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Abstract : The energy transition requires massive and costly investments in low-carbon power generation and storage. The private sector, however, is increasingly reluctant to undertake such investments. One of the main reasons is that electricity markets are incomplete: risk-averse investors are facing growing risk factors, but are unable to exchange or mitigate these risks beyond a few years. Hybrid market designs, by adding Capacity Remuneration Mechanisms, Contracts for Difference (CfDs), Power Purchase Agreements, and other financial instruments to the energy spot market, allow a better risk allocation between market agents, and have been shown to efficiently foster investment in new generators. Few studies have, however, quantified their efficiency in future systems with a high penetration of both renewable and storage technologies. The present paper tries to fill this research gap. We first propose to generalize the concept of Financial CfDs introduced in the literature to all assets, including storage and consumption assets, into what we define as Financial Twins: financial contracts that fully replicate physical asset's profits. We then show that a hybrid market design with one Financial Twin per technology is optimal in a power economy: it allows to reach the first best welfare, risk allocation, and investment decisions. To do so, we develop a two-stage stochastic partial equilibrium model of a power system in which agents invest in the first stage in an uncertain environment before trading electricity in the spot market in the second stage. After formulating the model and deriving some useful properties of Financial Twins, we apply the model to the Spanish electricity market to quantify the combined impacts of various Financial Twins in a real-world situation. We also propose and successfully apply a methodology to rank their added value by computing their Shapley values. Our findings indicate that Financial Twins for generators and demand have a far higher value than those for storage. Since over-the-counter battery contracts can already hedge most of a project's lifetime, policy makers should thus focus on ensuring adequate hedging for more critical technologies through well-designed Financial Twins.

Keywords: Capacity expansion, risk aversion, risk trading, complete or incomplete risk market, coherent risk measure, financial twins.

JEL Classification: D81, C72, C73, Q41

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Abstract

The energy transition requires massive and costly investments in low-carbon power generation and storage. The private sector, however, is increasingly reluctant to undertake such investments. One of the main reasons is that electricity markets are incomplete: risk-averse investors are facing growing risk factors, but are unable to exchange or mitigate these risks beyond a few years. Hybrid market designs, by adding Capacity Remuneration Mechanisms, Contracts for Difference (CfDs), Power Purchase Agreements, and other financial instruments to the energy spot market, allow a better risk allocation between market agents, and have been shown to efficiently foster investment in new generators. Few studies have, however, quantified their efficiency in future systems with a high penetration of both renewable *and* storage technologies. The present paper tries to fill this research gap. We first propose to generalize the concept of *Financial CfDs* introduced in the literature to all assets, including storage and consumption assets, into what we define as *Financial Twins*: financial contracts that fully replicate physical asset's profits. We then show that a hybrid market design with one Financial Twin per technology is optimal in a power economy: it allows to reach the first best welfare, risk allocation, and investment decisions. To do so, we develop a two-stage stochastic partial equilibrium model of a power system in which agents invest in the first stage in an uncertain environment before trading electricity in the spot market in the second stage. After formulating the model and deriving some useful properties of Financial Twins, we apply the model to the Spanish electricity market to quantify the combined impacts of various Financial Twins in a real-world situation. We also propose and successfully apply a methodology to rank their added value by computing their Shapley values. Our findings indicate that Financial Twins for generators and demand have a far higher value than those for storage. Since over-the-counter battery contracts can already hedge most of a project's lifetime, policy makers should thus focus on ensuring adequate hedging for more critical technologies through well-designed Financial Twins.

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Introduction

The global energy transition has accelerated over the past decade, driven by ambitious decarbonization targets to mitigate climate change, and rapid technological advances. In particular, two structural shifts have triggered a Copernician revolution in electricity markets worldwide: the sharp declining costs of i) Variable Renewable Energy Sources (VRES), and ii) Battery Energy Storage Systems (BESS).

Between 2010 and 2022, the levelized cost of electricity (LCOE) fell by over 80% for utility-scale solar photovoltaics (PV) and around 60% for onshore wind [IRENA, 2024], driving a massive expansion of VRES, which represented about 90% of global net capacity additions in 2024 [IRENA, 2025] and will cover 28% of the global generation mix in 2030 [IEA, 2025]. This rising penetration has increased supply variability and unpredictability, resulting in higher intraday price volatility and frequent negative prices, particularly in PV-dominant systems such as California, Texas or Australia [Hartner and Permoser, 2018] [da Silva and Horta, 2019]. Europe has not been spared by these adverse effects: in Germany for instance, the number of hours with negative wholesale electricity prices has more than tripled between 2015 and 2023 [Engie EnergyScan, 2025]. These phenomena signal the need for flexibility to manage intraday imbalances. While flexibility can stem from both the demand side (e.g., demand response) and the supply side (e.g., dispatchable generation and storage), the declining costs of BESS have positioned them as a key candidate for intraday arbitrage and system balancing [Volta Foundation, 2024].

BESS are thus becoming the workhorse of the energy transition, providing a range of essential services: short-term frequency regulation, reserve capacity, congestion management, and the temporal shifting of energy through day-ahead and intraday arbitrage. Predictable ancillary service revenues, often capacity-based, combined with cost declines, have underpinned the large deployment of batteries globally: 69 GW (169 GWh) were added in 2024, bringing total capacity to 150 GW (363 GWh), led by China (36 GW), the US (13 GW), Europe (10GW), and Australia (2 GW) [Volta Foundation, 2024]. Looking ahead however, decreasing costs and markets saturation will compress ancillary service revenues. They already fell by 48% in the US (2021-2023), and their share in total BESS revenues in Europe dropped from 40% to 33% between 2023 and 2024[EY, 2024]. With revenues shifting toward energy arbitrage, new battery projects will face greater exposure to volatile spot markets, whose uncertainty has deepened since the 2022 energy crisis—due to renewable intermittency amplified by ill-designed support schemes, fuel price shocks, and regulatory interventions to cite but a few.

The new risks emerging with these two technologies (VRES and BESS) would not be problematic *per se* if agents were able to hedge them efficiently, by buying for instance insurances against some extreme outcomes. As a matter of fact, several risk-hedging instruments do exist today, allowing partial coverage, mainly against price risk and over limited maturities—such as Contract for Differences (CFDs), Power Purchase Agreements (PPAs), etc. Yet most available hedging instruments were designed for the conventional thermal systems and are poorly adapted to the risk profiles of new technologies. This is specifically true for long-term regulatory instruments, as the private sector seems to have adapted its hedging practice on short-term financial markets. In the Copernician revolution of electricity markets alluded to before, the thermal system is now orbiting around renewables and batteries, but the market design remains organized around thermal peaking units: many risk sources (such as the volume risk of renewable assets) and longer term uncertainties remain largely unhedgeable, leading private investors to undervalue the profitability of renewable or storage projects. To a risk-averse investor, a riskier project will induce a higher weighted average cost of capital, ultimately discouraging investment in projects that might have been profitable otherwise [IEA, 2024]. Of course, this effect is worrying inasmuch as these hard-to-hedge risks may depress investment below the socially optimal level [de Maere d'Aertrycke et al., 2017] [Dimanchev, 2023]. This market failure, known as *market incompleteness* or *missing markets*, has been recognized as one of the major reasons behind the low level of investments in new capacities in Europe, especially for technologies with no available long-term support mechanism.

This raises a fundamental question for policymakers, regulators and private agents: why are these financial markets currently missing? In a long-term equilibrium without transaction costs indeed, according to the Coase Theorem [Coase, 1960], risk-averse agents should spontaneously exchange their risks to 'complete' a market and achieve the optimal risk allocation, regardless of their initial risk endowments. Two rationales—non mutually exclusive—can explain this current incompleteness:

1. In a static equilibrium approach, from a positive economics standpoint, the observed non-optimal risk allocation characterizing incomplete markets implies (by contraposition of the Coase Theorem) that some transaction costs or frictions must exist.[1] These transaction costs may arise from a variety of economic phenomena, such as information asymmetry, credit risk [Deng and Oren, 2006], moral hazard [Batlle et al., 2023], unhedgeable risks and deep uncertainties [Abada and Ancel, 2025], the irreversible nature of some specific contracts [Soumoy and Welgryn, 2025], or even behavioral biases. At equilibrium, if some contracts fail to emerge spontaneously, it is because some of these underlying frictions outweigh agents' willingness to hedge their positions.

2. The second reason, in a dynamic setting, is that markets for financial instruments and support mechanisms may simply not have yet reached this long-term equilibrium. A rich literature on innovation indeed explains that *"an innovation is never adopted from the outset by all the economic actors likely to do so in the long run"* [Baudry, 2021]. Applied to financial markets, this suggests that financial innovations following a technological breakthrough take time to emerge, or may even fail to diffuse, due to learning spillovers, limited cooperation, or coordination failures [Waidelich et al., 2025]. This leads to a transitory undersupply of securities—in others words, a transient market incompleteness—on top of the structural, steady-equilibrium one described above. In the long run, agents might introduce the best financial instruments possible, given potential transaction costs, as in [Duffie, 1994]; but in the meantime, some agents can face new risks with no access yet to adequate financial hedging instruments.

[1] Or that property rights are not well defined.

These two reasons are usually invoked in the literature to explain illiquidity in derivative markets between *private* agents. Often, the regulator is considered to be better placed to complete the market, either by providing hedges to the private sector and taking the residual risk, or by imposing a long-term derivative market clearing. But ultimately, the regulator itself has to be prone to one or both of the phenomena described above—if not, why has it not been able to complete current electricity markets?

This paper, though grounded in a static equilibrium framework, follows the second line of reasoning inasmuch as it abstracts away from transaction costs and market failures. We assume that, even if private agents can never fully complete the market because of long-term frictions, the regulator can always do so in the long-run by introducing new contracts, market designs or market-clearing obligations. We thus consider the currently observed market incompleteness as stemming solely from the dynamics of financial innovation and the delayed adaptation of market designs to renewable and storage technologies. Therefore, we describe a long-term equilibrium without transaction costs, focusing only on our first research question: Which financial instruments, if widely adopted in the long-run, could optimally allocate risks in power markets with high VRES and BESS penetration? Answering this question typically requires not only considering a wide spectrum of possible contract designs, including contracts for storage and other flexibilities, but also quantifying their effect on risk allocation, the cost of capital, and the resulting capacity expansion equilibrium. To the best of our knowledge, these two aspects were never considered together in the literature.[2] This question is all the more relevant given the impossibility in real markets to offer protection against any possible market outcome. Since only a finite number of contracts can be implemented, identifying which contracts are the most valuable will certainly constitute a precious input for policymakers. This motivates our second research question: By constructing a merit order of long term contracts, which risk-mitigating schemes should constitute the focus of policymakers in their effort to foster investments and increase welfare? In passing, our research will investigate whether it is more relevant to deploy new long-term contracts for generation or for storage assets.

To answer these questions, a model is needed as many complex intricacies and feedback effects exist between risk, contacts, installed capacity, and power prices in a power economy. We therefore develop a structural, stochastic, computable, and partial two-stage equilibrium model of the power economy with risk-averse agents along with its derivative market in the long-run. The two-stage timeline, now standard in the literature on investment under incomplete risk markets, represents the following logic: investors build their capacity in the first stage given a set of possible realizations (or scenarios) that could occur in the second stage. This latter stage models the dynamic clearing of spot markets and optimal operations of the assets. Of course, in the investments phase, agents do not know which scenario will occur in the second stage, but they can infer the distribution of scenarios via past market data. This model allows us to test the impact of any combination of contracts on welfare, installed capacity, flexibility, etc. In a second step, we develop a methodology inspired by the game theory to isolate the added value of each possible contract and hence

[2] See the literature review in Section 1.

quantify their relative importance for the electricity system.

The remainder of the paper is structured as follows: After a short literature review in **Section 1**, the equilibrium model is thoroughly presented in **Section 2**. Readers mainly interested in the economic intuition and results may proceed directly to **Section 3** where we present *Financial Twins*, a new market design that efficiently completes the market. In **Section 4**, we apply our model to a case study inspired by the Spanish market and compute, for each asset, the marginal increase in welfare after introducing its corresponding Financial Twin. As this marginal value depends on the combination of other Financial Twins already in place, we use the Shapley value to estimate the added value of each contract in the welfare increase. **Section 5** finally offers a summary and some concluding remarks, notably highlighting that Financial Twins are less valuable when applied to storage than to other assets.

1 Literature review—contract designs & capacity expansion equilibrium models with risk aversion

1.1 Market failures undermining the long-term capacity expansion

In theory, liberalized power markets should give the right price signal to incentivize electricity producers (resp. consumers) to invest in the optimal generation capacity mix (resp. in the optimal electrification investments) in the long-run [Boiteux, 1960] [Schweppe, 1988]. In practice, however, many market failures undermine this result [Joskow, 2006] [Batlle and Pérez-Arriaga, 2008] [Arango and Larsen, 2011] [Lebeau et al., 2024] [Lebeau, 2024]. Examples include market power exercise [Newbery, 1995], non-priced externalities such as CO_2 emissions, and truncated returns on investment when market prices are capped by the regulator. This last market failure, referred to as the missing money issue, can be (often imperfectly) corrected by Capacity Remuneration Mechanisms (CRMs) [Joskow, 2008] [Newbery, 2016] and more efficiently by reliability options [Oren, 2005] [de Vries and Heijnen, 2008] [Cramton et al., 2013].

But capacity remuneration mechanisms and reliability options have another virtue. They allow to partially correct another crucial market failure: the incompleteness of electricity markets [Magill and Quinzii, 2002], [Föllmer and Schied, 2016]. A financial market is said to be complete if the return of any physical asset (such as capacities for generation, storage and demand) can be totally hedged by a portfolio of financial instruments (such as futures, Contracts for Difference, or Power Purchase Agreements) [Arrow and Debreu, 1954] [Danthine and Donaldson, 2005]. In practice, all markets are incomplete, as a complete market for risk is but a theoretical chimera that necessitates an abnormally high number of risk-mitigating instruments. To complete a market, indeed, one should indeed introduce as many instruments as "states of the world" in which the market can be (scenarios and time steps). In that respect, the case of power markets is particularly worrying. First, they have long been considered as far from being complete, because there exist only a very few number of contracts with maturities long enough to match the investment in new generation capacities. This has led to the introduction of price caps, CRMs, reliability options and State-backed long-term contracts, in an attempt to correct the market failure.[3] But even if these remedies were perfectly efficient, a second reason still worsens the incompleteness of electricity markets: the rapid breakthrough of renewable and storage technologies, which increased the number of risks and "state of the world" underlying the agent's profits, and thereby the number of contracts necessary to approach market completeness (see Fig 4 in Appendix B for a schematic illustration).

In the remainder of this section, we review proposals of regulators and academics for novel designs and implementation of long-term contracts to mitigate the extent of market incompleteness.

1.2 A first phase of financial innovation: the introduction of long-term contracts for renewables

The emerging Variable Renewable Energy Sources soon revealed to be inefficiently supported—if at all—by capacity pricing and reliability options, due to their non-dispatchable nature. These technologies were thus left fully exposed to the aforementioned incompleteness of electricity markets, facing higher risks and therefore higher financing costs. A large zoology of long-term contracts appeared both in the literature and in public support policies in order to provide new and convenient hedging instruments, such as Contracts for Difference or Power Purchase Agreements. This emergence of new contracts can be seen as a phase of financial innovation, as described in [Duffie, 1994], where new contracts helped to better allocate the new risks introduced with VRES (mainly price and volume risks) and to increase welfare and investment in renewables. We refer to [Kitzing et al., 2024] for a recent review and comparison of various VRES long-term contract designs, considered as variations of standard Contracts for Difference. Among the many contract designs and publications studied in the review, three propose a payment indexed on a mathematical benchmark model instead of real generation [Elia, 2022] [Newbery, 2023] [Schlecht et al., 2024], which will be at the core of our work, and which solve the dilemma between short and long-term incentives described in [Favre, 2025]. Other studies explore the impact of long-term contracts on the cost of capital, in a project finance framework.

Quantifying the efficiency of long-term contracts to restore an optimal capacity expansion remains however a challenge, because of the intricate relationship between investment and hedging decisions on the one hand, and the associated cost of capital, which depends on the realization of market prices, on the other hand. [Ehrenmann and Smeers, 2011] first developed a risk-averse, stochastic, partial, computable and two-stage equilibrium model that allows to capture these intricacies, thanks to the use of convex risk measures introduced by [Artzner et al., 1999]. These measures of risk, which include the famous Conditional Value

[3]By introducing a capacity market alongside a price cap, regulators force generators to exchange a risky revenue—that accrued during hours of very high and fluctuating price peaks—for a less risky one —that accrued with a lower but guaranteed cap price and that generated from the capacity remuneration mechanism in place. Similarly, reliability options allow to hedge prices for a larger number of hours in the year—up to the entire revenues of a given generator if the strike price equals the plant's marginal cost.

at Risk, have become standard in modeling risk aversion when analyzing incompleteness of power markets ([de Maere d'Aertrycke et al., 2017] and related works). An interesting property of convex risk measures is that it can be shown that a complete market for risk can be modeled via the classical Centralized Generation Expansion Planning (GEP) used in the literature and the industry (see [Koltsaklis and Dagoumas, 2018] for an extensive review), but other models pricing long-term contracts in a perfect and complete market also exist ([Bessembinder and Lemmon, 2002][Benth and Koekebakker, 2008][Benth et al., 2018]). In the case of incompleteness, the model departs from this perfect case, necessitating the computation of the market outcome as an equilibrium to derive the added value of long-term contracts [de Maere d'Aertrycke et al., 2017]. Although incomplete markets can yield several equilibrium solutions [Gérard et al., 2018], [Abada et al., 2017] shows that such solutions are isolated and of odd number, and we observe that the equilibrium model developed in [Ehrenmann and Smeers, 2011] have proven to be useful in many studies to explore the effects of incompleteness on various VRES contract designs [de Maere d'Aertrycke et al., 2017], their number [Willems and Morbee, 2010], the short-term distortions they can cause [Abada and Ehrenmann, 2025], market power [Abada and Ehrenmann, 2025], or CO_2 emissions [Dimanchev, 2023].

