scenarios, which is an impossible task. Therefore, the complete market benchmark will serve as a proxy for an efficient economy: the closer the system is to aligning with this benchmark, the more efficient it is. Interestingly, Current regulation makes the system worse than when the market is fully incomplete. This example illustrates perfectly how inadequate risk-mitigating schemes might make the power system actually worse off than leaving market agents to manage market risk independently with no intervention. This outcome mainly reflects market distortions. Indeed, as we show when analyzing invested capacity, Current regulation leads to massive over-investments in wind and PV, favoring market distortions: at this benchmark, RES receive the strike price irrespective of the realization of the spot-market price, prompting them to produce even during hours of oversupply and low demand. This, in turn, likely increases the number of occurrences of negative prices, as we will see. If we consider the fully incomplete benchmark as a reference case, we estimate that Current regulation reduces social welfare by 21 B €/year. The complete market, on the other hand, increases welfare by 48 B €/year.

Moving on, we observe that Current regulation $^+$ does much better: it also enhances system welfare when compared with the incomplete case by 7 B €/year with the natural consequence that market distortions are mitigated because renewable producers are left with some price risk to manage and over-investments in PV and wind capacity are reduced, as we show below. We also find that, when contracts are optimized by the State (the Optimal regulation benchmark), system welfare is much higher than at the incomplete benchmark: +22 B €/year. This is higher than for Current regulation $^+$, which suggests that making the CfD's payment naught when the market price is negative is already a good means of amending Current regulation with the objective of limiting market distortions, but the State has additional leverage with which it can increase the benefits of contracts even further via generalized CfDs and price markups such as those we study, *if optimized properly*.

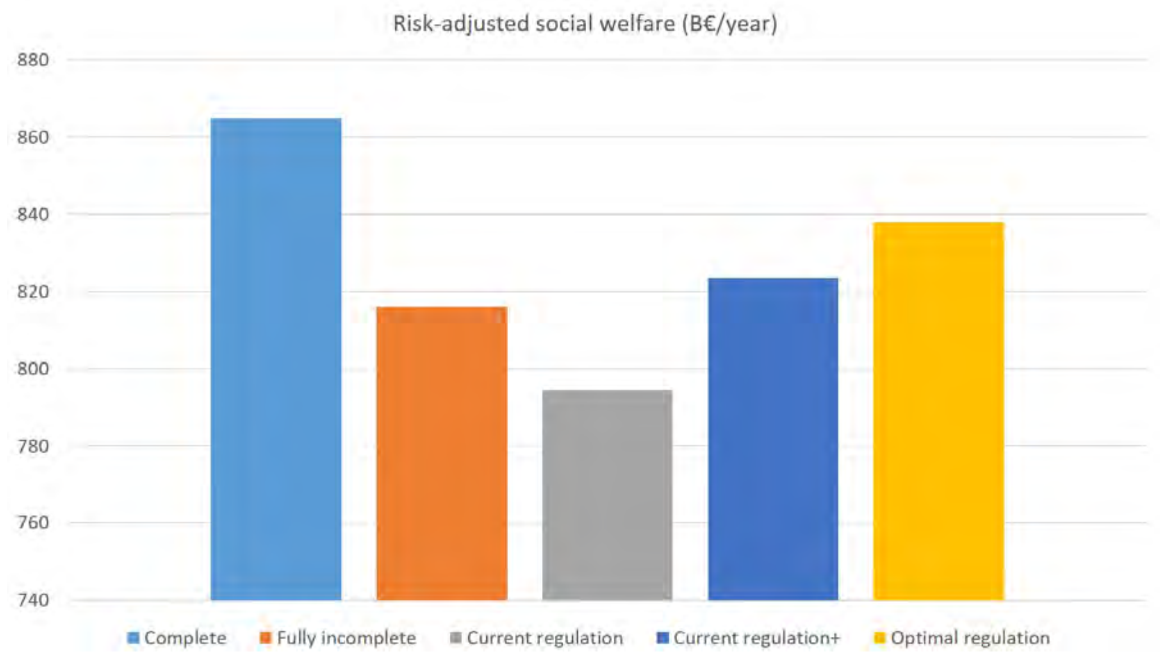

Figure 1: Risk-adjusted social welfare.