1.3 A second phase of financial innovation: the need for long-term contracts for storage

With rapidly declining costs and an increasing penetration of renewables, Battery Electricity Storage Systems seem to follow the same path as renewables a decade ago: They are already largely deployed in some markets (CAISO, ERCOT, . . .) and the rise of larger daily price spreads makes them increasingly profitable. If the financial sector has already tailored instruments (Virtual Tolls, Revenue Swaps, ...) to hedge medium-term risks [Modo Energy, 2025], BESS cannot fully hedge their revenues in the longer run through capacity prices and reliability options, because they cannot be dispatched at will anytime. Long-term contracts for renewable generation do not help either, as they guarantee fixed prices, not a dynamic spread of prices that a storage asset could arbitrage. Academics and public regulators are still discussing this second phase of financial innovation, in order to delineate the adequate financial instruments for electricity storage. In that vein, many regulators have already implemented —or are in the process of designing—support mechanisms for BESS, as highlighted by the analysis and classification proposed in [Mastropietro et al., 2024]. Indeed, we observe a wide diversity of contracts deployed throughout the world, ranging from revenue CfDs, revenue floors and caps (UK, Australia, South Africa [Ministry of Electricity and Energy, Republic of South Africa, 2025], . . .), to capacity subsidies (Italy).

On the academic side, some articles have recently characterized and valued the risk of BESS revenues with the objective to define revenue hedging strategies [Boonstra and Oosterlee, 2021] [Karaduman, 2021] [Bovera et al., 2025]. As an example, the last chapter of [Favre, 2025] studies the optimal operation and contract choice to hedge a battery. [Schlecht et al., 2024] shortly state that their concept of Financial CfDs could be applied to storage in theory, but only to characterize it as unrealistic, without precising how it could be adapted. [Billimoria and Simshauser, 2023] provides a classification of storage contract designs along some features and recommends to use revenue caps and floors with a yardstick benchmark for batteries, in line with several implemented mechanisms. In a more systematic approach, [Zucker et al., 2024] provides a literature review of 200 publications to assess storage value in electricity markets. The authors regret that most studies, as those mentioned above, "use engineering models [. . .] without assessing [their] impact on the system", and they recommend to study how different market integration options could affect the deployment of storage capacities.

1.4 Closest literature, research gap, and contributions

Our assessment of the literature points in the same direction: we observe that almost all studies analyzing support schemes for storage either miss the feedback effect between revenue risk and investments or do not consider the impact of these schemes on the entire power system. This lack of endogeneity is however problematic: As argued above, a support mechanism affects the riskiness of an investment and in turn modifies its profitability. Therefore, it has an (indirect) impact on the installed capacity. Furthermore, from a system's perspective, the installed capacity of storage affects the formation and dynamics of spot prices, changing in turn the profitability of all generation and storage assets. That said, to the best of our knowledge, there are two exceptions which we discuss now.

Both exceptions adapt the holistic framework of [Ehrenmann and Smeers, 2011] to account for battery storage. [Dimanchev, 2023] introduces a BESS technology in its equilibrium framework, but emphasizes on CO_2 emissions rather than financial securities to promote storage. Closer to our research, [Mays and Jenkins, 2023] is, to the best of our knowledge, the only work that studies BESS investments, risk, and financial support schemes using a stochastic two-stage equilibrium model with risk aversion. By allowing agents to trade one contract per generation and storage technology, they show how the cost of capital and investments in storage capacities can be computed endogenously in an equilibrium model. They do not exploit, however, their model to quantify the added value of new long-term contract designs, leaving unanswered our research question and the concerns raised by [Zucker et al., 2024] quoted above.

The goal of the present work is precisely to fill this gap in the literature. Our methodology is close to that developed in [Mays and Jenkins, 2023], but it contributes to the literature in at least two directions. First, we introduce a new type of financial generation, demand, and storage contracts, that we call Financial Twins and we account for their joint effects on welfare and investments from the whole power system's perspective. Indeed, these contracts can be written for any underlying technology: Not only for thermal, renewable generation, and storage, as in [Mays and Jenkins, 2023], but also for demand, resulting in this last case in contracts close to the Standardized Fixed-Price Forward Contracts (SFPFC) proposed by [Wolak, 2022] and studied by [Shu and Mays, 2023]. By defining these Financial Twins in a systematic way for all technologies —instead of choosing arbitrary contracts as in [Mays and Jenkins, 2023]— we can show that they fully complete the market and achieve the optimal welfare, risk allocation among agents, and capacity expansion equilibrium. Second, by comparing different equilibrium outcomes with all possible combinations of Financial Twins, we were able to compute their relative added value via the Shapley value.

2 Theoretical Model: A computable risky capacity expansion equilibrium

In order to assess the impact of different long-term contracts on generation and storage deployment, we model the power spot and derivative markets as a two-stage, partial, and computable equilibrium, as developed by [Ehrenmann and Smeers, 2011], [Abada et al., 2017], and related works. Contract designs are chosen exogenously (their revenue, maturity, etc.), but their prices and contracted volumes are derived endogenously by market participants. Our model consists in:

- A second stage equilibrium that models the short-term dispatch and trading in the spot market. The stage accommodates seasonality inasmuch as it will encompass several representative days with an hourly granularity.
- A first stage equilibrium that models the investment decisions in power generation, demand, and storage capacities, as well as the derivative market where contract volumes are agreed upon.

In a nutshell, agents in the power economy are averse to risk. Risk drivers are modeled via a set of scenarios in the second stage. Risk pertains to spot prices, demand, fuel costs, and plants' availability. In the first stage, market agents undertake their investments and exchange contracts before the realization of uncertainty. In this stage, they only know the distribution of scenarios. As in now the tradition in models of power systems under risk and incompleteness, we resort to coherent risk measures to represent risk aversion. Producers using the same generation technology are assumed to face the same costs and efficiency; as such they can be aggregated into a single agent. In other words, producers are modeled via the technology they use: nuclear, solar, wind, thermal, etc. We now explain all these building blocks in greater detail. In the remainder of the paper, we sometimes write some relevant dual variables next to their constraints. Appendix A provides a comprehensive summary of our notation —particularly for technical variables and parameters not explicitly introduced in the text.

2.1 Short-term equilibrium: The second stage

Following a backward induction logic, we first present the second-stage of the equilibrium model, which describes the behavior of electricity market participants in the short run, once investments and contracts have been determined. In each scenario ω, and for every representative day d and hour h, agents optimize their operational decisions while the market price clears supply and demand. All agents are considered price takers, in a perfectly competitive setting, and therefore take the market price $\lambda_{d,h}(\omega)$ as an exogenous parameter.[4]

[4]The price is still optimized endogenously by the market maker agent.

Generators. A generator $g \in \mathcal{G}$ decides on its hourly production level $p^g_{d,h}(\omega)$ in order to maximize operational profit. The objective is to sell electricity at the prevailing spot price $\lambda_{d,h}(\omega)$, net of marginal cost $C^g_{d,h}(\omega)$, over all representative days and hours of the second stage:

$$\begin{aligned}
&\max_{p^g_{d,h}(\omega)} \sum_d N_d \sum_h p^g_{d,h}(\omega)\left(\lambda_{d,h}(\omega) - C^g_{d,h}(\omega)\right) \\
&\text{s.t. } 0 \le p^g_{d,h}(\omega) \le x^g f^g_{d,h}(\omega) \qquad (\mu^g_{d,h}(\omega)), \forall (d,h,\omega) \in \mathcal{D}\times\mathcal{H}\times\Omega.
\end{aligned} \tag{1}$$

The production level is limited by the available capacity x^g and the technology's availability factor $f^g_{d,h}(\omega)$. The associated shadow price $\mu^g_{d,h}(\omega)$ captures the marginal value of additional dispatch capability in each scenario. It also represents the marginal value of technology g, sometimes called scarcity rent.

Storage. A storage unit $s \in \mathcal{S}$ aim to exploit price fluctuations by charging during low-price periods and discharging when prices are high, with the objective to maximize profit. Their revenue is obtained from arbitraging the spot price over time as follows:

$$\begin{aligned}
&\max_{wi,in,lev} \sum_d N_d \sum_h \left[wi^s_{d,h}(\omega)(\lambda_{d,h}(\omega) - C^s) - in^s_{d,h}(\omega)(\lambda_{d,h}(\omega) + C^s)\right] \\
&\text{s.t. } 0 \le wi^s_{d,h}(\omega) \le x^s_p \qquad (\mu^s_{wi,d,h}(\omega)), \forall (d,h,\omega) \in \mathcal{D}\times\mathcal{H}\times\Omega \\
&\quad 0 \le in^s_{d,h}(\omega) \le x^s_p \qquad (\mu^s_{in,d,h}(\omega)), \forall (d,h,\omega) \in \mathcal{D}\times\mathcal{H}\times\Omega \\
&\quad 0 \le lev^s_{d,h}(\omega) \le x^s_e \qquad (\mu^s_{e,d,h}(\omega)), \forall (d,h,\omega) \in \mathcal{D}\times\mathcal{H}\times\Omega \\
&\quad lev^s_{d,h}(\omega) = -\frac{wi^s_{d,h}(\omega)}{\sqrt{\varepsilon^s}} + in^s_{d,h}(\omega).\sqrt{\varepsilon^s} + Dis^s_{d,h}(\omega) \begin{cases} lev^s_{d,24}(\omega) & \text{if } h = 1 \\ lev^s_{d,h-1}(\omega) & \text{otherwise} \end{cases} \qquad (\eta^s_{d,h}(\omega)), \forall (d,h,\omega) \in \mathcal{D}\times\mathcal{H}\times\Omega.
\end{aligned} \tag{2}$$

Operational constraints include maximum charging/discharging rates x^s_p, energy storage capacity x^s_e, and intertemporal energy balance that account for storage losses and assuming daily periodicity of the state of the battery. $\eta^s_{d,h}(\omega)$ reflects the marginal value of stored energy at each time, while $\mu^s_{wi}, \mu^s_{in}, \mu^s_e$ indicate the cost of capacity constraints being binding.

Consumers. On the demand side, consumers $l \in \mathcal{L}$ are modeled with their demand capacities x^l, their inelastic load profiles $L^l_{d,h}(\omega)$, and can consume an amount of energy $z^l_{d,h}(\omega)$ up to their load profile (or less if they want to shed load). The benefit of consuming electricity is valued at the consumer's Value Of Lost Load $VOLL^l_{d,h}(\omega)$:

$$\begin{aligned}
&\max_{z^l_{d,h}(\omega)} \sum_d N_d \sum_h (VOLL^l_{d,h}(\omega) - \lambda_{d,h}(\omega)) z^l_{d,h}(\omega) \\
&\text{s.t. } 0 \le z^l_{d,h}(\omega) \le x^l L^l_{d,h}(\omega) \qquad (\mu^l_{d,h}(\omega)), \forall (d,h,\omega) \in \mathcal{D}\times\mathcal{H}\times\Omega.
\end{aligned} \tag{3}$$

Our model encompasses the standard case of a single aggregated demand with a fixed historical capacity x^l (the sum of installed equipment such as heaters, industrial loads, etc.). Such a demand typically represent the aggregation of national consumers, retail companies, and the State or regulator—as in our case study. The model also allows to dis-aggregate these actors, by modeling the suppliers and the State as separate consumer agents with zero (or negligible) load, without altering our theoretical results. Finally, our framework naturally extends to new types of demand—such as data centers—which can build their own capacity x^l, operate under a seasonal and stochastic load profile $L^l_{d,h}(\omega)$, and earn a linear revenue $VOLL^l_{d,h}(\omega)$ per MWh consumed. This formulation implies that load shedding only takes place when the cost of electricity exceeds the consumer's valuation $VOLL^l_{d,h}(\omega)$.

Spot market clearing. The spot market clears at every hour and scenario by equating total supply and demand:

$$\sum_g p^g_{d,h}(\omega) + \sum_s wi^s_{d,h}(\omega) - \sum_s in^s_{d,h}(\omega) - z^l_{d,h}(\omega) = 0 \quad (\lambda_{d,h}(\omega)), \forall\, (d,h,\omega) \in \mathcal{D} \times \mathcal{H} \times \Omega. \tag{4}$$

The dual variable $\lambda_{d,h}(\omega)$ associated with equation (4) models the electricity price, ensuring that equilibrium prices emerge from the interaction of decentralized decisions.

At equilibrium, all agents maximize their profits and the market clears. For each agent's problem, the Karush-Kuhn-Tucker (KKT) conditions describe the sufficient and necessary conditions for optimality (as standard constraint qualifications hold in our case). Therefore, the concatenation of all these KKT conditions in a single Mixed Complementarity Problem (MCP) characterizes the equilibrium in a unified framework. At the equilibrium, the short-term physical profits of market agents can also be computed either using the primal or dual versions of agents' optimization problems:

$$\begin{aligned}
Z^g(\omega, x^g) &= \sum_{d,h} N_d\ p^g_{d,h}(\omega) \left(\lambda_{d,h}(\omega) - C^g_{d,h}(\omega)\right) = \sum_{d,h} N_d\ x^g \mu^g_{d,h}(\omega) f^g_{d,h}(\omega) && \forall g \in \mathcal{G} \\
Z^s(\omega, x^s_p, x^s_e) &= \sum_{d,h} N_d \left[wi^s_{d,h}(\omega)(\lambda_{d,h}(\omega) - C^s) - in^s_{d,h}(\omega)(\lambda_{d,h}(\omega) + C^s) \right] \\
&= \sum_{d,h} N_d \left[x^s_p \left(\mu^s_{wi,d,h}(\omega) + \mu^s_{in,d,h}(\omega)\right) + x^s_e \mu^s_{e,d,h} \right] && \forall s \in \mathcal{S} \\
Z^l(\omega, x^l) &= \sum_{d,h} N_d\ z^g_{d,h}(\omega) \left(VOLL_{d,h}(\omega) - \lambda_{d,h}(\omega)\right) = \sum_{d,h} N_d\ x^l \mu^l_{d,h}(\omega) L^l_{d,h}(\omega) && \forall l \in \mathcal{L}.
\end{aligned}$$

The agents' short-term physical profits depend on the capacity investments x^g, x^s_p, x^s_e, and x^l. For simplicity of notation, we introduce the following generic notation: for a market agent $a \in \mathcal{A} := \mathcal{G} \cup \mathcal{S} \cup \mathcal{L}$, its investment decision is x^a is[5]

$$x^a = \begin{cases} x^g \text{ when } a \text{ is a producer } g \\ \begin{pmatrix} x^s_p \\ x^s_e \end{pmatrix} \text{ when } a \text{ is a storage operator } s \\ x^l \text{ when } a \text{ is a consumer } l. \end{cases}$$

[5]This vectorial notation also helps to acknowledge that this framework could easily be extended to an equilibrium with value stacking in different markets, as long as the investment cost are linear — i.e. a linear CAPEX for increasing the ramping constraints.

2.2 Long-term equilibrium: The first stage

The first stage is the investment and contracting phase. Agents invest in new demand, generation, and storage capacities and trade long-term contracts to share risks and hedge their investment. The contract designs are chosen exogenously to test their impact on the equilibrium. Agents are, however, free to choose whether to trade a contract, and in which quantity. The specific contract designs we will study will be presented in Subsection 2.3. For now, we only assume that each agent of the power economy $a \in \mathcal{A}$ can trade different financial contracts $c \in \mathcal{C}$ in quantities K_c^a (a positive quantity models a purchase of the contract and a negative quantity models a sale). Each contract c is characterized by its stochastic unitary net payoff $W_c(\omega, P_c^1)$ at equilibrium, where P_c^1 is the price of the contract which is settled in the first stage. As such, it should reflect an absence of arbitrage property in the financial market between the first and second stages (Cochrane [2005]). Therefore, contracts' prices are endogenous to our model.

2.2.1 Estimating the investment and financial positions via optimization problems

Premises. We remind the reader that the second stage equilibrium, derived in subsection 2.1, determines the short-term physical profit $Z^a(\omega, x^a)$ of each agent $a \in \mathcal{A}$, which we expressed in (5). In addition to this physical profit, each agent also receives a net payoff $W^a(\omega, K^a_{c\,\in\,\mathcal{C}}, P^1_{c\,\in\,\mathcal{C}})$ resulting from the financial positions K_c^a taken for each contract c:

$$W^a(\omega, K^a_{c\,\in\,\mathcal{C}}, P^1_{c\,\in\,\mathcal{C}}) = \sum_c K_c^a W_c(\omega, P_c^1). \tag{5}$$

Agent a thus earns a total short-term profit $\Pi^a(\omega, x^a, K^a_{c\,\in\,\mathcal{C}}, P^1_{c\,\in\,\mathcal{C}})$ expressed as:

$$\Pi^a(\omega, x^a, K^a_{c\,\in\,\mathcal{C}}, P^1_{c\,\in\,\mathcal{C}}) = Z^a(\omega, x^a) + W^a(\omega, K^a_{c\,\in\,\mathcal{C}}, P^1_{c\,\in\,\mathcal{C}}). \tag{6}$$

For ease of notation, we will simply write total, physical, and financial profits as $\Pi^a(\omega)$, $Z^a(\omega)$, and $W^a(\omega)$ henceforth.

Risk measures. Agents being risk-averse, we assume that they value their assets using coherent measures of risk as introduced in [Artzner et al., 1999]. In other words, each agent a values the risk of its random payoff $\Pi^a(\omega)$ via the prism of a risk measure $\rho^a(.)$ that can be expressed as

$$\rho^a(\Pi^a(\omega)) := \max_{\zeta^a \in \mathcal{M}^a} \left(-\mathbb{E}_{\zeta^a}[\Pi^a(\omega)]\right), \tag{7}$$

where $\mathcal{M}^a$ is a compact and convex set of probability measures. As such, viewed from period 1, the agent values its asset's profitability via its risk-adjusted short-term profit (also called certainty equivalent) defined as the negative of its risk:

$$-\rho^a(\Pi^a(\omega)). \tag{8}$$

We remind the reader that this risk-adjusted profit depends on variables x^a,$K^a_{c\,\in\,\mathcal{C}}$, and $P^1_{c\,\in\,\mathcal{C}}$ although they do not appear explicitly in the notation.

Each agent maximizes its risk-adjusted profit net from the capital expenditures by choosing its invested capacity and financial positions. To model possible limited liquidity of the financial market, we introduce maximal quantities of contracts' purchase/sales of the form $K_c^a \leq \overline{K}_c^{x^a} x^a$ depending linearly on the agents' invested capacities, with $0 \leq \overline{K}_c^{x^a} \leq \infty$.[6] This procedure is in line with many existing asset-based long-term contracts in power markets, or could alternatively model prudential rules limiting the amount of financial contracts to the size of one agent/project.

Introducing the generic notation I^a to represent CAPEX costs I^g (for producers), I^l (for consumers), or the row vector $\left(I_p^s, I_e^s\right)$ (for storage), we can now express the first stage optimization problems of all agents. These programs are coupled through the financial market, and are subject to individual capacity and contract constraints, forming the first-stage equilibrium :

Agent a's program.

$$\min_{x^a \geq 0, K_c^a} \quad \rho^a(\Pi^a(\omega)) + I^a x^a \qquad = \min_{x^a \geq 0, K_c^a} \Big[\quad \max_{\zeta^a \in \mathcal{M}^a} \Big(\quad - \sum_{\omega \in \Omega} \zeta^a(\omega) \Pi^a(\omega, x^a, K_c^a) \Big) + I^a x^a \Big] \tag{9}$$

$$\text{s.t.} \quad K_c^a \leq \overline{K}_c^{x^a} x^a \qquad \left(\mu_{K_c}^a\right), \forall c \in \mathcal{C} \tag{10}$$

Financial Market clearing

$$\sum_{a \in \mathcal{A}} K_c^a = 0 \qquad \left(P_c^1\right), \forall c \in \mathcal{C}. \tag{11}$$

Because the financial market is competitive, we hold that the dual variable associated with its clearing constraint represents the exchange price of contracts P_c^1. For the same reason, P_c^1 is considered as a parameter (and not a variable) by all price-taking agents. As shown in [Abada et al., 2017], the use of coherent risk measures guarantees the convexity of each optimization problem individually. We can therefore derive the KKT conditions for each agent $a \in \mathcal{A}$:[7]

$$\begin{aligned} 0 \leq x^a \perp I^a + \partial_{x^a} \rho^a(-\Pi^a(\omega)) \geq 0 \\ K_c^a \perp \partial_{K_c^a} \rho^a(-\Pi^a(\omega)) = 0 \qquad \forall c \in \mathcal{C}. \end{aligned} \tag{12}$$

Using the envelope theorem and denoting by ζ^{a*} the risk-adjusted probabilities (i.e. the optimal probabilities defining the risk measure of agents a), one can rewrite 12 as:

$$\begin{aligned} 0 \leq x^a \perp I^a - \sum_{\omega} \zeta^{a*} \partial_{x^a} \Pi^a(\omega) \geq 0 \\ K_c^a \perp - \sum_{\omega} \zeta^{a*} \partial_{K_c^a} \Pi^a(\omega) = 0 \qquad \forall c \in \mathcal{C}. \end{aligned} \tag{13}$$

[6] The abusive notation of infinity equality corresponds to the case with no upper limit

[7] In line with our aggregate notation, ∂_{x^a} can either denote a scalar derivative for variables x^g or x^l, or the column gradient for storage $\begin{pmatrix} x_p^s \\ x_e^s \end{pmatrix}$.

Taken together, these two conditions respectively impose that investment is undertaken if the cost is recovered through a risk-adjusted expectation of scarcity margins, and that there is no arbitrage between the first and second stages in the financial market. Moving on, to facilitate economic interpretation of our mathematical developments, we now replace the variable associated with the purchased quantity of a contract, K_c^a, by a new variable y_c^a, which quantifies the difference between the maximal purchase volume limit and the quantity of contract c purchased:

$$y_c^a := \overline{K}_c^{x^a} x^a - K_c^a \geq 0, \tag{14}$$

and using the dual formulations of profits $\Pi^a(\omega)$, we can write the formulation of the first stage as a complementarity equilibrium problem:

Producers

$$0 \leq x^g \perp I^g - \sum_\omega \zeta^{g*} \sum_d N_d \sum_h \mu_{d,h}^g(\omega) f_{d,h}^g(\omega) + \sum_c \overline{K}_c^{x^g} W_c\left(\omega, P_c^1\right) \geq 0 \qquad \forall g \in \mathcal{G} \tag{15}$$

$$0 \leq y_c^g \perp \sum_\omega \zeta^{g*} W_c\left(\omega, P_c^1\right) \geq 0 \qquad \forall (g,c) \in \mathcal{G} \times \mathcal{C}. \tag{16}$$

Storages

$$0 \leq x_p^s \perp I_p^s - \sum_\omega \zeta^{s*} \sum_d N_d \sum_h \left(\mu_{wid,h}^s(\omega) + \mu_{ind,h}^s(\omega)\right) + \sum_c \overline{K}_c^{x_p^s} W_c\left(\omega, P_c^1\right) \geq 0 \qquad \forall s \in \mathcal{S} \tag{17}$$

$$0 \leq x_e^s \perp I_e^s - \sum_\omega \zeta^{s*} \sum_d N_d \sum_h \mu_{ed,h}^s(\omega) + \sum_c \overline{K}_c^{x_e^s} W_c\left(\omega, P_c^1\right) \geq 0 \qquad \forall s \in \mathcal{S} \tag{18}$$

$$0 \leq y_c^s \perp \sum_\omega \zeta^{s*} W_c\left(\omega, P_c^1\right) \geq 0 \qquad \forall (s,c) \in \mathcal{S} \times \mathcal{C}. \tag{19}$$

Demands

$$0 \leq x^l \perp I^l - \sum_\omega \zeta^{g*} \sum_d N_d \sum_h \mu_{d,h}^l(\omega) L_{d,h}^l(\omega) + \sum_c \overline{K}_c^{x^l} W_c\left(\omega, P_c^1\right) \geq 0 \qquad \forall l \in \mathcal{L} \tag{20}$$

$$0 \leq y_c^l \perp \sum_\omega \zeta^{l*} W_c\left(\omega, P_c^1\right) \geq 0 \qquad \forall (l,c) \in \mathcal{L} \times \mathcal{C}. \tag{21}$$

Financial Market clearing

$$P_c^1 \perp \sum_{g \in \mathcal{G}} \overline{K}_c^{x^g} x^g + \sum_{s \in \mathcal{S}} \left(\overline{K}_c^{x_p^s} x_p^s + \overline{K}_c^{x_e^s} x_e^s\right) + \sum_{l \in \mathcal{L}} \overline{K}_c^l - \sum_a y_c^a = 0 \qquad \forall c \in \mathcal{C}. \tag{22}$$

Remark 1 ***A note on historical capacities.*** *Our model assumes that capacity is built from scratch. It can easily accommodate existing or exogenous capacities, by dropping conditions 15, 17 and 18, or 20 out of the model, and fixing the corresponding capacity variable x^a as an exogenous parameter in the remaining conditions.*

2.2.2 The particular case of the Conditional Value at Risk

In this work, we resort to the expectation minus CVaR (or Conditional Value at Risk) to model risk aversion (used in [Downward et al., 2016] for instance). In this paradigm, agents use a convex combination of the expectation (under natural probabilities $\theta(\omega)$) and the Conditional Value at Risk (CVaR), also called Expected Shortfall or Average Value at Risk to value a risky payoff of the form:

$$\rho^a(\Pi^a) := -(1-\kappa^a)\mathbb{E}_\theta\Big[\Pi(\omega)\Big] + \kappa^a CVaR\Big[\Pi(\omega)\Big] \quad \forall a \in \mathcal{A}, \tag{23}$$

with $\kappa^a \in (0,1)$. In this case, it can be shown that risk-adjusted probabilities ζ^{a*} can be computed linearly as

$$\zeta^{a*}(\omega) = (1-\kappa^a)\theta(\omega) + \kappa^a \psi^{a*}(\omega) \tag{24}$$

where ψ^{a*} is the risk-adjusted probability of the CVaR, which we determine by solving the following linear program (this is an instance of a coherent risk measure, see [Rockafellar and Uryasev, 2000]):

$$\begin{aligned} \max_{\psi^a} \quad & -\sum_{\omega\in\Omega} \psi^a(\omega)\Pi^a(\omega) \\ \text{s.t.} \quad & \sum_{\omega\in\Omega} \psi^a(\omega) = 1 \\ & 0 \le \psi^a(\omega) \le \frac{\theta(\omega)}{1-\alpha^a} \quad \forall \omega \in \Omega \end{aligned} \tag{25}$$

and where $\alpha^a \in (0,1)$ is the level of risk aversion of agent a. Beyond its numerical tractability, the use of CVaR captures the risk aversion of investors with more realism than expected utility [Downward et al., 2016]. As reported in [Wang and Zitikis, 2020], it is also the state-of-the-art metric adopted by financial institutions since the 2016 Basel Accords [BCBS, 2016].

2.2.3 The two-stage equilibrium problem as a complementarity problem

At the equilibrium of the power economy, both the short-term (second stage) equilibrium and the long-term (first stage) equilibrium occur along with clearings of the spot and financial markets. The two-stage fully incomplete equilibrium is therefore characterized as a Mixed Complementarity Problem by solving joint KKT conditions of these subproblems. These conditions can be found in Appendix D.

2.3 General contracts designs

We now turn to delineating the contracts that can be exchanged between agents. This subsection methodically presents the linear contracts that can be modeled in our framework. This allows us to show how, for any asset in the market, one can naturally derive a contract providing a (theoretically) perfect hedge from its (benchmarked) profit function. This generalized family of contracts—that we call "Financial Twins"—will be extensively presented in Section 3.

In power markets, long-term contracts that allow hedging a market agent's spot profit are essentially derivatives indexed on revenues of physical products owned by agents—commodities and/or real assets. Using financial jargon, these physical products are also referred to as the *underlying* of the long-term contracts.

Underlying physical products To unify our notation, we will state that a physical product m has a (stochastic) market value $S_m(\omega)$, endogenously estimated and which depends on some market outcomes of the second stage (the spot price, the operational cost of the asset, etc.). In our model typically, the underlying physical products are:

FOR GENERATORS:

- Electricity in day d, scenario ω, and hour h
  — Sold in quantity $p^g_{d,h}(\omega)$ with a value $S_m(\omega) = N_d \left(\lambda_{d,h}(\omega) - C^g_{d,h}(\omega)\right)$.
- Generation capacities
  — Bought in quantity x^g with a value $S_m(\omega) = -I^g + \sum_{d,h} N_d \; \mu^g_{d,h}(\omega) \; f^g_{d,h}(\omega)$.

FOR STORAGE AGENTS:

- Electricity in day d, scenario ω, and hour h
  — Bought in quantity $in^s_{d,h}(\omega)$ with a value $S_m(\omega) = N_d \left(\lambda_{d,h}(\omega) + C^s_{d,h}(\omega)\right)$.
  — Sold in quantity $wi^s_{d,h}(\omega)$ with a value $S_m(\omega) = N_d \left(\lambda_{d,h}(\omega) - C^s_{d,h}(\omega)\right)$.
- Storage power capacities
  — Bought in quantity x^s_p with a value $S_m(\omega) = -I^s_p + \sum_{d,h} N_d \; \left(\mu^s_{wi\ d,h}(\omega) + \mu^s_{in\ d,h}(\omega)\right)$.
- Storage energy capacities
  — Bought in quantity x^s_e with a value $S_m(\omega) = -I^s_e + \sum_{d,h} N_d \; \mu^s_{e\ d,h}(\omega)$.

FOR DEMAND AGENTS:

- Electricity in day d, scenario ω, and hour h
  — Bought in quantity $z^l_{d,h}(\omega)$ with a value $S_m(\omega) = N_d \left(VOLL^l_{d,h} - \lambda_{d,h}(\omega)\right)$.
- Demand capacities
  — bought in quantity x^l with a value $S_m(\omega) = -I^l + \sum_{d,h} N_d \; \mu^l_{d,h}(\omega) \; L^l_{d,h}(\omega)$.

For the sake of simplicity, we restrict our model to these underlying products only. The same logic would however apply to other products, possibly including additional markets (to the energy market), such as markets for carbon quotas, capacity markets, or ramping capacities. Furthermore, we also limit the class of derivatives studied to swaps written on these underlying products.[8] When an agent buys a swap contract c indexed on an underlying m, it pays to the selling counterpart the underlying's stochastic value $S_m(\omega)$; in return, the agent receives from the seller a—possibly stochastic—revenue $S_c^1(\omega, P_c^1)$, indexed on the contract's market price P_c^1. The buyer's net payoff for a given contract c thus writes:

$$W_c(\omega, P_c^1) := S_c^1(\omega, P_c^1) - S_m(\omega). \tag{26}$$

The contract's revenue $S_c^1(\omega, P_c^1)$ is designed exogenously. In other words, for a single underlying product m, several different swap contracts can be designed depending on the chosen revenue $S_c^1(\omega, P_c^1)$.

The main interest of these contracts is that they allow to hedge a stochastic revenue $S_m(\omega)$ by swapping it with a less fluctuating revenue $S_c^1(\omega, P_c^1)$. To make things clearer, let us present an example. By buying a swap contract characterized by fixed and deterministic revenue $S_c^1(P_c^1)$—in the sense that it is scenario independent, an agent can build a fully-hedged portfolio composed of i) its real profit $S_m(\omega)$, and ii) the net contract payoff $W_c(\omega, P_c^1) := S_c^1(P_c^1) - S_m(\omega)$. The resulting portfolio would then have a deterministic risk-free profit $S_c^1(P_c^1)$. Of course, the agent should first find a counterpart willing to bear the risk. It can therefore be interesting to study other swap contracts, where the contract's revenue $S_c^1(\omega, P_c^1)$ remains partially risky in order to share risks among both parties.

Considering all underlying products we listed above and the different possible levels of risk-sharing, we could derive and classify a large variety of swap contracts, which are presented in Tables 1 to 3. To span different contract revenues $S_c^1(\omega, P_c^1)$ and thus different levels of risk-sharing, we first consider all stochastic variables and parameters appearing in the expression of the real product's value $S_m(\omega)$. We then progressively hedge $S_m(\omega)$ by replacing one or a combination of these parameters/variables by a deterministic contract price P_c^1. This process allows to construct several revenues $S_c^1(\omega, P_c^1)$, and thus several net payoffs $W_c(\omega, P_c^1)$. Taking the example of energy generators, we can define four swap contracts written on the spot electricity (no hedging, electricity price or fuel price hedging, or both) and four written on the installed capacity (no hedging, price-cost margin or volume hedging, or both).

[8] This class of contract could be easily extended to options by multiplying the contract's payoff by an index function, taking the value 1 under certain conditions (e.g. the payoff is greater than zero) and zero otherwise.

	Long-term hedges for Electricity Generator g	
Set of hedged parameters	**Capacity derivatives**	**Energy derivatives**
	$S_m(\omega) = -I^g + \sum_{d,h} N_d\ \underline{\mu^g_{d,h}(\omega)}\ \underline{f^g_{d,h}(\omega)}$	$S_m(\omega) = N_{d_c}\left(\underline{\lambda_{d_c,h_c}(\omega)} - \underline{C^g_{d_c,h_c}(\omega)}\right)$ for day d_c and hour h_c
$\emptyset$ None	$W_c = 0$ Full Merchant	$W_c = 0$ Full Merchant
$\{1^{st}\}$	$W_c = \sum_{d,h} N_d \left(P^1_c - \mu^g_{d,h}(\omega)\right) f^g_{d,h}(\omega)$ As-produced revenue CfD	$W_c = N_{d_c}\left(P^1_c - \lambda_{d_c,h_c}(\omega)\right)$ Electricity forward
$\{2^{nd}\}$	$W_c = \sum_{d,h} N_d\ \mu^g_{d,h}(\omega)\left(P^1_c - f^g_{d,h}(\omega)\right)$ Volume hedge	$W_c = N_{d_c}\left(-P^1_c + C^g_{d_c,h_c}(\omega)\right)$ Fuel forward
$\{1^{st}, 2^{nd}\}$ All	$W_c = \sum_{d,h} N_d\left(P^1_c - \mu^g_{d,h}(\omega) f^g_{d,h}(\omega)\right)$ Financial CfD	$W_c = N_{d_c}\left(P^1_c - (\lambda_{d_c,h_c}(\omega) - C^g_{d_c,h_c}(\omega))\right)$ Spread forward

Table 1: Long-term hedges for electricity generation.

Each product m (in columns) has a value S_m indexed on several stochastic parameters/variables (underlined). By hedging none, the first one, the second one, or all of these parameters, one can define as many new contracts (in lines). In general, for n stochastic parameters appearing in the value function S_m, one would have 2^n possible contracts/lines in the table—depending on which parameters are hedged.

Energy derivative contracts c are defined for a delivery in a representative day d_c and hour h_c.

	Long-term hedges for Electricity Storage s		
Set of hedged parameters	**Capacity derivatives**		**Energy derivatives**
	$S_m(\omega) = -I^s_p + \sum_{d,h} N_d \left(\underline{\mu^s_{in\ d,h}(\omega)} + \underline{\mu^s_{wi\ d,h}(\omega)}\right)$	$S_m(\omega) = -I^s_e + \sum_{d,h} N_d\ \underline{\mu^s_{e\ d,h}(\omega)}$	$S_m(\omega) = N_{d_c}\left(\underline{\lambda_{d_c,h_c}(\omega)} \pm C^s\right)$ for day d_c and hour h_c
$\emptyset$ None	$W_c = 0$ Full Merchant	$W_c = 0$ Full Merchant	$W_c = 0$ Full Merchant
$\{1^{st}\}$	$W_c = \sum_{d,h} N_d\left(P^1_c - \mu^s_{wi_{d,h}}(\omega)\right)$ Discharging revenue CfD	$W_c = \sum_{d,h} N_d\ \left(P^1_c - \mu^s_{e_{d,h}}(\omega)\right)$ Energy Financial CfD	$W_c = N_{d_c}\left(P^1_c - \lambda_{d,h}(\omega)\right)$ Electricity forward
$\{2^{nd}\}$	$W_c = \sum_{d,h} N_d\left(P^1_c - \mu^s_{in_{d,h}}(\omega)\right)$ Charging revenue CfD		
$\{1^{st}, 2^{nd}\}$ All	$W_c = \sum_{d,h} N_d\left(P^1_c - (\mu^s_{wi_{d,h}}(\omega) + \mu^s_{in_{d,h}}(\omega))\right)$ Power Financial CfD		

Table 2: Long-term hedges for electricity storage.