4.5 Results for investments

Figure 2 depicts invested capacity. The most interesting result is probably the invested capacity in wind and PV. When the market is fully incomplete, investment in these technologies is substantially lower than for all other benchmarks because RES are the only technologies for which investors must hedge the price *and* volume risks simultaneously. Therefore, when risk cannot be swiftly traded, some form of subsidy is necessary to increase their capacity in the system. Interestingly, Current regulation leads to massive over-investments in these technologies because of market distortions. When conditioning the CfD's revenue on the non-negativity of the market price (Current regulation $^+$), we still observe some over-investments, a result that is driven in part by the strike prices we consider. Market distortions are, however, limited, as we highlight in the following section, where it is observed that RES increase their curtailment substantially, leading to very few occurrences of negative prices. When CfDs and markups are optimized (Optimal regulation), investments in PV capacity are very close to that of the complete market case (+6 %) but remain high for wind production (+ 22%). When compared with welfare outcomes, these results are encouraging: with a limited number of contracts—specifically, a Generalized CfD with a price markup for three technologies—the State has some levers it can use to optimize their design to bring the system relatively close to the complete market benchmark. Naturally, CCGTs and GTs adapt to the investment in renewables to provide peak capacity to the system.

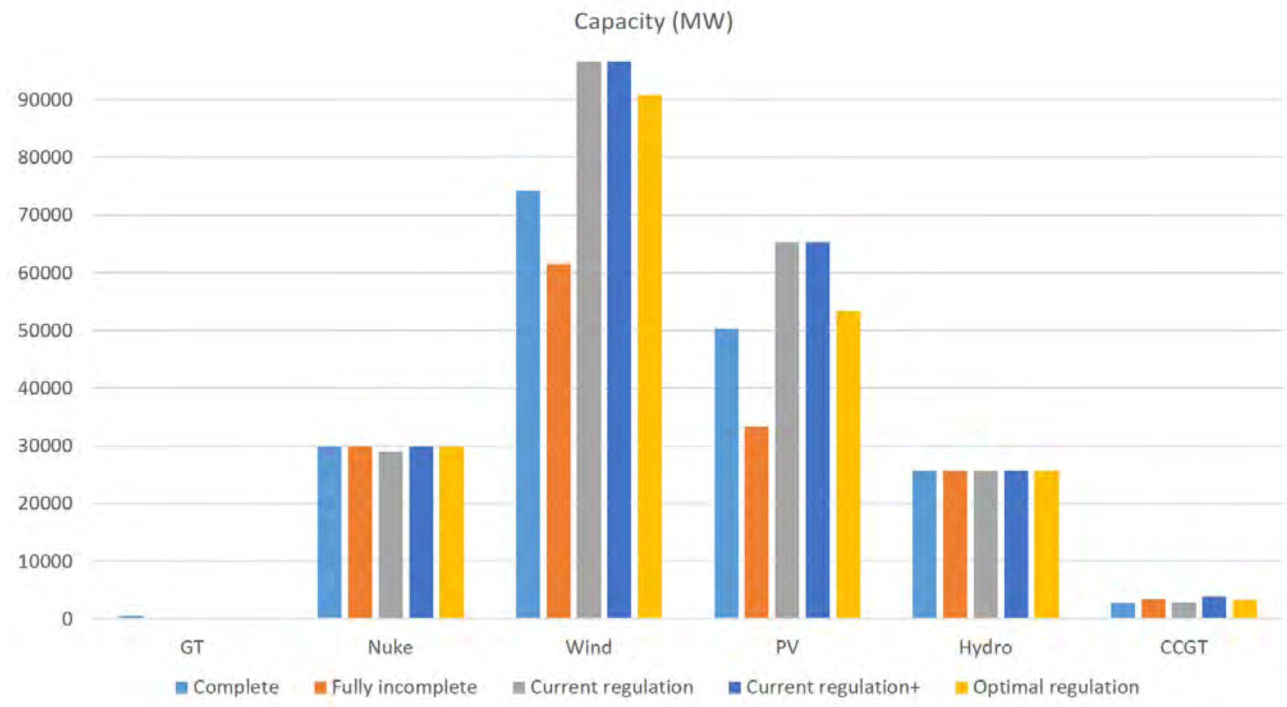

Figure 2: Invested capacity.

4.6 Results for system flexibility, the occurrence of negative prices, and the CO_2 price

Figure 3 presents our results for system flexibility, which we measure through the invested capacity in storage (K_s) and the volumes of wind and PV energy that RES producers voluntarily curtail in response to price signals. Investment in storage is, overall, riskier than investment in thermal power plants because a battery captures price arbitrage in time, causing its profit generally to fluctuate.[21] This explains why invested capacity in storage is very low when the market is fully incomplete. This result is particularly relevant as it questions European policymakers' decision *not* to subsidize flexibility, and confirms some results reported in the extant literature (Billimoria and Simshauser [2023b]). Under Current regulation, RES producers do not have a strong enough incentive to curtail, increasing the need for batteries. Of course, the curtailment of RES is the highest under Current regulation $^+$, as producers lose profit if they sell at hours with negative prices and the installed RES capacity is high. Therefore, the need for batteries is drastically reduced at this benchmark. These results highlight how the design of support schemes for RES technologies can substantially affect the business model for battery operators. Interestingly, when

[21] In practice, the claim is true because prices show some correlation in time.