The notation is explained in Table 1

	Long-term hedges for Electricity Demand l	
Set of hedged parameters	**Capacity derivatives**	**Energy derivatives**
	$S_m(\omega) = -I^l + \sum_{d,h} N_d \ \underline{\mu^l_{d,h}(\omega)} \ \underline{L^l_{d,h}(\omega)}$	$S_m(\omega) = N_{d_c} \left(\underline{VOLL^l_{d_c,h_c}(\omega)} - \underline{\lambda_{d_c,h_c}(\omega)} \right)$ for day d_c and hour h_c
$\emptyset$ None	$W_c = 0$ Full Merchant	$W_c = 0$ Full Merchant
$\{1^{st}\}$	$W_c = \sum_{d,h} N_d \left(P^1_c - \mu^l_{d,h}(\omega)\right) L^l_{d,h}(\omega)$ As-consumed revenue CfD	$W_c = N_{d_c} \left(\lambda_{d_c,h_c}(\omega) - P^1_c\right)$ Electricity forward
$\{2^{nd}\}$	$W_c = \sum_{d,h} N_d \ \mu^l_{d,h}(\omega) \left(P^1_c - L^l_{d,h}(\omega)\right)$ Volume hedge	$W_c = N_{d_c} \left(P^1_c - VOLL^l_{d,h}(\omega)\right)$ Utility forward
$\{1^{st}, 2^{nd}\}$ All	$W_c = \sum_{d,h} \left(P^1_c - \mu^l_{d,h}(\omega) L^l_{d,h}(\omega)\right)$ Financial CfD	$W_c = N_{d_c} \left(P^1_c - (VOLL^l_{d_c,h_c}(\omega) - \lambda_{d_c,h_c}(\omega))\right)$ Spread forward

Table 3: Long-term hedges for electricity demand.
The notation is explained in Table 1

The contract classification proposed in Tables 1 to 3 allows to formally and systematically (for any technology) define a family of perfect asset-based hedges. By building a portfolio of all Financial CfDs defined on a given asset, its owner can indeed fully replicate and hedge its profit.[9] In Tables 1 to 3, this corresponds to the last line of the "Capacity derivatives" columns. Alternatively, they can be seen as Financial CfDs written not on a commodity price (as in [Schlecht et al., 2024]), but rather on a profit index, computed using an agreed asset's benchmark model and some market indices (spot price, etc.).

These contracts, that we call "Financial Twins", are presented in more details in the next section.

3 Financial Twins: An optimal hybrid market design

In this section, we introduce a family of asset-based contracts termed "Financial Twins" and formally defined at the end of the previous section. A Financial Twin is a contract between the owner of a physical asset (a power plant, a factory, ...) and a counterpart. The counterpart pays a fixed revenue to the asset's owner, and receive in return a theoretical profit of the asset. This theoretical profit is defined as the optimal profit achievable by a benchmark model of the asset—a function defined on several indexes (market prices, meteorological data, ...) and returning the optimal profit. We show that these contracts, tailored to the new fundamentals of power markets with high renewable and battery penetration, offer an optimal market design and fully correct the missing market failure. Beyond their formal definition, Financial Twins constitutes an incremental contribution to three strands of literature, and serves as a bridge between them to guide policymakers toward effective risk-allocating schemes:

[9] In our model, we only consider an energy-only market. If other markets were considered (for carbon quotas, capacity or ancillary services for example), one would have to add Financial CfDs written on those markets (as Carbon Contract for Difference for the carbon market) to build the right contract again.

First, Financial Twins generalize the Financial CfDs proposed by [Schlecht et al., 2024] to any asset—in particular to demand-side capacities. Building on [Newbery, 2023], [Schlecht et al., 2024] acknowledges that introducing a 'yardstick' benchmark model for a physical asset allows hedging not only the hourly electricity price, but the entire asset's hourly revenue from electricity sales—including the volume risk.[10] Financial Twins extend this idea further: once a benchmark is introduced, it becomes possible to hedge the asset's full profit over a relevant timeframe (e.g.,hourly, daily, or yearly). For renewable assets, Financial Twins coincide with Financial CfDs: we thus refer readers to [Schlecht et al., 2024] for practical implementation details. However, for thermal and storage assets, Financial CfDs—defined on an hourly electricity revenue—struggle to incorporate fluctuating fuel and opportunity costs. While a cost-indexed strike price tweak is proposed by the authors to address fuel cost variability, opportunity costs are considered as an irreducible hurdle. The Financial Twin framework, by hedging the full profit function over appropriate timeframes (daily for a batteries, weekly or yearly for hydro and nuclear), naturally integrates these costs into the benchmark, with no fundamental difference to renewable benchmarks. The practical implementation of such Financial Twins would closely follow the approach in [Schlecht et al., 2024], but with a benchmark modeling the asset's profit on a chosen timeframe, indexed on all relevant hourly prices and volumes rather than a single hourly revenue.[11] For BESS in particular, this would correspond to the implementation discussed in [Billimoria and Simshauser, 2023] and [Mastropietro et al., 2024]. Finally, Financial Twins also generalize Financial CfDs to demand-side assets, which were not considered by [Schlecht et al., 2024]. For large industrial sites, implementation would mirror that of thermal assets and could efficiently support clean reindustrialization and data center deployment. Defining a profit (utility) benchmark for residential demand would be more complex and may limit the applicability of Financial Twins in that segment.

Financial Twins also serve as a unifying framework structuring various existing efforts to adapt market design and financial hedging to emerging technologies. Table 4 presents a non-exhaustive overview of asset-based instruments and assesses how closely they align with the Financial Twin concept. These real-world examples demonstrate that Financial Twins are not only conceptually sound but also already deployed in practice. Moreover, they offer regulators concrete references for designing a coherent set of Financial Twins.

[10] A benchmark model is a theoretical representation of the physical asset used to compute the contract's payoff, indexed to publicly available indicators accessible to both parties.

[11] For example, the 24 hourly spot prices required to compute a BESS' daily arbitrage strategy.

Thermal assets

- **Price cap and Capacity Remuneration Mechanism (CRM).** Together, these mechanisms are equivalent to the Financial Twin of a thermal asset (or load shedding) with a variable cost (or value of lost load) equal to the price cap. In an energy-only market, such an asset earns inframarginal rents only when the price exceeds its marginal cost. When a price cap is imposed, these rents disappear and are replaced by capacity revenues. If those payments are optimally calibrated, they exactly replicate the missing-money compensation of a Financial Twin. However, because CRMs apply system-wide, they fit only assets whose risk profile is close to the underlying design. The derating factors applied to VRES and BESS in many CRMs reflect this imperfect replication.
- **Reliability Options** offer a more flexible version of Price caps and CRM, where the strike price is set to the marginal cost of each thermal unit. These contract perfectly replicates the (simplified) profit function of the corresponding asset, and can therefore be interpreted as an exact Financial Twin. They are already implemented in Belgium, Italy, and Ireland [Mastropietro et al., 2024].
- **Spark-spread and clean-spark-spread options** extend the logic to assets with stochastic variable costs, such as gas or emission quotas. They provide a good hedge for thermal assets but remain poorly adapted to renewable or storage risks.

Storage and hydro

- **BESS Virtual Tolls.** These contracts, already traded over the counter, demonstrate that Financial Twins can be implemented in practice for batteries [Modo Energy, 2025]. They coincide with the "revenue swap" studied by [Billimoria and Simshauser, 2023] and are used in public support schemes in Greece and Hungary [Mastropietro et al., 2024].
- **Hydropower contracts.** Financial Twins for hydropower could be defined in a similar way as for batteries, but with a longer-term reference benchmark. Such instruments would resemble the Brazilian *Mecanismo de Realocação de Energia*, which redistributes hydro inflow risks across market participants [CCEE, 2023].

Demand-side applications

- **Indexed demand contracts.** Financial Twins applied to demand have been less explored. Wolak [2022] proposes forwards indexed on the load level, but these contracts only hedge price risk, not volume. A more complete design could define a reference load profile and a reference willingness to pay (possibly time-dependent or indexed on market indicators). The consumer would then exchange the stochastic profit from its consumption flexibility for a fixed, certain payment. This concept can be implemented through Energy Performance Contracts, for instance, to de-risk investment in a hybrid heat-pump system: the consumer would transfer the uncertain benefit from the gas–electricity price spread to the counterpart, while receiving a guaranteed return.

Renewables

- **Renewable Financial or Capability CfDs.** As extensively discussed by Schlecht et al. [2024], these contracts directly correspond to Financial Twins defined for renewable assets.

Table 4: Existing Financial Twins implementations

Third and most importantly, Financial Twins can be interpreted as a direct application of the *fixed-price contracts* studied in [Laffont and Tirole, 1993]. In their notation, regulated firms may invest in new capacities with a constant marginal cost net of market revenues, given by

$$C(\omega, e(\omega)) + \psi(\omega, e(\omega)) := -S_m(\omega), \tag{27}$$

where ω denotes the scenario (their β), e the short-term dispatch decision (generation or consumption), and $S_m(\omega)$ the marginal capacity value defined in 2.3. Without a contract, the regulated firm generally perceives the risk-adjusted expectation of this cost as positive, even when the investment is socially optimal. The regulator can therefore offer a payment to induce the efficient level of capacity provision.
Under complete information (as assumed in our work), the regulator can observe ω ex-post. [Laffont and Tirole, 1993] show that it can then optimally offer a fixed-price contract $t(\omega) = \psi(\omega, e^*(\omega)) + C^*(\omega, e^*(\omega)) = -S_m(\omega)$, where $e^*(\omega)$ is the firm's optimal short-term dispatch in scenario ω. The firm is the residual claimant of its cost savings and will choose $e = e^*$, as long as the benchmark is accurate: no short-term incentive distortion arises.
This equivalence between fixed-price contracts and Financial Twins has significant implications for both their practical implementation and future research. Practically, it suggests that regulators can rely on their established expertise to design appropriate Financial Twins benchmarks. For future research, it also indicates how Financial Twins mechanisms might be adapted to optimally account for the different variants explored in [Laffont and Tirole, 1993]—starting with asymmetric information. We therefore believe that applying Incentive Regulation Theory to study long-term contract designs is a promising direction for subsequent work.

The replication of a physical asset's risk is pursued by [Schlecht et al., 2024], achieved in general by Financial Twins and their existing implementations, and optimal in the theoretical, centralized model of [Laffont and Tirole, 1993]. But is it necessarily desirable in decentralized power economies with storage and renewables? If an agent is willing to transfer all its physical risk through a Financial Twin, will there be a counterpart willing to receive it? In other terms, at equilibrium, are Financial Twins really efficient? We prove in Proposition 1 that the answer is yes. The reason for this is that introducing one Financial Twin per agent allows each agent in the economy to sell or buy all real assets: either by investing in their own asset, or by exchanging Financial Twins of other assets. Imagine, for instance, that all agents invest a given amount in their respective real assets. Then, we can let all agents but the least risk-averse of them sell the same amount of Financial Twins to the least averse agent. This latter agent will then be able to build the optimal market portfolio, by buying all Financial Twins and investing in its own asset. It will face exactly the same problem of the complete market case, which is equivalent to a social planner (endowed with the lowest risk aversion) optimizing social welfare and centrally undertaking investment and contracting decisions (see Ralph and Smeers [2015]).

Proposition 1 *Introducing one Financial Twin per agent in the market allows to retrieve the first best, socially optimal outcome.*
In such a configuration, the risk is optimally allocated, the welfare is maximized, and investment and dispatch follow the social optimal capacity planning and dispatch.

Proof 1 *See Appendix E*

Proposition 1 shows that Financial Twins, built as a bundle of Financial CfDs, are an optimal and ideal market design for hybrid electricity markets. They allow, in theory, to fully solve the missing market failure and to complete financial market. In practice, however, completing the market by a Financial Twins hybrid market design remains an unreachable ideal. Designing one Financial Twin contract for each agent in the power economy is unrealistic. Indeed, if one goes beyond the simplified profit function presented here and accounts for all stochastic parameters affecting the formation of the real profit of a given asset (like a wind turbine) to build the minimal number of Financial Twins to complete the market, one would need an extremely large number of parameters in the contract benchmark, and an untractable number of different Financial CfDs (one per agent on the market). This last point would in turn induce a lower market liquidity and its usual consequences (an increased market power, irreversibility, ...) It is, however, still possible to approach completeness by implementing a limited number of Financial Twins. One could, for example, define optimal clusters of agents with profits functions similar enough, so that the loss in welfare from imperfect hedging would be exactly compensated by the gain in liquidity, and then implement one average Financial Twin per cluster. We leave the investigation of this method for future research. Another approach, considered in Section 4, is to quantify the welfare increase allowed by each technology-specific Financial Twin. Ranking these Financial Twins by their marginal contribution to welfare defines a merit order, that can be followed to introduce first the highest-priority contracts—up to the maximal number of contracts that can realistically be implemented. This is the task we now turn to.

4 A Merit order for Financial Twins in the Spanish context

As shown in Section 3, covering each asset with a Financial Twin can, in theory, fully complete electricity markets—whatever the numerical calibration. Yet we also acknowledged that this task is infeasible, given the large number of real assets and their heterogeneity. A central policy question is therefore which contracts deliver the highest efficiency gains. What happens if some assets are not covered by Financial Twins? To which extend would the partially completed equilibrium diverge from the first best outcome, in terms of welfare, installed capacities, etc.?

This section proposes a methodology to quantify the impact of Financial Twins for key technologies (here applied to the Spanish market), and to rank them in a *merit order* according to their marginal welfare contribution. Our main results are summarized in Table 7. We proceed as follows: first, we set out the

Spanish context (4.1) and calibration (4.2); second, we present equilibrium results across different sets of available Financial Twins (4.3); and finally, we compute Shapley values to isolate the intrinsic contribution of each Financial Twin and build their merit order (4.4).

4.1 The Spanish context

The Spanish electricity market is a compelling case for long-term contracting: roughly 59% of its generation now comes from renewables (up from 40% in 2018) [Red Electrica, 2025] and Spain aims for 100% clean power by 2050, including phasing out its 20%-share nuclear fleet by 2035 [MTERD, 2024]. The rapid deployment of VRES has been supported by the successive Royal Decrees' mechanisms (Feed-in Tariffs, CfDs,...) [Kröger and Newbery, 2024] [CEER, 2025] and a Power Purchase Agreement (PPA) market among the most dynamic in Europe Pexapark [2025]. But these public and private hedging contracts are not well designed for storage assets. Battery projects are thus left with still no formal capacity-remuneration mechanism [Vector Renewables, 2025], and have to face future markets that are illiquid beyond a few years and have a low time-granularity (peak/off-peak profiles only) [Engie EnergyScan, 2025].

Despite this adverse regulative environment, market fundamentals are increasingly favorable to new BESS projects. As renewables are deployed, wholesale prices tend to fall, and daily spreads to rise. This dynamic—worsen by the peninsula's limited interconnection to the rest of the continent—is already evident: in 2024 Spain logged 196 hours of negative prices (and hundreds more at zero) [ENTSO-E, 2025], signaling chronic oversupply and the urgent need for storage. This led Spain to increase its storage target to 22.5 GW by 2030 [MTERD, 2024]. In short, the Iberian power market could follow the path of other systems with high PV potential such as California, Texas, Australia, or Germany, which have already seen renewable cannibalization, negative pricing, and rising storage deployment—situations that Spain is poised to match in the future.

4.2 Calibration

The calibration of our case study is inspired by the Spanish power market in a stylized way. Several assumptions are made to simplify computation and improve the readability of our results, while reflecting the main market fundamentals :

Agents First, we only consider three generation technologies: photovoltaic panels, onshore wind turbines, and one thermal technology—namely Combined Cycle Gas Turbines (CCGTs) ; one storage technology—Battery Electricity Storage Systems (BESS) ; and one historical, inelastic, and aggregated demand for the entire country. Secondly, the model is "Greenfield": we do not consider existing power plants and focus on the long-run market design, once all existing plants are decommissioned.[12] This also explains why

[12] This definition of a greenfield approach, with an elastic park adapting to cover a fixed demand, is traditionally used in the literature. A pure greenfield model however would also consider symmetric investments in new demand capacities. Here, we stick to the traditional approach for data availability reasons, assuming the future demand will remain close to the historical

	PV (€/MW/d)	Wind (€/MW/d)	CCGT (€/MW/d)	BESS P. (€/MW/d)	BESS E. (€/MWh/d)
CAPEX	105.85	155.03	173.07	56.07	43.51

Table 5: CAPEX Calibration

Methodology	Average Spanish GDP	Spanish Blackout losses	Spanish Blackout losses
Sources	[World Bank, 2025] [ENTSO-E, 2025]	[CEOE, 2025] [ENTSO-E, 2025]	[Caixa Bank Research, 2025] [ENTSO-E, 2025]
Kept in the calibration?	yes	no	no
VOLL (k€/MWh)	7.36	11.78	2.94

Table 6: VOLL Calibration

we do not model nuclear: Spain has no new nuclear program, and still plans to decommission its current power-plants by 2035 [MTERD, 2024]. To be consistent to this long-term focus, we also apply the Greenfield assumption to contract designs, independently on current designs in force, and make a focus on Financial Twins only.

Cost & VOLL calibration We consider the fixed capital expenditures (CAPEX) and the Value Of Lost Load (VOLL) as deterministic. As for the battery storage, we only keep a negligible deterministic variable cost for computational reasons, and consider the dissipation factor to be 1 (no dissipations). Using data from the NREL's 2024 Annual Technology Baseline (ATB), we annualize the CAPEX's 2030 projections with a risk-free rate of 2% and divide them to get daily CAPEX. The VOLL is calibrated using its theoretical definition: the ratio of the agent's wealth by its energy consumption. Here, as we have only one aggregated demand agent, we take the VOLL equal to the average hourly Spanish GDP, divided by the average hourly load.[13] This theoretical value is similar to other estimations of VOLL we made from the April 28th Spanish blackout's load shedding and existing estimations of the subsequent GDP loss. All calibrations can be found in Table 5 and 6.

Scenario calibration We consider a vector of exogenous stochastic parameters that we calibrate on time series from 2015 to 2024. The 73 scalar components of this vector are the 24 hourly load, PV and Wind availability rates, and a daily clean fuel price—the sum of the gas price and the necessary carbon quotas to consume one unit of gas, using the efficiency of the only thermal plant of our model. They realize simultaneously. To annualize our problem, the probability distribution of this stochastic vector has to be constant over all years of the investment's lifetime. This is not the case for long-term risks, such as variations

one even in the long-run.