CfDs and markups are optimized, a balance between storage and RES curtailment is restored, much like what we observe at the complete market benchmark, but with a lower amplitude. This result holds because, with G-CfDs and markups, RES producers are still at least partially exposed to price risk, retaining an incentive to curtail when prices are substantially negative. However, because their G-CfD with price markup remuneration is of the form

$$R_{G-CfD-Markup} = \Big[\lambda_i p^t(\omega) + (1-\lambda_i)\, s_i + \beta_i\Big] x_i^t(\omega), \tag{48}$$

they could be incentivized to produce during some hours with negative prices, depending on the strike prices and optimal variables on the upper level λ_i and β_i with $i \in \{\text{Wind},\ \text{PV}\}$—we analyze these values in the next section. In other words, we note that optimizing CfDs and price markups as we propose in the present paper mitigates market distortions but does not eliminate them entirely because we still need to protect RES producers from the price risk to some extent to encourage sufficient investments.

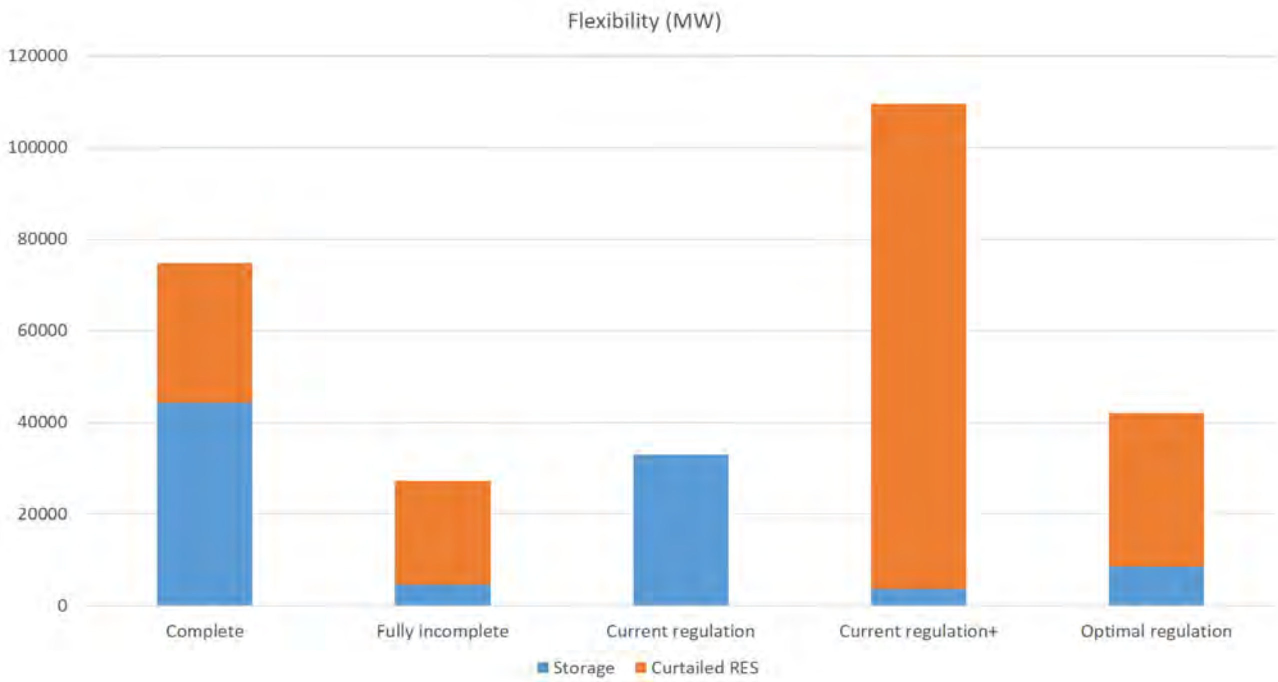

Figure 3: Invested capacity in storage and voluntary curtailment of RES.