[13]The choice not to calibrate the VOLL on the market price cap comes from our will to model the market fundamentals with no missing market bias. Our framework could still take into account a price cap, that would be modeled as a mandatory long-term option contract.

of the yearly wind production between years, or geopolitical shocks. We therefore consider that our time serie is a realization of a stochastic process which is separable into a product of 4 factors : i) a deterministic long-term average, ii) a deterministic seasonal deviation from this average, iii) a random short-term (daily) multiplicative deviation, and iv) a random long-term (yearly) multiplicative deviation. We do not study long-term risk, and select representative seasonal and short-term deviations by a k-medoids clustering to build our scenarios.[14] We use the ENTSO-E data from 2015 to 2024 for the hourly load, PV and Wind production and installed capacities, using the realized ratio production/capacity as a proxy for the availability factor (considering the amount of economic curtailment to be zero on those past years)[ENTSO-E, 2025]. The clean fuel price time serie is taken on the same period using the gas PVB price and the EU-ETS price from the database [Engie EnergyScan, 2025]. Finally, we increase the historical long-term average prices of gas and CO_2 up to 40€/MWh and 100€/tCO_{2eq} respectively to match existing forecasts.

4.3 Completing the electricity market with Financial Twins

The first result of our work is to quantify the welfare gap between the optimal social welfare (in a complete market) and the worst possible welfare (in a fully incomplete market, with no contracts): in our calibration the exogenous risk sources lead to a reduction by 4% of the Spanish GDP (about 60 billions €). This order in magnitude is in line with previous quantitative works on incomplete markets (e.g. -4% in [de Maere d'Aertrycke et al., 2017]) and justify the relevance of the current public debate about long-term contracts. It is of course a rough estimation, which could be underestimated as we only take short-term risks into account and do not consider ambiguity and/or overestimated because agents can hedge their investments up to a few years in reality.

Between these two extreme cases, we also assess the welfare achieved by introducing an increasing number of Financial Twins. In Figure 1, we add Financial Twins sequentially, covering an increasing number of technologies, in an arbitrary order (first renewables, then batteries, then CCGTs and finally demand). The impact of this order will be discussed later, but we can already highlight some interesting results from this graph. First, in line with [Willems and Morbee, 2010], the marginal value of introducing a new Financial Twin is decreasing: the first few contracts are sufficient to achieve a large increase in welfare, whereas the last ones only help to converge to the social optimum.[15] This result is encouraging, insofar as it justifies the practical utility of long-term contracts and Financial Twins: even if we cannot retrieve the first best social optimum, implementing a few contracts appears more feasible and could already correct a large part of the market failure. Second, when all Financial Twins are available, we also retrieve numerically the theoretical result of Proposition 1: the risk-averse equilibrium outcome is the same as in the first best, complete case, which can be computed as a capacity expansion planning optimized by a benevolent central planner. In

[14] Taking into account long-term risks could be done with multiple timesteps as in [de Maere d'Aertrycke, 2011]. However, the distribution of long-term stochastic factors are hard to quantify given the recent liberalization of energy markets and the subsequent lack of data. Such a model is thus inherently ambiguous, and should be modeled as such. On this topic, see [Abada and Ancel, 2025].

[15] This result also holds if we add contracts in a different order (cf. Appendix C)

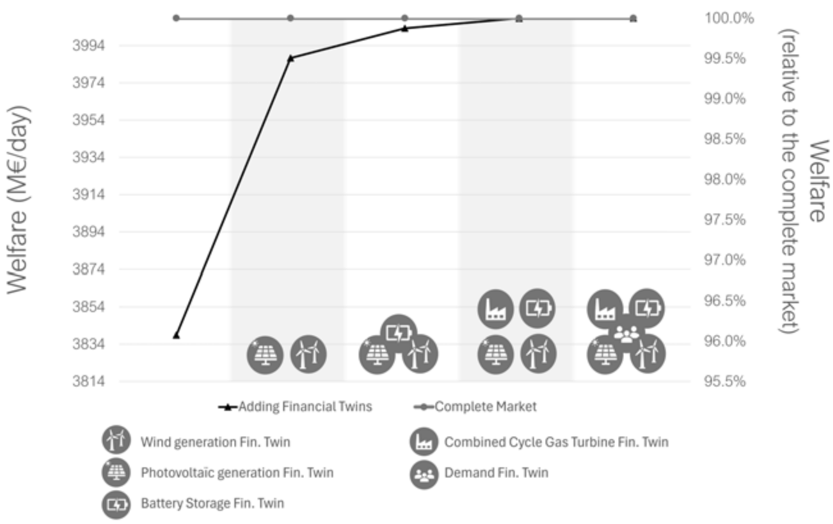


Figure 1: Completing the market with Financial Twins.
Welfare increases and reaches its optimal level by progressively adding one Financial Twin per asset.

this specific calibration, where all agents are endowed with the same risk aversion, the optimal outcome is already reached when all but one Financial Twins are implemented. In the general case however, one would need to introduce the last Financial Twin to ensure that the market risk portfolio can be allocated to the least risk-averse agent. This convergence to the first best outcome is visible on Figure 1 for welfare, but does also holds for all other indicators (see Figure 2 for installed capacities for example).

In Figure 2, the order in which we introduced Financial Twins was chosen arbitrarily. One could have chosen to implement first Financial Twins for CCGT, and the marginal increase in welfare achieved by the CCGT contract would have been higher. To be able to find the best order of adding Financial Twins, we compute the equilibrium for all possible configurations and orders. If we have N technologies and therefore N potential Financial Twins, we can compute 2^N possible configurations: each configuration is determined by the availability or not of each of the N contract. The equilibrium outcomes for all these configurations can be found in Appendix C.[16]

For all generation and demand technologies, the effect of adding a Financial Twin is monotonous on welfare: it always leads to an increase in welfare. However, adding a Financial Twins to cover BESS can lead to a small reduction in welfare in some cases. This can seem counterintuitive but is a well-known feature of

[16]The attentive reader will notice that we group PV and Wind together. This is done to limit the number of configurations: PV and Wind are still different agents in the equilibrium problem, but we will always introduce or remove their Financial Twins together.

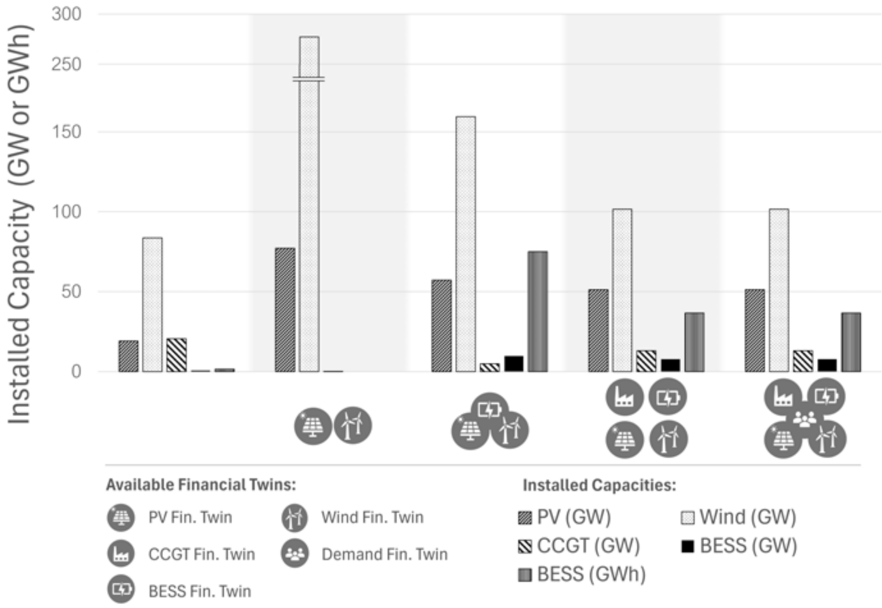


Figure 2: Installed Capacities when adding Financial Twins.
Installed capacities are at their optimal levels when all assets are covered by Financial Twins.

equilibrium problems (see [Willems and Morbee, 2010] for electricity market equilibrium, or [Hart, 1975] for incomplete markets in general). This highlights that synergy effects between long-term contracts matters, when choosing an hybrid market design. Another noteworthy result of our analysis is that introducing hedges only for renewables reduces investment into batteries, despite their well-known complementarity: when a financial hedge is available, batteries are no longer needed as natural hedges.

4.4 Ordering Financial Twins by their intrinsic added values

In this subsection, we propose an intuitive indicator to measure the added value of a given Financial Twin (or a given contract in general), independently of the mix of other contracts also available on the market. We call this indicator the *intrinsic added value* of the contract. We show that, in our case study, introducing Financial Twins by decreasing intrinsic added values coincide with the optimal deployment order that can be derived from the exhaustive results presented in Appendix C. We thus advocate that, even if our indicator averages out some synergy effects discussed earlier, it can still be useful to highlight the most efficient contracts on which regulators should concentrate their efforts in priority.

We define the intrinsic added value of a contract as its Shapley value. In cooperative game theory, the Shapley value, introduced by [Shapley, 1953], is a widely used metric that represents the contribution of a player in a coalition. Here, the "players" are Financial Twins, which can contribute to different possible market designs, defined as their possible coalitions—or combinations. Thus, the intrinsic added value or Shapley value of a Financial Twin is essentially the average marginal social benefit from introducing a given contract among all possible market designs it can be part of. The Shapley value $\varphi_i(v)$ for a given contract i is defined as:

$$\varphi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\ (n - |S| - 1)!}{n!} \left(v(S \cup \{i\}) - v(S)\right) \tag{28}$$

where i is the considered Financial Twin, S are all the sets of other Financial Twins without i (including the empty set), n is the number of Financial Twins considered, and v is the value of a market indicator (most notably welfare) when the set S of Financial Twins is available on the market. Social welfare is the most natural indicator to look at, allowing to derive the intrinsic added value of the contracts. But we also compute the Shapley values for the load shedding, the average gas-fired generation, the average electricity price, and the installed capacities for each technology.

Shapley values of different contracts				
Indicator	VRES Fin. Twins	BESS Fin. Twin	CCGT Fin. Twin	Demand Fin. Twin
Welfare (M€/day)	**+ 65.45**	**+ 1.88**	**+ 67.18**	**+ 35.45**
Load Shedding	+ 10.27	− 9.04	− 9.59	− 3.63
Gas gen. (MWh/d)	− 54.48	− 1.81	+ 4.95	− 11.20
Elec. price (€/MWh)	− 35.06	+ 11.11	− 27.39	− 15.50
PV capa. (GW)	+ 29.12	− 0.67	− 4.61	+ 8.21
Wind capa. (GW)	+ 78.56	− 23.91	− 30.37	− 6.38
CCGT capa. (GW)	− 9.96	− 0.77	+ 4.53	− 1.37
BESS P. capa. (GW)	+ 1.07	+ 4.07	− 0.55	+ 2.44
BESS E. capa. (GWh)	+ 9.13	+ 20.99	− 3.38	+ 8.44

Table 7: Shapley values of different Financial Twins, for different indicators.

The Shapley values of different Financial Twins are reported in Table 7. Following intuition, all contracts have a positive intrinsic added value (in bold in the Table) and increase investment in the technology they support. In particular, BESS Financial Twins improve security of supply by decreasing load shedding, and re-equilibrate capacities between renewable and storage. Less intuitively yet, the expected electricity price slightly increases under natural probabilities. This would usually lead to a decrease in welfare. But here the effect is more than counterbalanced by the hedging provided to all agents, who in turn reduce their subjective probabilities in the most adverse scenarios, increasing their subjective expected profits and thus welfare.

Ranking contracts by decreasing intrinsic added value, one can build a merit order in which they should be introduced. In our case study, this means implementing Financial Twins first for CCGTs, then for Renewables, then for demand and finally for BESS. That merit order allows to increase welfare in the fastest way, as confirmed by the figures of Table 8 in Appendix C. If a nearly optimal welfare can be retrieved with Financial Twins for generators only (VRES and CCGT), Figure 3 shows that this welfare is achieved with no batteries at all and a slight over-investment in gas-fired units. This could lead to a significative decrease in welfare if the carbon value were to rise far above the 100€/tCO_{2eq} average taken in our calibration. To this regard, BESS Financial Twins could be needed to approach the optimal capacity deployment and would do so in an efficient manner.

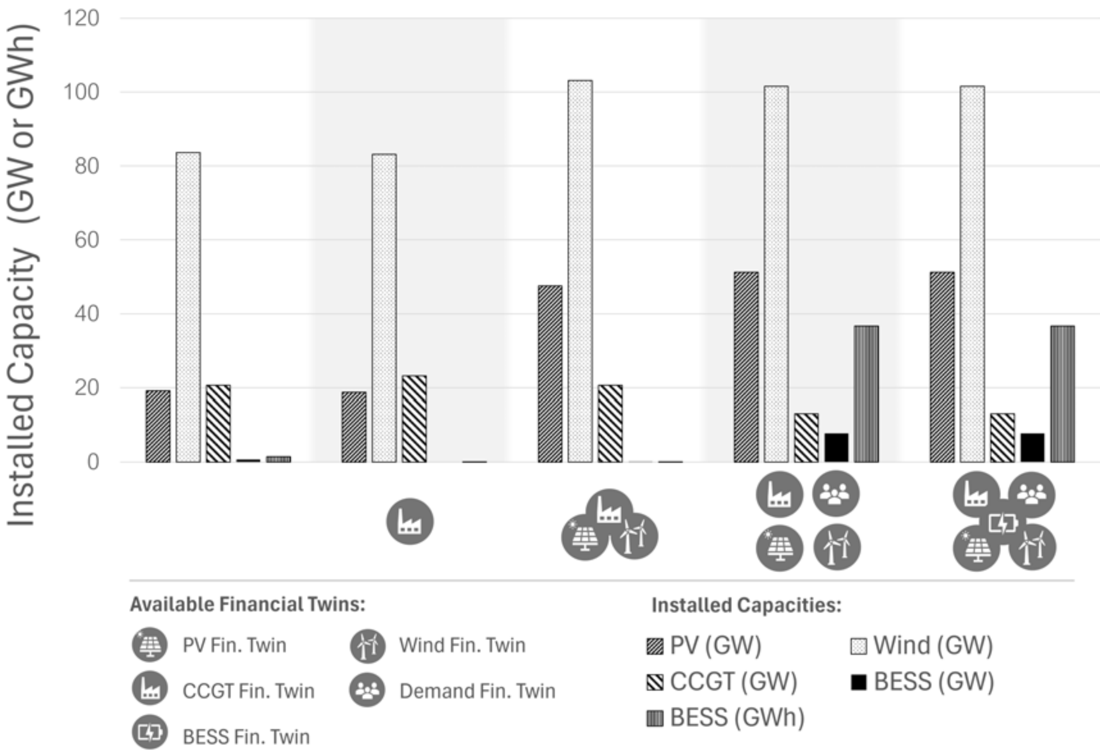


Figure 3: Installed capacities when introducing Financial Twins following the merit order

By applying this methodology to the Spanish power market, we show that generation Financial Twins have a larger impact on welfare than demand Financial Twins, and a far larger impact than storage Financial Twins. For the demand Financial Twin, this slightly lower added value is probably due to the fact that the demand capacity is fixed in our calibration. If investments in new demand capacities were considered, this could increase the impact of the demand's risk-aversion on the market, and thus the value of an associated

Financial Twin. If we show that Financial Twin for the historical demand are not very efficient, they could be much more relevant if tailored to manage the risk of new demand assets (Electric Vehicles, Data centers, Industrial decarbonization, etc.).

As for the low value of Battery Financial Twins, the explanation probably lies in the small traded volumes compared to generators. This low added value would probably be even more diluted, if one had also modeled other storage assets such as pumped hydroelectric storage. Financial Twins for generators help to roughly supply the demand, and storage Financial Twins can be seen as a fine-tuning to achieve the optimal level of storage integration. Furthermore, the rather low intrinsic added value of BESS Financial Twins represents both the value of private contracts and public support mechanisms—as there are not distinguished in our model. Virtual Tolls are already traded over-the-counter in many countries, with maturities sufficient to cover most of the lifetime of a BESS asset ($\sim$ 10-15 years). Much of the intrinsic added value computed here could therefore already be recovered through such private contracts, reducing further the rationale for State-backed support schemes for batteries.

These numerical results *per se* are a valuable contribution for policymakers. They show that a better long-term hedging of generation and demand assets through state-of-the-art support mechanisms (based on non-distortive benchmarks and transferring all risks) should be prioritized over the introduction of specific instruments for storage. But they also show how our methodology could be applied to other case studies and technologies to compute *ex-ante* a merit order for new support mechanisms, based on their intrinsic added value.

5 Discussion and Conclusion

5.1 Discussion

In this paper, we model a risky capacity expansion equilibrium, integrated with a financial market equilibrium for derivatives—which allows to quantify the added value of various long-term contracts. A systematic approach to derive different asset-based long-term contracts directly from agents' profit functions is introduced, provided these functions remain linear in installed capacities. We then demonstrate how a combination of several Financial Contracts for Differences—defined on electricity spot markets or other underlying indices—can be used to construct what we term Financial Twins. When implemented for all assets in the market, these Financial Twins constitute an optimal market design that fully completes the market.
Recognizing that, in practice, only a limited number of Financial Twins can be introduced, we finally apply our model to a case study to quantify the marginal value of each Financial Twin. Ranking them by their Shapley values, we establish a merit order for implementation. This provides a systematic guide for policymakers to prioritize market-completion efforts based on each contract's marginal contribution to welfare.

In our Spain-inspired case study, we show that storage-based Financial Twins are far less valuable than those written on generation or demand capacities. We expect this result to hold for other markets with high shares of renewables and BESS. Our methodology could, of course, be applied in different contexts—other geographies, or additional markets to capture value stacking—to test whether our numerical findings can be generalized. Shapley values could likewise be used to identify which market revenues should be covered in priority for each asset.

The model itself could be enhanced by disentangling existing medium-term financial markets from long-term State-backed instruments. This refinement would likely reduce the added value of new public support mechanisms, as such instruments would be redundant with the private market in the medium-term, and provide an additional hedge in the longer-term only. Another limitation of this work is that it abstracts from all market failures except a transient market incompleteness—stemming from delayed financial innovation. This simplification allows us to derive Financial Twins as a first-best policy in the long-term. A natural extension would be to incorporate other market failures or frictions—as evoked in our introduction—in order to characterize a second-best contract design. A promising research direction would be to find the optimal clusters of assets with similar risk profiles, balancing the basis risk arising from imperfect Financial Twin benchmarks against the inefficiencies caused by reduced liquidity or increased counterparty risks.

5.2 Conclusion

The ongoing decarbonization of power systems has brought forth new technologies—variable renewables and battery storage—that have transformed the economics of electricity supply. These innovations, however, have also shifted and multiplied the risks borne by market participants, with an increased dependency on daily price fluctuations or weather conditions for example. Traditional long-term market instruments—initially designed for thermal systems—no longer provide adequate coverage, leading to under-investment in assets that are essential for the energy transition.

This paper responds to that challenge by proposing Financial Twins, a general class of contracts that replicate the revenues of physical assets and thereby complete the market for risk. Using a two-stage stochastic equilibrium model with risk-averse agents, we show analytically and numerically that introducing one Financial Twin per technology restores the first-best welfare and investment allocation. Even when only a few contracts can exist, targeting generation-focused Financial Twins captures most of the welfare improvement. More generally, our work shows how to construct *ex-ante* a merit order that points out which assets should be hedged in priority by support mechanisms.

Beyond this specific modeling result, Financial Twins also provide a conceptual framework for policy design. They make it possible to read the diversity of existing instruments—CfDs, reliability options, capacity mechanisms, revenue floors—as particular approximations of the same underlying principle: aligning financial markets with the risk structure of emerging technologies. Viewing these heterogeneous instruments through the single conceptual lens of Financial Twins highlights which risks are effectively transferred and which remain unhedged.

As new technologies continue to emerge and reshape market risks—long-duration storage, hydrogen, new flexible demand—the same logic will apply: each innovation requires a corresponding evolution of the financial layer. Designing these instruments explicitly through the Financial Twin framework can help regulators and investors anticipate rather than react to the next wave of transformation. By grounding long-term market designs in rigorous stochastic equilibrium theory, this approach offers both a normative benchmark and a practical road-map for building resilient, investable and socially efficient power systems.

Appendices

A Notations

Sets

$g \in \mathcal{G} = \{PV, Wind, CCGT\}$	Set of generators technologies
$s \in \mathcal{S} = \{BESS\}$	Set of storage technologies
$l \in \mathcal{L} = \{\text{Aggregate inelastic load}\}$	Set of loads / demands
$a \in \mathcal{A} = \mathcal{G} \cup \mathcal{S} \cup \mathcal{L}$	Set of all agents
$h \in \mathcal{H} = [\![1\ ;\ 24]\!]$	Hours of the day
$d \in \mathcal{D} = [\![1\ ;\ 12]\!]$	Representative days of the year
$c \in \mathcal{C}$	Set of contracts
$\omega \in \Omega = [\![1\ ;\ 16]\!]$	short-term scenarios from 1 to 16

Parameters

I^g	Annualized CAPEX per rated power for generator g [€/MW/y]
I^s_p	Annualized CAPEX per rated power for storage s [€/MW/y]
I^s_e	Annualized CAPEX per rated energy stock for storage s [€/MWh/y]
I^l	Annualized CAPEX per rated power for demand l [€/MW/y]
$C^g_{d,h}(\omega)$	Variable cost of generator g – day d, hour h, scenario ω [€/MWh]
C^s	Variable cost of storage s [€/MWh]
$f^g_{d,h}(\omega)$	Load factor of generator g – day d, hour h, scenario ω [%]
$L^l_{d,h}(\omega)$	Inelastic load of demand l – day d, hour h, scenario ω [MW]
$Dis^s_{d,h}(\omega)$	Dissipation factor of storage s [%/h]
ε^s	Round-trip efficiency of storage s [%]
$VOLL^l_{d,h}(\omega)$	Value Of Loss Load for demand l [€/MWh]
$\theta(\omega)$	Natural probability of scenario ω [%]
N_d	Proportion of representative day d in a year [%]
α^a	CVaR parameter for agent a [%]
κ^a	weight of the CVAR in the linear combination $\mathbb{E}$ - CVaR for agent a [%]
$\overline{K}^a_c$	Maximal sale of contract c for agent a, in proportion of its installed capacity x^a [%]
$p^2_c(\omega)$	Cost of contract c in scenario ω [€]

Variables

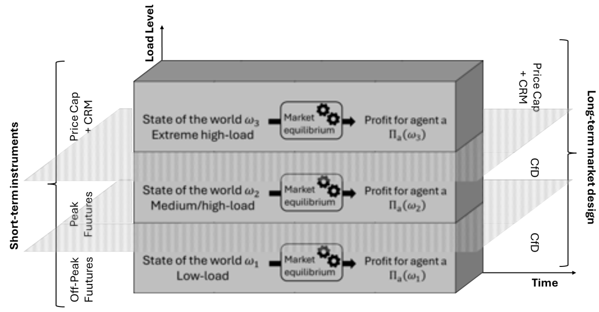
Primal

x^g	Installed capacity of generator g	[MW]
x_p^s	Installed power capacity of storage tech. s	[MW]
x_e^s	Installed energy capacity of storage tech. s	[MWh]
x^l	Installed capacity of demand l	[MW]
$p_{d,h}^g(\omega)$	Production level of generator g – day d, hour h, scenario ω	[MW]
$wi_{d,h}^s(\omega)$	Withdrawal from storage s – day d, hour h, scenario ω	[MW]
$in_{d,h}^s(\omega)$	Injection in storage s – day d, hour h, scenario ω	[MW]
$lev_{d,h}^s(\omega)$	Level of charge (SOC) of storage s – day d, hour h, scenario ω	[MWh]
$z_{d,h}^l(\omega)$	Non-shed Load of demand l – day d, hour h, scenario ω	[MW]
K_c^a	Volume of contract c sold by agent a	[MW]
y_c^a	Volume of contract c bought or not sold by agent a	[MW]

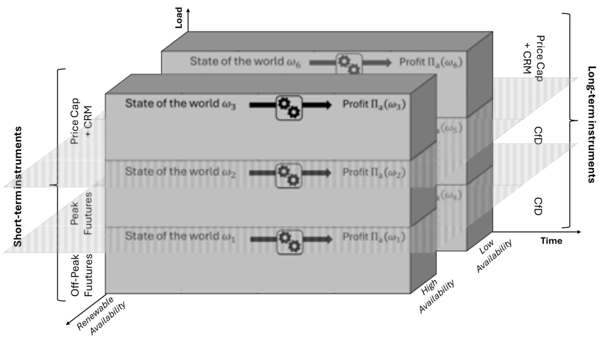
Dual

$\lambda_{d,h}(\omega)$	Marginal price of electricity – day d, hour h, scenario ω	[€/MWh]
P_c^1	Strike price of contract c	[€/MWh]
$\mu_{d,h}^g(\omega)$	Inframarginal rent for generator g – day d, hour h, scenario ω	[€/MWh]
$\mu_{d,h}^l(\omega)$	Short-term margin for demand l – day d, hour h, scenario ω	[€/MWh]
$\zeta^a(\omega)$	Subjective probability of scenario ω for agent a	[%]
$\mu_{wid,h}^s(\omega)$	Dual var. $\sim$ maximal withdrawal from storage s	[€/MWh]
$\mu_{ind,h}^s(\omega)$	Dual var. $\sim$ maximal injection in storage s	[€/MWh]
$\mu_{ed,h}^s(\omega)$	Dual var. $\sim$ maximal level of charge for storage s	[€/MWh]
$\eta_{d,h}^s(\omega)$	Dual var. $\sim$ intertemporal constraint for storage s	[€/MWh]
$\mu_{K_c}^a$	Dual var. $\sim$ maximal purchase constraint of agent a for contract c	

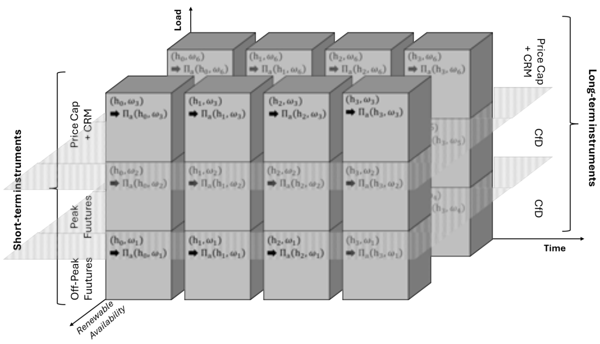
B A visual intuition on new risks introduced by renewables and batteries



(a) For a thermal-only capacity mix (with constant costs), intertemporal constraints are neglectable : the state of the electric system only depends on the load level, and so do the agents' profits. The conventional short-term instruments and long-term market design are both (approximately) tailored to these states of the world to complete the market.



(b) For a mix with high renewable-penetration , intertemporal constraints are still neglectable, but the state of the electric system also depends on renewable availability, and so do the agents' profits. The conventional short-term instruments and long-term market design are less adapted to these new states of the world : the market is less complete than before.



(c) For a mix with high renewable- and storage-penetration, intertemporal constraints are not neglectable anymore. The conventional short-term instruments and long-term market design are even less adapted to these new states of the world. Introducing new contracts with a higher granularity for each state of the world (e.g. Financial Twins), both in the short- and long-run, is necessary to restore welfare.

Figure 4: Increasing penetration of Renewables (b) and BESS (c) multiplies the number of states of the world, and therefore increases the number of short-term (financial) and long-term (market design) instruments required. The grey volume shows all states of the world that a capacity can encounter over its lifetime, with each state defined as $(t, \omega) \in T \times \Omega$, where t represents time and ω represents an elementary event (the sample space Ω is orthogonal to time and assumed to be time-invariant). In a fully thermal mix (a), profits depend mainly on the load level, so a partition of $T \times \Omega$ based on load is sufficient, corresponding to traditional market contracts (light grey planes). For systems with renewables (b) and batteries (c), the minimal partition must be *refined*, which requires designing new contracts to maintain market completeness.

C Exhaustive results for all Financial Twins configurations

Set of assets covered by Financial Twins	Complete Market Benchmark	∅ (Fully incomplete)	{VRES}	{BESS}	{CCGT}	{Demand}	{VRES, BESS}	{VRES, CCGT}	{VRES, Demand}
Welfare (M€/day)	4008.77	3838.81	3987.33	3859.34	3994.06	3963.91	4003.31	4003.56	3991.69
Exp Load Shedding (MW)	0.38	12.36	39.32	0.00	0.20	0.00	4.23	0.53	36.90
Exp. CO_2 intensity (gCO_2/kWh)	28.32	90.86	0.03	92.13	93.31	72.08	4.57	39.76	0.19
Exp. price (€/MWh)	85.80	152.47	71.58	152.95	87.39	86.74	84.88	52.49	66.57
PV Capa (GW)	51.20	19.15	77.26	22.26	18.72	36.12	57.29	47.49	74.18
Wind Capa (GW)	101.55	83.66	277.23	78.06	83.12	76.15	159.42	103.13	270.28
CCGT Capa (GW)	13.05	20.61	0.13	18.03	23.22	18.14	4.87	20.62	0.97
BESS P. Capa (GW)	7.72	0.69	0.00	5.74	0.00	5.72	9.72	0.00	0.00
BESS E. Capa (GWh)	36.64	1.46	0.00	22.35	0.00	22.23	75.06	0.00	0.00

Set of assets covered by Financial Twins	{BESS, CCGT}	{BESS, Demand}	{CCGT, Demand}	{RE, BESS, CCGT}	{RE, BESS, Demand}	{RE, CCGT, Demand}	{BESS, CCGT, Demand}	All
Welfare (M€/day)	3994.03	3875.80	3997.94	4008.65	4008.65	4008.65	4008.65	4008.76
Exp Load Shedding (MW)	0.20	0.00	0.00	0.38	0.38	0.38	0.38	0.38
Exp. CO_2 intensity (gCO_2/kWh)	93.31	78.44	81.49	28.32	28.32	28.32	28.32	28.32
Exp price (€/MWh)	87.39	145.93	78.43	85.80	85.80	85.80	85.80	85.63
PV Capa (GW)	18.72	34.15	27.41	51.20	51.20	51.20	51.20	51.20
Wind Capa (GW)	83.12	73.81	81.26	101.55	101.55	101.55	101.55	101.55
CCGT Capa (GW)	23.22	17.65	23.35	13.05	13.05	13.05	13.05	13.05
BESS P. Capa (GW)	0.00	6.50	0.00	7.72	7.72	7.72	7.72	7.72
BESS E. Capa (GWh)	0.00	26.47	0.00	36.64	36.64	36.64	36.64	36.64

Table 8: Financial Twins results for all contract configurations.

D MCP formulation of the 2-stage equilibrium problem

Producer g

$$\begin{aligned}
0 \le p^g_{d,h}(\omega) &\perp\ C^g_{d,h}(\omega) - \lambda_{d,h}(\omega) + \mu^g_{d,h}(\omega) \ge 0 && \forall d,h,\omega \\
0 \le \mu^g_{d,h}(\omega) &\perp f^g_{d,h}(\omega)x^g - p^g_{d,h}(\omega) \ge 0 && \forall d,h,\omega \\
0 \le x^g &\perp I^g - \sum_\omega \zeta^{g*} \sum_d N_d \sum_h \mu^g_{d,h}(\omega) f^g_{d,h}(\omega) + \sum_c \overline{K}^{x^g}_c W_c\left(\omega, P^1_c\right) \ge 0 \\
0 \le y^g_c &\perp \sum_\omega \zeta^{g*} W_c\left(\omega, P^1_c\right) \ge 0 && \forall c \\
0 \le \psi^{g*}(\omega) &\perp \Pi^g(\omega, x^g, K^g_c) + \delta^g - \sigma^g(\omega) \ge 0 && \forall \omega \\
\delta^g &\perp \sum_{\omega\in\Omega} \psi^{g*}(\omega) - 1 = 0 \\
0 \le \sigma^g(\omega) &\perp \frac{\theta(\omega)}{1-\alpha^g} - \psi^{g*}(\omega) \ge 0 && \forall \omega
\end{aligned} \tag{29}$$

With: $\zeta^{g*} = (1-\kappa^g)\theta(\omega) + \kappa^g \psi^{g*}(\omega)$

$$\Pi^g(\omega, x^g) = \sum_d N_d \sum_h x^g \mu^g_{d,h}(\omega) f^g_{d,h}(\omega) + \sum_c (\overline{K}^{x^g}_c x^g - y^g_c) W_c\left(\omega, P^1_c\right)$$

Demand l

$$\begin{aligned}
0 \le z^l_{d,h}(\omega) &\perp\ VOLL^l - \lambda_{d,h}(\omega) \ge 0 && \forall d,h,\omega \\
0 \le \mu^l_{d,h}(\omega) &\perp L^l_{d,h}(\omega)x^l - z^l_{d,h}(\omega) \ge 0 && \forall d,h,\omega \\
0 \le x^l &\perp I^l - \sum_\omega \zeta^{g*} \sum_d N_d \sum_h \mu^l_{d,h}(\omega) L^l_{d,h}(\omega) + \sum_c \overline{K}^{x^l}_c W_c\left(\omega, P^1_c\right) \ge 0 \\
0 \le y^l_c &\perp \sum_\omega \zeta^{l*} W_c\left(\omega, P^1_c\right) \ge 0 && \forall c \\
0 \le \psi^{l*}(\omega) &\perp \Pi^l(\omega, x^l, K^l_c) + \delta^l - \sigma^l(\omega) \ge 0 && \forall \omega \\
\delta^l &\perp \sum_{\omega\in\Omega} \psi^{l*}(\omega) - 1 = 0 \\
0 \le \sigma^l(\omega) &\perp \frac{\theta(\omega)}{1-\alpha^l} - \psi^{l*}(\omega) \ge 0 && \forall \omega
\end{aligned} \tag{30}$$

With: $\zeta^{l*}(\omega) = (1-\kappa^l)\theta(\omega) + \kappa^l \psi^{l*}(\omega)$

$$\Pi^l(\omega, x^l) = \sum_d N_d \sum_h x^l \mu^l_{d,h}(\omega) L^l_{d,h}(\omega) + \sum_c (\overline{K}^{x^l}_c x^l - y^l_c) W_c\left(\omega, P^1_c\right)$$

Storage s

$$
\begin{aligned}
0 \leq wi^s_{d,h}(\omega) &\perp \; C^s - \lambda_{d,h}(\omega) + \mu^s_{wid,h}(\omega) + \frac{\eta^s_{d,h}(\omega)}{\sqrt{\varepsilon^s}} \geq 0 && \forall d,h,\omega \\
0 \leq in^s_{d,h}(\omega) &\perp \; C^s + \lambda_{d,h}(\omega) + \mu^s_{ind,h}(\omega) - \eta^s_{d,h}(\omega).\sqrt{\varepsilon^s} \geq 0 && \forall d,h,\omega \\
0 \leq lev^s_{d,h}(\omega) &\perp \; \mu^s_{ed,h}(\omega) + \eta^s_{d,h}(\omega) - \eta^s_{d,h+1}(\omega) \geq 0 && \forall d,h,\omega \\
\eta^s_{d,h}(\omega) &\perp \; \frac{wi^s_{d,h}(\omega)}{\sqrt{\varepsilon^s}} - in^s_{d,h}(\omega).\sqrt{\varepsilon^s} + lev^s_{d,h}(\omega) - Dis^s_{d,h}(\omega) lev^s_{d,h-1}(\omega) = 0 && \forall d,h,\omega \\
0 \leq \mu^s_{wid,h}(\omega) &\perp \; x^s_p - wi^s_{d,h}(\omega) \geq 0 && \forall d,h,\omega \\
0 \leq \mu^s_{ind,h}(\omega) &\perp \; x^s_p - in_{s,h}(\omega) \geq 0 && \forall d,h,\omega \\
0 \leq \mu^s_{ed,h}(\omega) &\perp \; x^s_e - lev^s_{d,h}(\omega) \geq 0 && \forall d,h,\omega \\
0 \leq x^s_p &\perp I^s_p - \sum_\omega \zeta^{s*} \sum_d N_d \sum_h \left(\mu^s_{wid,h}(\omega) + \mu^s_{ind,h}(\omega)\right) + \sum_c \overline{K}^{x^s_p} W_c\left(\omega, P^1_c\right) \geq 0 \\
0 \leq x^s_e &\perp I^s_e - \sum_\omega \zeta^{s*} \sum_d N_d \sum_h \mu^s_{ed,h}(\omega) + \sum_c \overline{K}^{x^s_e} W_c\left(\omega, P^1_c\right) \geq 0 \\
0 \leq y^s_c &\perp \sum_\omega \zeta^{s*} W_c\left(\omega, P^1_c\right) \geq 0 && \forall c \\
0 \leq \psi^{s*}(\omega) &\perp \Pi^s(\omega, x^s, K^s_c) + \delta^s - \sigma^s(\omega) \geq 0 && \forall \omega \\
\delta^s &\perp \sum_{\omega \in \Omega} \psi^{s*}(\omega) - 1 = 0 \\
0 \leq \sigma^s(\omega) &\perp \frac{\theta(\omega)}{1-\alpha^s} - \psi^{s*}(\omega) \geq 0 && \forall \omega
\end{aligned}
$$

$$
\begin{aligned}
&\text{With: } \zeta^{s*}(\omega) = (1-\kappa^s)\theta(\omega) + \kappa^s \psi^{s*}(\omega) \\
&\Pi^s(\omega, x^s_p, x^s_e) = \sum_d N_d \sum_h \left(x^s_p(\mu^s_{wid,h}(\omega) + \mu^s_{ind,h}(\omega)) + x^s_e \mu^s_{ed,h}(\omega)\right) + \sum_c (\overline{K}^{x^s_p} x^s_p + \overline{K}^{x^s_e} x^s_e - y^s_c) W_c\left(\omega, P^1_c\right)
\end{aligned}
\tag{31}
$$

Spot Market clearing

$$
\lambda_{d,h}(\omega) \perp \sum_g p^g_{d,h}(\omega) + \sum_s \left(wi^s{}_{d,h}(\omega) - in^s_{d,h}(\omega)\right) - \sum_l \left(L^l_{d,h}(\omega) - z^l_{d,h}(\omega)\right) = 0 \quad \forall d,h,\omega \tag{32}
$$

Financial Market clearing

$$
P^1_c \perp \quad \overline{K}^{x^g}_c x^g + \overline{K}^{x^s_p}_c x^s_p + \overline{K}^{x^s_e}_c x^s_e + \overline{K}^l_c - \sum_a y^a_c = 0 \qquad \forall c \tag{33}
$$

E Proof of Proposition 1

The proof of Proposition 1 is structured as follows: we look for an equilibrium point by fixing "by hand" some variables and complementarity conditions to zero. We then show that the remaining KKT conditions are exactly the same as those stemming from a central planner optimization problem.