The previous results are reflected in the occurrence of negative prices, as illustrated in Figure 4. The figure shows the amplitude of negative prices, which we define as the average market price conditional on the price being non-positive:

$$\text{Amplitude of negative prices} = \frac{1}{T}\sum_{t=1}^{T} \mathbb{E}_\theta\Big(p^t \mid \{p^t \leq 0\}\Big). \tag{49}$$

We observe that, when the market is complete, the amplitude of negative prices is very low and is nonexistent at the Current regulation $^+$ benchmark. When the market is fully incomplete, negative prices persist despite RES curtailment because of a lack of storage capacity. Indeed, as we have remarked, as the business model for storage is highly risky, an incomplete market for risk will not foster the needed battery capacity. Under Current regulation, the amplitude of negative prices is the highest, illustrating even further the detrimental impact of market distortions when price risk is completely removed: RES capacity indeed rises but at the expense of market efficiency. Under optimal CfDs and markups, negative prices are strongly limited but they are not entirely eliminated because, as we argue above, G-CfDs with markups do not eliminate market distortions entirely as the strike price still influences remuneration to producers. In particular, based on equation (48), we can calculate that, for technology $i \in \{\text{Wind, PV}\}$, curtailment occurs only when the spot price drops below a threshold p_0, the expression of which is (assuming $\lambda_i \neq 0$)

$$p_0 = -\frac{(1-\lambda_i)s_i + \beta_i}{\lambda_i}. \tag{50}$$

Therefore, because $p_0 < 0$, we conclude that negative prices cannot be entirely eliminated. This is perhaps the cost the system must pay to incentivize sufficient investments in RES given the set of contracts we consider in this study and the fundamental non-completeness of spot electricity markets. We note, however, that the amplitude of negative prices is substantially lower with our proposal than when the market is incomplete or under Current regulation. We emphasize that these positive outcomes for the extent of negative prices are not achieved by design, but rather emerge as an unintended, yet positive, consequence of maximizing welfare on the upper level.

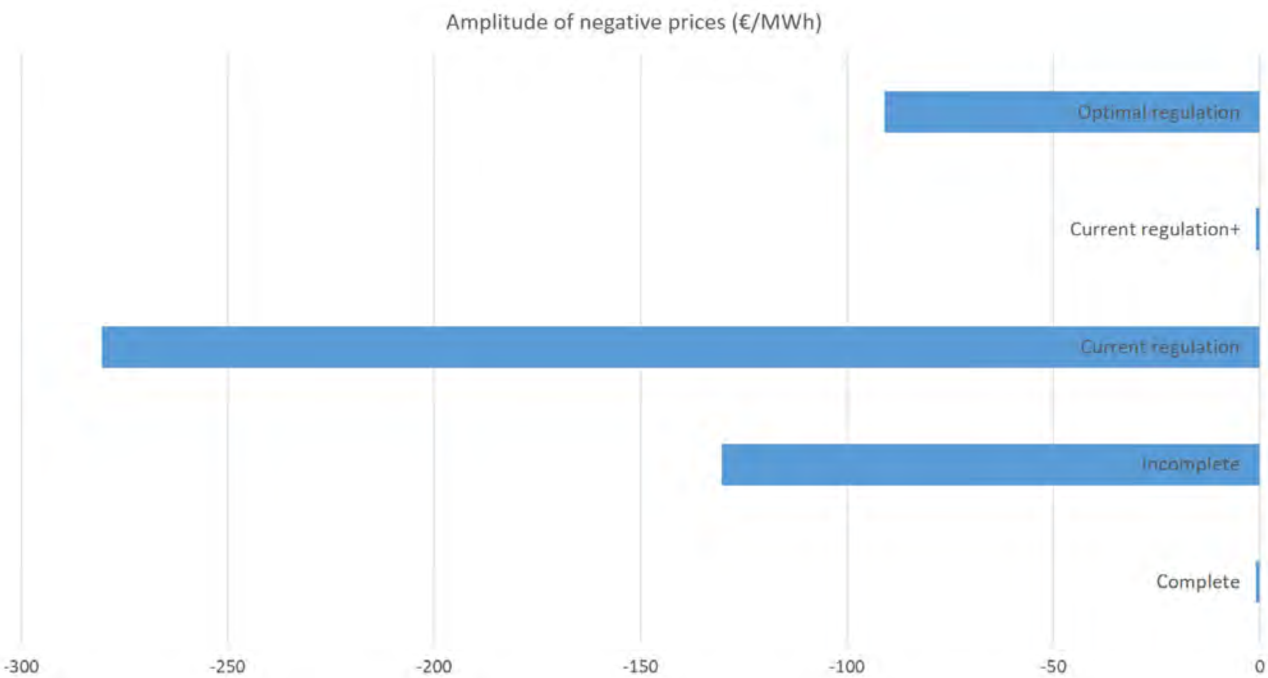

Figure 4: The amplitude of negative prices.

We conclude our analysis with an assessment of the CO_2 price. Figure 5 shows this price expressed as percentage differences with respect to the Complete market case. We first remark that, when the market is fully incomplete, the CO_2 price is much higher than at the other benchmarks. This is the direct consequence of the difficulty of triggering the necessary investments in RES and battery technologies because of high risk, as discussed above. Interestingly, with some CfDs, the CO_2 price is lower, as renewables are incentivized in the system at levels higher than in the complete market case. We also observe that the highest incentive (Current regulation) leads to the lowest CO_2 price. With a more parsimonious subsidy

(Current regulation$^+$) the price is a bit lower and even more so when CfDs and markups are optimized (Optimal regulation). Here again, these results follow the optimization of welfare.