Let us first recall the net payoff of a Financial CfD:

$$
\begin{aligned}
W_c(\omega, P^1_{\text{F-CfD(g)}}) &= \sum_{d,h} N_d \left(P^1_{\text{F-CfD(g)}} - \mu^g_{d,h}(\omega) f^g_{d,h}(\omega) \right) && \text{for a generator} \\
W_c(\omega, P^1_{\text{F-CfD(s,p)}}) &= \sum_{d,h} N_d \left(P^1_{\text{F-CfD(s,p)}} - (\mu^s_{wi_{d,h}}(\omega) + \mu^s_{in_{d,h}}(\omega)) \right) && \text{for a storage (power part)} \\
W_c(\omega, P^1_{\text{F-CfD(s,e)}}) &= \sum_{d,h} N_d \left(P^1_{\text{F-CfD(s,e)}} - \mu^s_{e_{d,h}}(\omega) \right) && \text{for a storage (energy part)} \\
W_c(\omega, P^1_{\text{F-CfD(l)}}) &= \sum_{d,h} \left(P^1_{\text{F-CfD(l)}} - \mu^l_{d,h}(\omega) L^l_{d,h}(\omega) \right) && \text{for a consumer}
\end{aligned} \tag{34}
$$

We first make the standard assumption that all Financial CfDs have a maximal contract limit relative to the installed capacity $\overline{K}^a$ of one (100%) only for the agent owning the considered technology, and zero for all other agents. In the KKT conditions complementary to the capacity variables (conditions 15, 17, 18 and 20), the sums on all contracts therefore reduce to the net payoff of the Financial CfD corresponding to the agent's technology. Replacing the net contract's payoffs by their expressions, the market profit terms (inframarginal rents) cancel out. We finally look for an equilibrium point where these conditions, once simplified, are binding:

$$
\begin{aligned}
0 \leq x^g &\perp I^g - P^1_{\text{F-CfD(g)}} = 0 \\
0 \leq x^s_p &\perp I^s_p - P^1_{\text{F-CfD(s,p)}} = 0 \\
0 \leq x^s_e &\perp I^s_e - P^1_{\text{F-CfD(s,e)}} = 0 \\
0 \leq x^l &\perp I^l - P^1_{\text{F-CfD(l)}} = 0
\end{aligned} \tag{35}
$$

This sets the Financial CfDs' prices to their equilibrium values P^{1*}_c. Let us make the technical assumption that agents can be ranked by increasing risk aversion (for example if they all have the same parametric coherent risk measure that only differ by one increasing parameter). Then their characteristic sets can be ordered in a nested sequence of sets, monotonously increasing, where each agent's risk set is included in the risk sets of all more risk-averse agents :

$$
\mathcal{M}^{a_1} \subseteq \mathcal{M}^{a_2} \subseteq ... \subseteq \mathcal{M}^{a_n} \tag{36}
$$

This also means that the intersection of all risk sets is equal to the risk set of the least risk-averse agent.

$$
\bigcap_i \mathcal{M}^{a_i} = \mathcal{M}^{a_1} \tag{37}
$$

Let us now fix the purchased volumes y^a_c to zero for all agents but the least risk-averse (a^1). This means that all market risks are transferred to the least risk-averse agent through Financial Twins. The financial clearing conditions thus become:

$$
\begin{aligned}
P^1_{\text{F-CfD(g)}} &\perp x^g = y^{a_1}_{\text{F-CfD(g)}} \\
P^1_{\text{F-CfD(s,p)}} &\perp x^s_p = y^{a_1}_{\text{F-CfD(s,p)}} \\
P^1_{\text{F-CfD(s,e)}} &\perp x^s_e = y^{a_1}_{\text{F-CfD(s,e)}} \\
P^1_{\text{F-CfD(l)}} &\perp x^l = y^{a_1}_{\text{F-CfD(l)}}
\end{aligned} \tag{38}
$$

This also mean that the profits $\Pi^{a_{i\neq 1}}(\omega, x^{a_i})$ of all agents but the less risk averse are zero—and thus deterministic. The subjective probabilities $\zeta^{a_i}(\omega)$ of such agents are therefore left free and can take any feasible value at equilibrium. Hence, without fixing yet the subjective probabilities $\psi^{a_1 *}$ of the least risk-averse agent, we can look for a solution where all other agents share these probabilities (which is feasible because of assumption 36) :

$$
\begin{aligned}
&\zeta^{a_i *}(\omega) = \zeta^{a_1 *}(\omega), \forall i, \forall \omega \\
&\{\zeta^{a_1 *}(\omega), \forall \omega\} = \text{Argmax}_{\ \zeta^{a_1} \in \mathcal{M}^{a_1}} \left(- \sum_{\omega \in \Omega} \zeta^{a_1}(\omega) \Pi^{a_1}(\omega, x^{a_1}, y^{a_1}_c) \right)
\end{aligned} \tag{39}
$$

The profit of the least risk-averse agent writes:

$$
\begin{aligned}
\Pi^{a_1}(\omega, x^{a_1}, y^{a_1}_c) &= Z^{a_1}(\omega, x^{a_1}) + \sum_c (\overline{K}^{x^{a_1}}_c x^{a_1} - y^{a_1}_c) W_c\left(\omega, P^1_c\right) \\
&= Z^{a_1}(\omega, x^{a_1}) - \sum_{a \neq a_1} y^{a_1}_{\text{F-CfD(a)}} W_c\left(\omega, P^1_c\right) \\
\Pi^{a_1}(\omega, x^{a}) &= Z^{a_1}(\omega, x^{a_1}) - \sum_{a \neq a_1} \left(x^a P^1_{\text{F-CfD(a)}} - Z^a(\omega, x^a) \right) \\
&= \sum_a Z^a(\omega, x^a) - \sum_{a \neq a_1} x^a I^a
\end{aligned} \tag{40}
$$

Because the risk measure characterized by $\mathcal{M}^{a_1}$ is coherent and thus translation invariant, it can be equivalently defined on the short-term profit $\tilde{\Pi}^{a_1}$:

$$
\begin{aligned}
&\tilde{\Pi}^{a_1}(\omega, x^a) = \sum_a Z^a(\omega, x^a) \\
&\{\zeta^{a_1 *}(\omega), \forall \omega\} = \text{Argmax}_{\ \zeta^{a_1} \in \mathcal{M}^{a_1}} \left(- \sum_{\omega \in \Omega} \zeta^{a_1}(\omega) \tilde{\Pi}^{a_1}(\omega, x^a) \right)
\end{aligned} \tag{41}
$$

The financial non-arbitrage conditions for agent a_1 can also be rewritten as follows :

$$
\begin{aligned}
& 0 \leq y^{a_1}_{\text{F-CfD(a)}} \perp \sum_\omega \zeta^{a_1 *} W_{\text{F-CfD(a)}}\left(\omega, P^1_{\text{F-CfD(a)}}\right) \geq 0 \qquad \forall a \\
\iff \quad & 0 \leq x^a \perp \sum_\omega \zeta^{a_1 *} \left(I^a - \frac{\partial Z^a}{\partial x^a}(\omega, x^a) \right) \geq 0 \qquad \forall a
\end{aligned} \tag{42}
$$

Taking into account all the changes introduced in equations 35, 51, 39, 41, and 42, the KKT conditions of the 2-stage problem D can finally be rewritten as:

Producer g

$$\begin{aligned} 0 \leq p^g_{d,h}(\omega) \perp \ C^g_{d,h}(\omega) - \lambda_{d,h}(\omega) + \mu^g_{d,h}(\omega) \geq 0 \qquad & \forall d,h,\omega \\ 0 \leq \mu^g_{d,h}(\omega) \perp f^g_{d,h}(\omega)x^g - p^g_{d,h}(\omega) \geq 0 \qquad & \forall d,h,\omega \end{aligned} \tag{43}$$

Demand l

$$\begin{aligned} 0 \leq z^l_{d,h}(\omega) \perp \ VOLL^l - \lambda_{d,h}(\omega) \geq 0 \qquad & \forall d,h,\omega \\ 0 \leq \mu^l_{d,h}(\omega) \perp L^l_{d,h}(\omega)x^l - z^l_{d,h}(\omega) \geq 0 \qquad & \forall d,h,\omega \end{aligned} \tag{44}$$

Storage s

$$\begin{aligned} 0 \leq wi^s_{d,h}(\omega) \perp \ & C^s - \lambda_{d,h}(\omega) + \mu^s_{wid,h}(\omega) + \frac{\eta^s_{d,h}(\omega)}{\sqrt{\varepsilon^s}} \geq 0 && \forall d,h,\omega \\ 0 \leq in^s_{d,h}(\omega) \perp \ & C^s + \lambda_{d,h}(\omega) + \mu^s_{ind,h}(\omega) - \eta^s_{d,h}(\omega).\sqrt{\varepsilon^s} \geq 0 && \forall d,h,\omega \\ 0 \leq lev^s_{d,h}(\omega) \perp \ & \mu^s_{ed,h}(\omega) + \eta^s_{d,h}(\omega) - \eta^s_{d,h+1}(\omega) \geq 0 && \forall d,h,\omega \\ \eta^s_{d,h}(\omega) \perp \ & \frac{wi^s_{d,h}(\omega)}{\sqrt{\varepsilon^s}} - in^s_{d,h}(\omega).\sqrt{\varepsilon^s} + lev^s_{d,h}(\omega) - Dis^s_{d,h}(\omega)lev^s_{d,h-1}(\omega) = 0 && \forall d,h,\omega \\ 0 \leq \mu^s_{wid,h}(\omega) \perp \ & x^s_p - wi^s_{d,h}(\omega) \geq 0 && \forall d,h,\omega \\ 0 \leq \mu^s_{ind,h}(\omega) \perp \ & x^s_p - in_{s,h}(\omega) \geq 0 && \forall d,h,\omega \\ 0 \leq \mu^s_{ed,h}(\omega) \perp \ & x^s_e - lev^s_{d,h}(\omega) \geq 0 && \forall d,h,\omega \end{aligned} \tag{45}$$

Investment conditions

$$\begin{aligned} 0 \leq x^g \perp I^g - P^1_{\text{F-CfD(g)}} = 0 \\ 0 \leq x^l \perp I^l - P^1_{\text{F-CfD(l)}} = 0 \\ 0 \leq x^s_p \perp I^s_p - P^1_{\text{F-CfD(s,p)}} = 0 \\ 0 \leq x^s_e \perp I^s_e - P^1_{\text{F-CfD(s,e)}} = 0 \end{aligned} \tag{46}$$

Financial non-arbitrage conditions for agents $a_i \neq a_1$

$$0 = y^{a_i}_c \perp \sum_\omega \zeta^{a_1 *} W_c\left(\omega, P^1_c\right) \geq 0 \qquad \forall c, \forall i \neq 1 \tag{47}$$

Financial non-arbitrage conditions for agent a_1

$$0 \leq x^a \perp \sum_\omega \zeta^{a_1 *} \left(I^a - \frac{\partial Z^a}{\partial x^a}(\omega, x^a) \right) \geq 0 \qquad \forall a \tag{48}$$

Risk-measure definition

$$\begin{aligned} &\{\zeta^{a_1 *}(\omega) \quad \forall \omega\} = \text{Argmax}_{\ \zeta^{a_1} \in \mathcal{M}^{a_1}} \left(-\sum_{\omega \in \Omega} \zeta^{a_1}(\omega) \tilde{\Pi}^{a_1}(\omega, x^a) \right) \qquad \forall a \\ &\text{With: } \tilde{\Pi}^{a_1}(\omega, x^a) = \sum_a Z^a(\omega, x^a) \end{aligned} \tag{49}$$

Spot Market clearing

$$\lambda_{d,h}(\omega) \perp \sum_g p^g_{d,h}(\omega) + \sum_s \left({wi^s}_{d,h}(\omega) - in^s_{d,h}(\omega) \right) - \sum_l \left(L^l_{d,h}(\omega) - z^l_{d,h}(\omega) \right) = 0 \quad \forall d,h,\omega \tag{50}$$

Financial Market clearing for the Financial Twin defined on technology a

$$P^1_{\text{F-CfD(a)}} \perp \quad x^a = y^{a_1}_{\text{F-CfD(a)}} \qquad \forall a \tag{51}$$

If we consider conditions 43, 44, 45, 48, 49, and 50 alone, we have exactly the same conditions than for the complete market problem, where all decisions are taken by a social planner, endowed with a risk-measure characterized by $= \mathcal{M}^{SP} = \bigcap_i \mathcal{M}^{a_i}$. Considering the equilibrium point verifying these conditions, the value of the remaining variables can then be derived using respectively the remaining equations 46 for $P^1_{\text{F-CfD(a)}}$ and 51 for $y^{a_1}_{\text{F-CfD(a)}}$. Equation 47 has its left-hand side already fixed and its right-hand side redundant with equation 48. This ends the proof, with every variables fixed and coinciding with the first-best complete market equilibrium.

F Numerical solution to the 2-stage equilibrium problem

Naive attempts to solve the problem directly as a MCP using the PATH solver did not converge. Similarily to the approach used in [Abada and Ehrenmann, 2025], we decompose the MCP problem into two subproblems:

- A Physical subproblem, where agents choose their installed capacities, their generation or demand, and the volume of Financial Twins they want to contract, while keeping their risk-averse probabilities fixed as parameters. This subproblem is solved directly as a MCP with PATH.
- A Financial subproblem, where agents choose their risk-neutral probabilities to minimize the short-term profit $\Pi^a(\omega)$ coming from physical operations and hedges, taken as exogenously given.This subproblem can be efficiently solved as a linear program, as shown in [Abada and Ehrenmann, 2025].

These two subproblems are solved iteratively, using a damping factor of 95%: the values of each fixed variables ($\Pi^a(\omega)$ and $\zeta^a(\omega)$) are updated at each cycle as the sum of 95% of their former value and 5% of their optimal value newly computed in the other subproblem. As the physical subproblem is much heavier and longer to converge than the Financial one, we cap the number of iterations of the PATH algorithm in the first steps of our main loop (while the infinite-norm relative error between two main-loop iteration is above 1%), in order to force the switch between our two subproblems before the full convergence of PATH, and to update the subjective probabilities as regularly as possible in the main problem. When the error reaches this 1% threshold, we remove this limit on PATH internal iterations. We finally assume convergence when the error between two main-loop iterations is bellow 0.5%.

The complete market case is directly solved as an optimization problem (see [Abada et al., 2019] for example), and its outcome is used as a warm starting point for all other equilibria computed. The convergence of such a procedure is not guaranteed, nor the uniqueness of the equilibrium points of the problem. However, a sensitivity analysis where we changed the warm starting point did not allow to find other equilibrium points.

References

[1] Ibrahim Abada and Julien Ancel. Capacity investment decisions in equilibrium: A distributionally robust approach. *SSRN*, 2025. doi: 10.2139/ssrn.5162527.

[2] Ibrahim Abada and Andreas Ehrenmann. When market incompleteness is preferable to market power: Insights from power markets. *Operations Research*, 2025.

[3] Ibrahim Abada and Andreas Ehrenmann. Mitigating market incompleteness with minor market distortions: the case of negative spot prices for electricity, 2025.

[4] Ibrahim Abada, Gauthier De Maere d'Aertrycke, and Yves Smeers. On the multiplicity of solutions in generation capacity investment models with incomplete markets: a risk-averse stochastic equilibrium approach. *Mathematical Programming*, 165(1):5–69, September 2017. ISSN 0025-5610, 1436-4646. doi: 10.1007/s10107-017-1185-9. URL `http://link.springer.com/10.1007/s10107-017-1185-9`. Publisher: Springer Science and Business Media LLC.

[5] Ibrahim Abada, Gauthier De Maere D'Aertrycke, Andreas Ehrenmann, and Yves Smeers. What Models Tell us about Long-term Contracts in Times of the Energy Transition. *Economics of Energy & Environmental Policy*, 8(1):163–182, 2019. ISSN 2160-5882. URL `https://www.jstor.org/stable/27030649`. Publisher: International Association for Energy Economics.

[6] Santiago Arango and Erik Larsen. Cycles in deregulated electricity markets: Empirical evidence from two decades. *Energy Policy*, 39(5):2457–2466, May 2011. doi: 10.1016/j.enpol.2011.02.010. MAG ID: 2073345316.

[7] Kenneth J. Arrow and Gerard Debreu. Existence of an equilibrium for a competitive economy. *Econometrica*, 22(3):265–290, 1954. ISSN 00129682, 14680262. URL `http://www.jstor.org/stable/1907353`.

[8] Philippe Artzner, Freddy Delbaen, Jean-Marc Eber, and David Heath. Coherent Measures of Risk. *Mathematical Finance*, 9(3):203–228, 1999. ISSN 1467-9965. doi: 10.1111/1467-9965.00068. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/1467-9965.00068`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1467-9965.00068.

[9] Carlos Batlle and Ignacio J. Pérez-Arriaga. Design criteria for implementing a capacity mechanism in deregulated electricity markets. *Utilities Policy*, 16(3):184–193, September 2008. doi: 10.1016/j.jup.2007.10.004. MAG ID: 1992985045.

[10] Carlos Batlle, Tim Schittekatte, Paolo Mastropietro, and Pablo Rodilla. The EU Commission's Proposal for Improving the Electricity Market Design: Treading Water, but not Drowning. *Current Sustainable/Renewable Energy Reports*, 10(4):197–205, December 2023. ISSN 2196-3010. doi: 10.1007/s40518-023-00223-4. URL `https://doi.org/10.1007/s40518-023-00223-4`.

[11] Marc Baudry. *Diffusion – Diffusion and Adoption Behavior of Innovations*, chapter 13, pages 123–129. John Wiley & Sons, Ltd, 2021. ISBN 9781119832492. doi: https://doi.org/10.1002/9781119832492.ch13. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119832492.ch13.

[12] BCBS. Basel Committee on Banking Supervision. Minimum Capital Requirements for Market Risk. Technical Report 352, Bank For International Settlements, January 2016. URL https://wwww.bis.org/publ/bcbs352.htm.

[13] Fred Espen Benth and Steen Koekebakker. Stochastic modeling of financial electricity contracts. *Energy Economics*, 30(3):1116–1157, May 2008. ISSN 0140-9883. doi: 10.1016/j.eneco.2007.06.005. URL https://linkinghub.elsevier.com/retrieve/pii/S0140988307000783. Publisher: Elsevier BV.

[14] Fred Espen Benth, Luca Di Persio, and Silvia Lavagnini. Stochastic Modeling of Wind Derivatives in Energy Markets. *Risks*, 6(2):56, May 2018. ISSN 2227-9091. doi: 10.3390/risks6020056. URL https://www.mdpi.com/2227-9091/6/2/56. Publisher: MDPI AG.

[15] Hendrik Bessembinder and Michael L. Lemmon. Equilibrium Pricing and Optimal Hedging in Electricity Forward Markets. *Journal of Finance*, 57(3):1347–1382, 2002. doi: 10.1111/1540-6261.00463. MAG ID: 3121701901.

[16] Farhad Billimoria and Paul Simshauser. Contract design for storage in hybrid electricity markets. *Joule*, 7(8):1663–1674, August 2023. ISSN 2542-4351. doi: 10.1016/j.joule.2023.07.002. URL https://linkinghub.elsevier.com/retrieve/pii/S2542435123002751. Publisher: Elsevier BV.

[17] Marcel Boiteux. Peak-Load Pricing. *The Journal of Business*, 33(2):157, January 1960. doi: 10.1086/294331. MAG ID: 1982152529.

[18] Wieb Boonstra and Cornelis W. Oosterlee. Valuation of electricity storage contracts: A Fourier approach. *arXiv preprint arXiv:2101.02917*, 2021.

[19] Filippo Bovera, Lorenzo Zapparoli, and Matteo Zatti. A new approach to long-term contracts to hit renewables and storage deployment targets while balancing private and public risks. SSRN working paper, 2025. URL https://ssrn.com/abstract=5198181.

[20] Caixa Bank Research. Caixa bank research estimation. https://www.caixabankresearch.com/en/sectoral-analysis/consumption/economic-impact-blackout-detail, 2025. Accessed: 2025-30-07.

[21] CCEE. Mecanismo de Realocação de Energia. Technical report, Câmara de Comercialização de Energia Elétrica – Agência Nacional de Energia Elétrica, 2023.

[22] CEER. Status review of renewable support schemes in europe for 2022 and 2023. Technical Report C24-RES WS-84-05, Council of European Energy Regulators (CEER), Brussels, July 2025.

[23] CEOE. CEOE announcement relayed by Reuters. https://www.reuters.com/business/energy/post-blackout-spain-portugal-companies-count-cost-2025-04-29, 2025. Accessed: 2025-30-07.

[24] R. H. Coase. The problem of social cost. *Journal of Law and Economics*, 3:1–44, 1960.

[25] John Cochrane. *Asset Pricing, Revised Edition.* Princeton University Press, 2005. ISBN 978-0-691-12137-6. URL `https://press.princeton.edu/books/hardcover/9780691121376/asset-pricing`.

[26] Peter Cramton, Axel Ockenfels, and Steven Stoft. Capacity Market Fundamentals. *Economics of Energy and Environmental Policy*, 2(2), September 2013. doi: 10.5547/2160-5890.2.2.2. MAG ID: 2067452523.

[27] Paulo Pereira da Silva and Paulo Horta. The effect of variable renewable energy sources on electricity price volatility: the case of the iberian market. *International Journal of Sustainable Energy*, 38(8):794–813, 2019. doi: 10.1080/14786451.2019.1602126. URL `https://doi.org/10.1080/14786451.2019.1602126`.

[28] Jean-Pierre Danthine and John B. Donaldson. *Intermediate Financial Theory.* Elsevier Academic Press. Chapter 8., 2005.

[29] Gauthier de Maere d'Aertrycke. *Financial engineering models for electricity market : futures pricing, liquidity risks and investment.* PhD thesis, 2011.

[30] Gauthier de Maere d'Aertrycke, Andreas Ehrenmann, and Yves Smeers. Investment with incomplete markets for risk: The need for long-term contracts. *Energy Policy*, 105:571–583, June 2017. ISSN 0301-4215. doi: 10.1016/j.enpol.2017.01.029. URL `https://www.sciencedirect.com/science/article/pii/S0301421517300411`.

[31] Laurens de Vries and Petra Heijnen. The impact of electricity market design upon investment under uncertainty: The effectiveness of capacity mechanisms. *Utilities Policy*, 16(3):215–227, September 2008. doi: 10.1016/j.jup.2007.12.002. MAG ID: 2000493106.

[32] S.J. Deng and S.S. Oren. Electricity derivatives and risk management. *Energy*, 31(6):940–953, 2006. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2005.02.015. URL `https://www.sciencedirect.com/science/article/pii/S0360544205000496`. Electricity Market Reform and Deregulation.

[33] Emil Dimanchev. Consequences of the missing risk market problem for power system emissions. *Energy Economics*, 2023. Forthcoming.

[34] Anthony Downward, David Young, and Golbon Zakeri. Electricity retail contracting under risk-aversion. *European Journal of Operational Research*, 251(3):846–859, 2016. ISSN 0377-2217. doi: https://doi.org/10.1016/j.ejor.2015.11.040. URL `https://www.sciencedirect.com/science/article/pii/S0377221715011145`.

[35] Darrell Duffie. Financial Market Innovation and security design: an introduction, 1994.

[36] Andreas Ehrenmann and Yves Smeers. Stochastic equilibrium models for generation capacity expansion. In M. Bertocchi, G. Consigli, and M. Dempster, editors, *Stochastic Optimization Methods in Finance and Energy*, volume 163 of *International Series in Operations Research & Management Science*. Springer, New York, NY, 2011. doi: 10.1007/978-1-4419-9586-5_13.

[37] Elia. Sustainable 2-sided Contract for Difference design and models for combination with Power Purchasing Agreements - Two-part explanatory note. Unpublished, 2022.

[38] Engie EnergyScan. EnergyScan. https://app.energyscan.engie.com/, 2025. Accessed: 2025-30-07.

[39] ENTSO-E. ENTSO-E Transparency Platform. https://transparency.entsoe.eu, 2025. Accessed: 2025-30-07.

[40] EY. Renewable Energy Country Attractiveness Index (RECAI), 63th edition. Technical report, Ernst & Young, 2024. URL `https://www.ey.com`.

[41] Kevin Favre. *Conception des contrats de long terme sur les marchés de l'électricité - incitations, allocation des risques, et défis pour l'exploitation du système électrique*. PhD Thesis, 2025. URL `/document`.

[42] Hans Föllmer and Alexander Schied. *Stochastic Finance: An Introduction in Discrete Time*. Walter de Gruyter, Berlin, 4th edition, 2016.

[43] Henri Gérard, Vincent Leclère, and Andy Philpott. On risk averse competitive equilibrium. *Operations Research Letters*, 46(1):19–26, January 2018. doi: 10.1016/j.orl.2017.10.011. MAG ID: 2963032042.

[44] Oliver D Hart. On the optimality of equilibrium when the market structure is incomplete. *Journal of Economic Theory*, 11(3):418–443, December 1975. ISSN 0022-0531. doi: 10.1016/0022-0531(75)90028-9. URL `https://www.sciencedirect.com/science/article/pii/0022053175900289`.

[45] Michael Hartner and Andreas Permoser. Through the valley: The impact of pv penetration levels on price volatility and resulting revenues for storage plants. *Renewable Energy*, 115:1184–1195, 2018. ISSN 0960-1481. doi: https://doi.org/10.1016/j.renene.2017.09.036. URL `https://www.sciencedirect.com/science/article/pii/S0960148117308984`.

[46] IEA. Reducing the Cost of Capital. Technical report, International Energy Agency, 2024. URL `https://www.iea.org`.

[47] IEA. *Renewable 2025 - Analysis and forecast to 2030*. IEA, 2025.

[48] IRENA. *Renewable Power Generation Costs in 2023*, volume 1. IRENA, 2024.

[49] IRENA. *Renewable Energy Capacity Statistics 2025*, volume 1. IRENA, 2025.

[50] Paul L. Joskow. Competitive Electricity Markets and Investment in New Generating Capacity, 2006.

[51] Paul L. Joskow. Capacity payments in imperfect electricity markets: Need and design. *Utilities Policy*, 16(3):159–170, September 2008. doi: 10.1016/j.jup.2007.10.003. MAG ID: 2018248975.

[52] Ömer Karaduman. Economics of grid-scale energy storage in wholesale electricity markets. In *Proceedings (working paper/doctoral series)*, 2021.

[53] Kitzing et al. *Contracts-for-difference to support renewable energy technologies: considerations for design and implementation.* Florence School of Regulation (FSR), Robert Schuman Centre for Advanced Studies, European University Institute, 2024. URL https://data.europa.eu/doi/10.2870/379508.

[54] Nikolaos E. Koltsaklis and Athanasios S. Dagoumas. State-of-the-art generation expansion planning: A review. *Applied Energy*, 230:563–589, November 2018. ISSN 0306-2619. doi: 10.1016/j.apenergy.2018.08.087. URL https://linkinghub.elsevier.com/retrieve/pii/S0306261918312583. Publisher: Elsevier BV.

[55] Mats Kröger and David Newbery. Renewable electricity contracts: lessons from European experience. *Papeles de Energía*, N.º 24, 2024.

[56] J.J. Laffont and J. Tirole. *A Theory of Incentives in Procurement and Regulation.* Mit Press. MIT Press, 1993. ISBN 978-0-262-12174-3. URL https://books.google.fr/books?id=4iH4Z2wbNqAC.

[57] Alexis Lebeau. *Analyse économique des impacts de l'architecture de marché et du comportement des investisseurs sur les dynamiques de long-terme dans un secteur électrique en décarbonation.* PhD Thesis, 2024. URL 2024UPAST054/document.

[58] Alexis Lebeau, Marie Petitet, Simon Quemin, and Marcelo Saguan. Long-term issues with the energy-only market design in the context of deep decarbonization. *Energy Economics*, 132:107418, 2024. ISSN 0140-9883. doi: https://doi.org/10.1016/j.eneco.2024.107418. URL https://www.sciencedirect.com/science/article/pii/S0140988324001269.

[59] Michael Magill and Martine Quinzii. *Theory of Incomplete Markets*, volume 1. MIT Press, 2002.

[60] Paolo Mastropietro, Pablo Rodilla, and Carlos Batlle. A taxonomy to guide the next generation of support mechanisms for electricity storage. *Joule*, 8(5):1196–1204, May 2024. ISSN 2542-4351. doi: 10.1016/j.joule.2024.03.015. URL https://linkinghub.elsevier.com/retrieve/pii/S2542435124001508. Publisher: Elsevier BV.

[61] Paolo Mastropietro, Pablo Rodilla, Michel Rivier, and Carlos Batlle. Reliability options: Regulatory recommendations for the next generation of capacity remuneration mechanisms. *Energy Policy*, 185: 113959, 2024. ISSN 0301-4215. doi: https://doi.org/10.1016/j.enpol.2023.113959. URL https://www.sciencedirect.com/science/article/pii/S030142152300544X.

[62] Jacob Mays and Jesse D. Jenkins. Financial Risk and Resource Adequacy in Markets With High Renewable Penetration. *Energy Economics*, 2023. Forthcoming.

[63] Ministry of Electricity and Energy, Republic of South Africa. Announcement of Preferred Bidders under the 3rd Bid Window of the Battery Energy Storage in Independent Power Procurement Programme (BESIPPPP). Technical report, Department of Mineral Resources and Energy, May 2025. URL https://www.dbsa.org/sites/default/files/media/documents/2025-06/Media%20Statement%20Preferred%20Bidders%20BESIPPPP%20BW3%2030052025.pdf.

[64] Modo Energy. The state of BESS offtakes in the NEM: Tolls, revenue swaps and PPAs. Industry research note, 2025. URL https://modoenergy.com/research/offtake-tolling-agreements-virtual-tolls-revenue-swap-bess-nem-explained.

[65] MTERD. Plan Nacional Integrado de Energía y Clima. Technical Report NIPO: 665-20-021-X, Ministerio para la Transición Ecológica y el Reto Demográfico, Madrid, September 2024.

[66] David Newbery. Missing money and missing markets: Reliability, capacity auctions and interconnectors. *Energy Policy*, 94:401–410, July 2016. ISSN 03014215. doi: 10.1016/j.enpol.2015.10.028. URL https://linkinghub.elsevier.com/retrieve/pii/S0301421515301555.

[67] David Newbery. Efficient renewable electricity support: designing an incentive compatible support scheme. *Energy Journal*, 44(3), 2023. doi: 10.5547/01956574.44.3.dnew.

[68] David M. Newbery. Power Markets and Market Power. *The Energy Journal*, 16(3):39–66, 1995. ISSN 01956574, 19449089. URL http://www.jstor.org/stable/41322605.

[69] Shmuel S. Oren. Generation Adequacy via Call Options Obligations: Safe Passage to the Promised Land. *The Electricity Journal*, 18(9):28–42, November 2005. doi: 10.1016/j.tej.2005.10.003. MAG ID: 2000179843.

[70] Pexapark. Renewable Market Outlook 2025. Technical report, Pexapark, 2025.

[71] Daniel Ralph and Yves Smeers. Risk trading and endogenous probabilities in investment equilibria. *SIAM Journal on Optimization*, 25:2589–2611, 2015. ISSN 1052-6234. doi: 10.1137/110851778.

[72] Red Electrica. Red Electrica database. https://www.ree.es/en/datos/generation/generation-structure, 2025. Accessed: 2025-30-07.

[73] R. Tyrrell Rockafellar and Stanislav Uryasev. Optimization of conditional value-at-risk. *The Journal of Risk*, 2:21–41, 2000. ISSN 1465-1211. doi: 10.21314/JOR.2000.038.

[74] Ingmar Schlecht, Christoph Maurer, and Lion Hirth. Financial contracts for differences: The problems with conventional CfDs in electricity markets and how forward contracts can help solve them. *Energy Policy*, 186, 2024. doi: 10.1016/j.enpol.2024.113981.

[75] Fred C. Schweppe. *A Spot Price Based Energy Marketplace*, pages 207–226. Springer Netherlands, Dordrecht, 1988. ISBN 978-94-009-1403-2. doi: 10.1007/978-94-009-1403-2_12. URL https://doi.org/10.1007/978-94-009-1403-2_12.

[76] L. S. Shapley. A Value for n-Person Games. *H. Kuhn and A. Tucker, Contribution to the Theory of Games*, II:303–317, 1953.

[77] Han Shu and Jacob Mays. Beyond capacity: contractual form in electricity reliability obligations. *Energy Economics*, 126:106943, October 2023. ISSN 0140-9883. doi: 10.1016/j.eneco.2023.106943. URL http://arxiv.org/abs/2210.10858. arXiv:2210.10858 [q-fin].

[78] Louis Soumoy and Jules Welgryn. Derisking Electricity Prices For Decarbonisation. working paper or preprint, 2025. URL https://hal.science/hal-05265342.

[79] Vector Renewables. Capacity Remuneration Mechanism in Spain - Regulatory Update. https://www.vectorenewables.com/en/blog/the-capacity-market-in-spain-regulatory-update-and-outlook-for-storage, 2025. Accessed: 2025-30-07.

[80] Volta Foundation. Battery report 2024. Technical report, Volta Foundation, 2024. URL https://wwww.volta.foundation.

[81] Paul Waidelich, Joscha Krug, and Bjarne Steffen. Mobilizing credit for clean energy: De-risking and public loan provision under learning spillovers. *Journal of Environmental Economics and Management*, 133:103222, 2025. ISSN 0095-0696. doi: https://doi.org/10.1016/j.jeem.2025.103222. URL https://www.sciencedirect.com/science/article/pii/S0095069625001068.

[82] Ruodu Wang and Ričardas Zitikis. An axiomatic foundation for the expected shortfall. *Management Science*, 67(3):1413–1429, 2020. ISSN 1413-1429.

[83] Bert Willems and Joris Morbee. Market completeness: How options affect hedging and investments in the electricity sector. *Energy Economics*, 32:4 – 786–795, 2010. doi: 10.1016/j.eneco.2009.10.019.

[84] Frank A. Wolak. Long-Term Resource Adequacy in Wholesale Electricity Markets with Significant Intermittent Renewables. *Environmental and Energy Policy and the Economy*, 3:155–220, January 2022. ISSN 2689-7857. doi: 10.1086/717221. URL https://www.journals.uchicago.edu/doi/10.1086/717221. Publisher: The University of Chicago Press.

[85] World Bank. World Bank Database. https://data.worldbank.org/country/ES, 2025. Accessed: 2025-30-07.

[86] Andreas Zucker, Timothée Hinchliffe, and Amanda Spisto. Assessing storage value in electricity markets: a literature review. Technical report, Publications Office of the European Union, Luxembourg, 2024. URL https://data.europa.eu/doi/10.2790/89242.