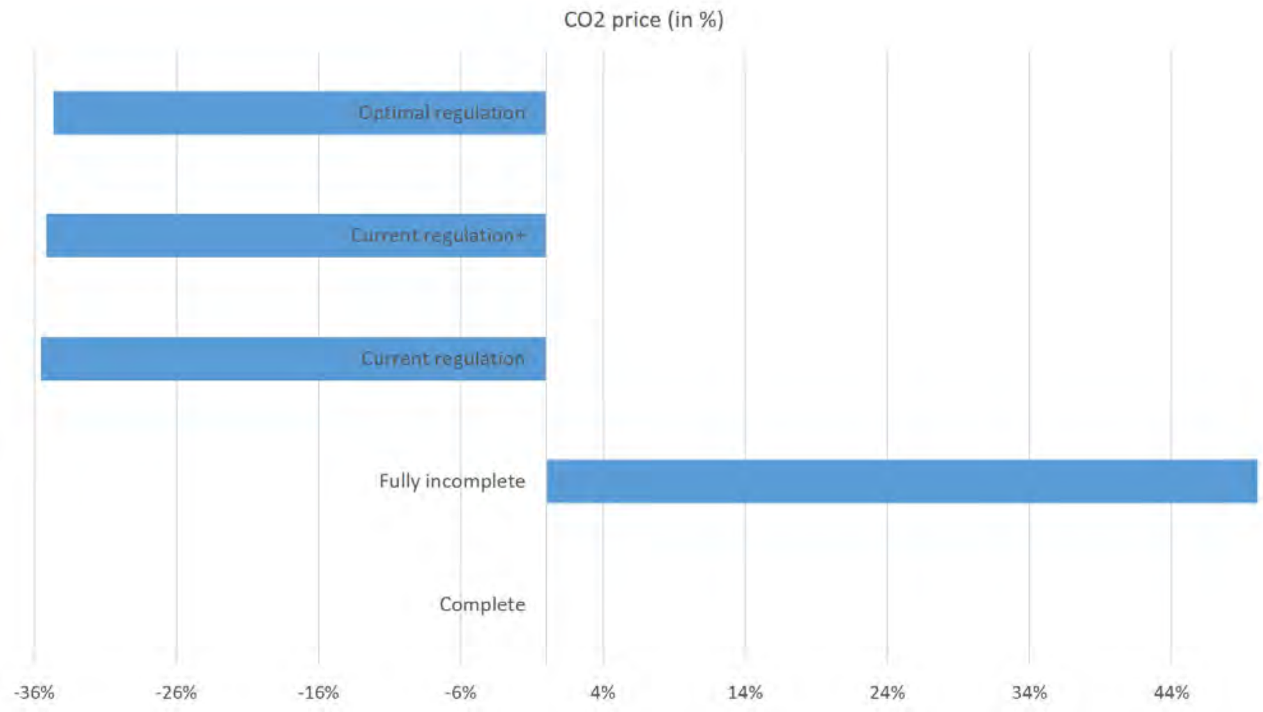

Figure 5: CO_2 prices expressed as % where the complete benchmark serves as a reference, i.e. 0%.

4.7 Optimal contracts and markups

We now present the optimal values of the Generalized CfDs and price markups obtained after solving the MPEC for the Optimal regulation benchmark. Table 1 summarizes the results. A few observations

	λ	β (€/MWh)
Nuclear	1	0
Wind	0.25	0.2
PV	0.67	0.4

Table 1: Optimal contracts and markups.

stand out. First, we observe that nuclear capacity does not need to be subsidized at all in France and can be left exposed to market risk. This finding is driven by the fact that we limit invested capacity to 30 GW, a value that is lower than current available capacity (61 GW). In a sensitivity analysis, we verify that when we no longer limit nuclear capacity, optimal contracts take up to 20% of the price risk in this case (meaning that $\lambda_{nuclear} = 0.8$), and we would end up with an invested capacity of 46 GW. Second, optimal contracts provide greater price-risk hedging against wind production than against PV: $\lambda_{wind} < \lambda_{PV}$. Our interpretation is that PV is, in fact, more likely to distort competition because it produces at hours when negative prices might occur, whereas wind production is spread more evenly over the course of a day. This phenomenon, underlying the so-called cannibalization effect of RES production (Prol et al. [2020]), can hence be mitigated by exposing solar production to the price risk to a greater extent than wind. This, in turn, encourages more voluntary curtailment of PV.

4.8 A sensitivity analysis

Our results highlight the harmful impact of inadequate subsidy schemes on welfare, investments, and negative prices. This impact in France is however mitigated by the presence of nuclear production. Therefore, we expect this adverse effect to be more pronounced in power systems that rely heavily on renewable energy with little capacity from alternative baseload technologies such as nuclear or hydropower plants. Examples of such systems in Europe include those in Germany, the Netherlands, and Portugal where, indeed, the surge in negative prices has been particularly significant in recent years. To verify this claim, we perform a simple sensitivity analysis of our base case, where we leave all data unchanged except for the capital and operational costs of power plants and storage assets, which we update to use 2025 figures. We do so because the costs of renewables and utility-scale battery storage have dropped in the last five years (by more than 15% for wind, 5% for PV, and more than 34% for batteries according to NREL [2025]). The natural consequence would be a stronger incentive to invest in wind and PV production, calling for cautious design of subsidy schemes.

Our main results of this sensitivity analysis with respect to the cost of renewables are concatenated in Figure 6. The ranking of benchmarks with respect to welfare is preserved; we observe interestingly that, compared with the fully incomplete benchmark, Current regulation diminishes welfare to a much greater extent in this sensitivity test. This is because over-investments in renewables are more pronounced, reducing nuclear capacity dramatically. Compared with the base case, the amplitude of negative prices here is substantially higher when the market is fully incomplete, both under Current regulation and also when contracts are optimized. Interestingly, when the financial market is complete, we still observe some negative prices, reflecting the fact that total elimination of negative prices would entail some over-investments in storage, ultimately diminishing welfare. Negative prices also persist when contracts and markups are optimized, as they result from the limited storage capacity induced at optimality. These findings underscore the idea that enhancing social welfare may come at the cost of enduring negative prices, especially when storage assets are *not* subsidized, as is the case in Europe today. Naturally, the results would have been different if we had applied an alternative optimization criterion in the upper level, such as a criterion that explicitly penalizes the occurrence of negative prices in the objective function. Furthermore, these findings highlight the even more crucial need to consider subsidizing storage batteries along with renewable production if policymakers aim to reduce the occurrence of negative prices.

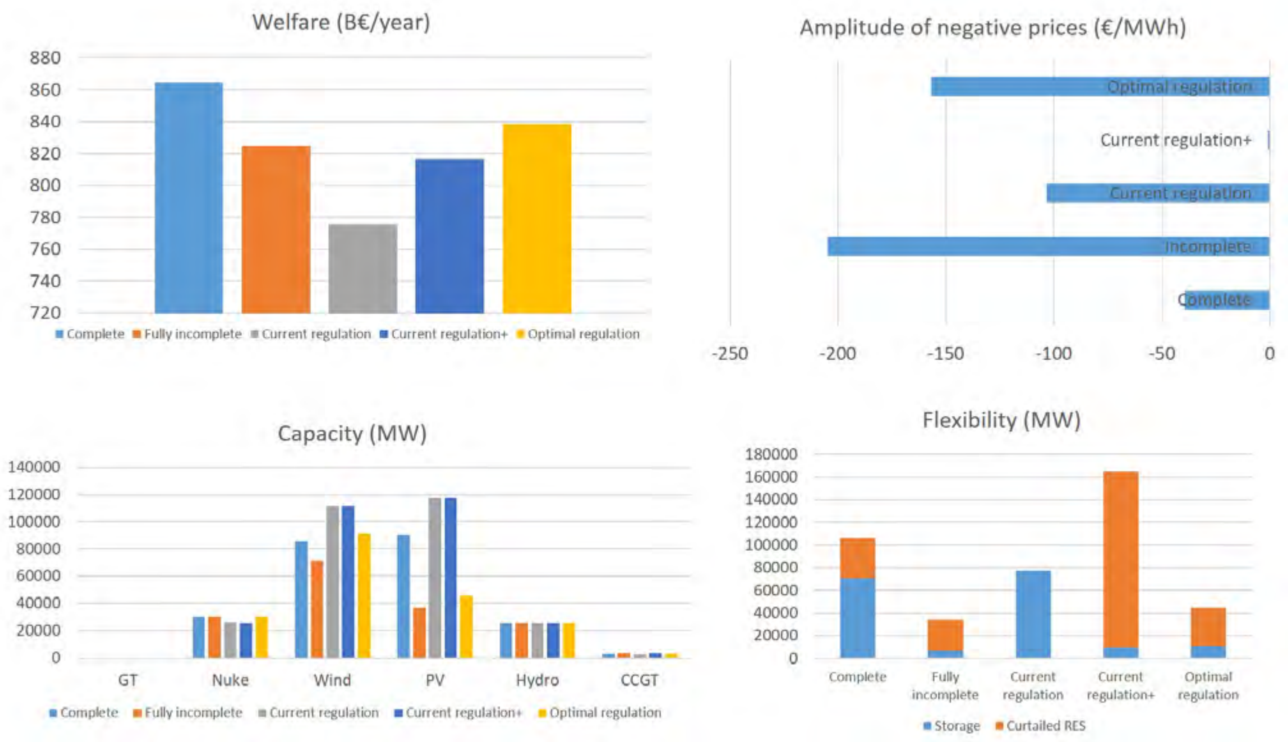

Figure 6: Results in the presence of lower investment costs of RES and storage technologies, calibrated with 2025 data.

5 Policy recommendations and concluding remarks

The profusion of research in energy economics and OR that studies the negative impact of risk aversion on investments in renewable technologies may have supported the belief that risk-sharing and risk-mitigating instruments invariably foster welfare and promote green investments. Our research highlights some limitations of this philosophy. While we demonstrate that, when risk cannot be swiftly traded between agents investments in RES production and storage are indeed limited, ultimately diminishing welfare, we also show that poorly designed contracts—such as Fixed-Price CfDs as implemented in many European countries—can cause greater damage to welfare by driving massive over-investments in wind and PV. A direct consequence of this imbalance is an abnormally high rate of negative prices in the market, mirroring what we are observing today. This phenomenon has even led some analysts to suggest that markets are in a crisis regime. Such a result is the consequence of market distortions and moral hazard when producers are not sufficiently exposed to market risk. Our research indicates that an arbitrage must be found between risk mitigation of green technologies and efficient bidding in the spot market when designing the kinds of contracts that will be implemented in the economy. In addition, our methodological proposal to model this choice explicitly via a bi-level approach looks promising.

Our first policy recommendation is that policymakers and energy economists should carefully balance risk-hedging and market distortions when proposing risk-sharing instruments to renewables in the market, primarily by incorporating some flexibility into their design. Indeed, when analyzing Generalized CfDs with markups, we were able to show their potential along multiple dimensions: first, they enhance welfare as compared with current implementations and bring the system closer to the ideal benchmark of a complete market for risk. Second, they encourage relatively adequate levels of RES and battery investments and, third, they also limit the amplitude of negative prices, at least with respect to some basic current implementations in our base case. In particular, our findings suggest that solar production should be protected from price risk but to a lesser extent than wind production. This is because solar irradiation follows a pattern that is perhaps more correlated with negative prices than wind. These observations support our second policy recommendation: the complete removal of RES subsidies, as proposed in some countries, might be inadvisable. Our findings indicate that, while certain subsidy schemes perform worse than the incomplete market benchmark, others can yield significantly better outcomes, starting by conditioning the remuneration of contracts on the non-negativity of market prices. The third policy recommendation focuses on storage subsidies. Our findings indicate that the profitability of the storage business model depends heavily on renewable-energy subsidy schemes. Without proper risk-sharing mechanisms, investment in storage capacity remains dramatically low, exacerbating the occurrence of negative prices. Given the energy transition's reliance on intermittent green electricity production, we strongly recommend that policymakers explore the possibility of providing subsidies encouraging battery storage to eliminate negative prices and provide the system with the needed flexibility.

Our model represents a first step in the process of finding optimal risk-mitigating instruments for the power system. It is intended to serve as a proof of concept that demonstrates, in a deliberately simple framework, that bi-level methods can help policymakers in this endeavor. To preserve the generality and explicative capacity of our approach, we had to simplify our modeling in many respects. First, our representation of the lower level can be enhanced by accounting for grid congestion costs and other technical constraints, such as ramp-up constraints, pertaining to the functioning of power plants and storage devices. Of course, other risk-mitigating schemes, such as capacity remuneration contracts and mechanisms that also hedge volume risk, can be optimized on the upper level. Second, strategic gaming by producers in the contracting stage and when operating in the spot market could enhance the realism of our approach when applied to systems that are dominated by large incumbents. Finally, other adapted heuristics for solving the bi-level problem more efficiently could be investigated with the objective to increase the number of representative days and scenarios modeled. All these enhancements could be considered and tested in future research.

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APPENDIX

A Proof of Theorem (1)

Proof. In this proof we demonstrate that set $\mathcal{H}$ can be cast into a compact set. First, it should be easy to see that our complementarity conditions (13), (18), (21), and (24), which define $Sol\left(\boldsymbol{\lambda}, \boldsymbol{\beta}\right)$, are schematically a concatenation of equations of the form

$$variable \geq 0,\ F(variable) \geq 0,\ variable.F(variable) = 0, \tag{51}$$

or of the form

$$G(variable) = 0, \tag{52}$$

with F and G representing continuous functions. In addition, all risk sets are closed because they are compact. Therefore, set $\left\{(\boldsymbol{X}, \boldsymbol{\lambda}, \boldsymbol{\beta}) \in \mathbb{R}^{m+2n} \text{ s.t. } \boldsymbol{X} \in Sol\left(\boldsymbol{\lambda}, \boldsymbol{\beta}\right)\right\}$ is closed. This implies that set $\mathcal{H}$ is also closed. We turn now to demonstrating that any solution to (30) can be bounded to obtain compactness. We proceed in two steps.

Step 1. First, we demonstrate that, for any upper-level variable $(\boldsymbol{\lambda}, \boldsymbol{\beta}) \in \mathbb{R}^{2n}$, any lower-level solution $\boldsymbol{X} \in (\boldsymbol{\lambda}, \boldsymbol{\beta})$ can be cast into a bounded set. We carry out the reasoning for a given producer $i \in I$ and remark that it applies to all other producers. Consider a producer i. Its production $x_i^t(\omega)$ is bounded because of the second equation in (24). If capacity K_i is higher than this bound, all scarcity rents $\mu_i^t(\omega)$ would equal zero, which would violate the investment criterion, i.e., the third equation in (13).

We now show that market prices are bounded. If the market price $p^t(\omega)$ is not bounded for some hour t and scenario ω, then, by the first equation of (13), scarcity rents for all producers $i' \in I'$ are unbounded at t and ω (we remind the reader that these are producers for which $\lambda_{i'} = 1$), which contradicts investment criterion $CI_{i'} - \sum_{\omega\in\Omega} \zeta_i^*(\omega) \left(\sum_{t=1}^{T} \mu_{i'}^t(\omega) g_{i'}^t(\omega)\right) \geq 0$ under Assumption H1 and assuming that at least one technology $i' \in I'$ is available for some $\omega \in \Omega$ and $t \in T$: $\exists i' \in I'$ such that $g_i'^t(\omega) > 0$. The latter assumption is natural for thermal plants which, indeed, are not subsidized.

We now demonstrate that scarcity rents $\mu_i^t(\omega)$ can be bounded. If the production profile $g_i^t(\omega)$ is zero for some scenario ω and hour t, then variable $\mu_i^t(\omega)$ is degenerate and, without any loss of generality, we can make it equal to $-CO_i^t(\omega) + \beta_i - \delta_i p_{CO_2}(\omega) + \lambda_i p^t(\omega) + (1 - \lambda_i)\, s_i$ while respecting all equations of (13), which makes $\mu_i^t(\omega)$ bounded. If $g_i^t(\omega) > 0$, then the investment criterion (third equation of (13)) is violated under Assumption H1 if $\mu_i^t(\omega)$ is not bounded.

Risk-adjusted probabilities are bounded because they belong to compact risk sets. We now prove that demand variables $d^t(\omega)$ are bounded. If this is not the case for some ω and t, then relationship (21) implies that $p^t(\omega) = a^t(\omega) - b^t(\omega) d^t(\omega)$, contradicting the fact that prices are bounded.

Regarding the storage operator, as in our treatment of producers, we can prove that variables $\mu_s^t(\omega)$, $\nu_s^t(\omega)$, and $\sigma_s^t(\omega)$ are bounded. Operational decisions regarding battery $x_s^t(\omega)$ are bounded as a natural consequence of market-clearing conditions $d^t(\omega) - \sum_{i=1}^n x_i^t(\omega) - x_s^t(\omega) = 0$ and the fact that electricity production is always bounded for all scenarios and hours. This implies, following the reasoning we applied to producers, that capacity K_s is bounded as well.

Step 2. We demonstrate now that any upper-level solution to (30) $(\boldsymbol{\lambda}, \boldsymbol{\beta}) \in \mathbb{R}^{2n}$ can be cast in a bounded set. Of course, all λ_i, $i \in I$ are bounded because, by construction, $\lambda_i \in [0, 1]$, $\forall i \in I$. Assume $\beta_i \geq 0$ is un-bounded for some i. If $K_i = 0$, we have a degenerate case, as β_i can take any non-negative value. Without loss of generality, we can assign a zero value to β_i without changing anything with respect to our problem. If $K_i > 0$, by the first equation of (13), scarcity rents $\mu_i^t(\omega)$ are un-bounded for all scenarios ω and hours t. Given that production levels $x_i^t(\omega)$ are bounded because of the CO_2 constraint, which in turns implies that K_i is bounded, if $\mu_i^t(\omega)$ are un-bounded for all scenarios ω and hours t, the investment criterion, i.e., the third equation in (13), is violated under Assumption H1 and if $\exists(\omega, t) \in \Omega \times T$ such that $g_i^t(\omega) > 0$. This latter condition is actually a very natural claim; otherwise, the technology is worthless for the system.