

Cambridge Judge Business School

EPRG Working Paper EPRG 2624

Cambridge Working Paper in Economics CWPE 2687

Long-term contracts for biomethane development in the energy transition

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JEL Classification : D81, C72, C73, Q41

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Publication November, 2026

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September 30, 2026

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*The opinions expressed in this paper are the authors' alone and might not represent the views of any institution. This research was funded by Grenoble Ecole de Management.

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1 Introduction and literature survey

1.1 The context of biomethane production in Europe and its externalities

Russia's full-scale invasion of Ukraine in February 2022 catalysed the most dramatic reordering of Europe's gas market in recent history. Sudden curtailments of Russian pipeline deliveries and disruptions in global LNG trade sent benchmark prices to unprecedented highs, forcing policymakers to reassess the EU's exposure to imported fossil gas and to prioritise domestically produced low-carbon substitutes. Within this crisis context, biomethane—a pipeline-quality renewable gas produced by upgrading biogas—was rapidly elevated from a niche fuel to a strategic instrument for security of supply, decarbonisation, and rural value creation. The European Commission's REPowerEU Plan crystallised this momentum, proposing to raise EU biomethane output to 35 bcm per year by 2030—roughly a tenfold increase over early-2020s volumes. Three years on, however, the divergence between ambition and reality has become stark. Updated national plans indicate that Member States collectively foresee only ∼12–15 bcm of biomethane by 2030, with combined biogas and biomethane production expected to reach approximately 26 bcm—well short of the headline 35 bcm target. The Commission's public communication has also softened, referring to the need to reach "35 bcm of biogas or its upgraded version" by 2030—a formulation that implicitly dilutes the original biomethane-specific goal.

European biogases have grown significantly over the past decade. Between 2015 and 2024, combined biogas and biomethane production rose by 34%, from 173 TWh to 232 TWh (≈ 22 bcm), with Europe now accounting for nearly half of global output. Biomethane itself reached 52 TWh (≈ 5.2 bcm) in 2024, supported by more than 1,600 plants and an installed capacity of about 7 bcm/year by mid-2025.[1] The centre of gravity shifted from biogas-fired combined heat and power (CHP) plants towards grid-injected biomethane, enabling its use in hard-to-electrify sectors—industry, buildings, and especially transport, where bio-liquefied natural gas (bio-LNG) is gaining traction. Yet, the sector remains highly policy-dependent. Production is concentrated in a handful of countries (France, Germany, Denmark, Italy, the Netherlands, and the UK), and deployment waves have closely tracked the generosity of feed-in tariffs (FITs), feed-in premiums (FIPs), and subsequent tenders. Where support was tightened—often due to budgetary pressures—momentum slowed. This policy cyclicality is one reason why the EU's aggregate trajectory is not aligned with the 35 bcm aspiration.

The central economic fact about biomethane in Europe is its persistent cost disadvantage rela-

[1] Unless otherwise stated, all figures related to biomethane potential and costs are taken from Olczak [2026].

tive to fossil gas—one that has not materially narrowed since the 2010s. Best-available estimates place production costs typically between €50 and €175/MWh, far above recent TTF (Title Transfer Facility, the reference gas spot market in Europe) levels after the 2022–2023 crisis spike receded. Even looking ahead to 2050, foresight studies surveyed in the literature do not anticipate widespread convergence with average natural-gas prices; the associated learning curve remains relatively flat compared with those observed for wind and solar technologies for instance. Five structural features explain this rigidity:

- High operational expenditure (OPEX) shares. For anaerobic digestion—the dominant production pathway—operating costs account for approximately 40–50% of total costs (and up to ∼75% for landfill-gas recovery). Beyond feedstock procurement and handling, plants incur substantial on-site energy demand to heat digesters and upgrade biogas, raising internal consumption and reducing net output.
- Feedstock constraints and logistics. A policy shift away from energy crops towards agricultural residues, manure, and organic waste has improved sustainability outcomes but increased the complexity and cost of collection, pre-treatment, and transport. Competition with other sectors (e.g., waste management and agriculture) can drive up feedstock prices, while regional availability constraints limit siting flexibility and economies of scale.
- Limited economies of scale. Because feedstocks are geographically diffuse and locally sourced, most plants remain relatively small (the average 2024 capacity was approximately 483 Nm^3/h), with notable cross-country variation (e.g., many small units in France versus fewer, larger units in Denmark). This decentralised production structure constrains the economies of scale available to larger industrial facilities.
- Slow technological learning. Promising innovations—including cryogenic upgrading, thermochemical gasification with methanation, and biological methanation—remain at limited scale or face significant integration-cost hurdles (e.g., the availability of renewable hydrogen for e-methane production). Near-term progress is therefore likely to be incremental (efficiency improvements and methane-slip reductions) rather than characterised by technological step changes.
- Social acceptance. Biomethane projects may face strong social opposition in rural areas, such as evidenced in Bourdin and Delcayre [2024] and Bharadwaj et al. [2023].

Downstream, the delivery pathway adds further costs. Grid injection averages approximately €5/MWh, whereas liquefaction for bio-LNG can add approximately €20–25/MWh. Digestate handling may add €20–55/MWh, while capturing and storing biogenic CO_2 can add €6–9/MWh (approximately €45–68/tCO_2). Such cost adders are material in a context where commodity gas prices have reverted to levels well below their crisis-era peaks. The post-2023 normalisation of gas prices has therefore re-exposed the underlying economics of biomethane: when natural gas

is inexpensive, unsubsidised biomethane seldom clears in competitive markets, and the public-finance burden of closing the cost gap becomes politically salient. The natural consequence is that biomethane deployment is driven by support mechanisms, from producer certainty to consumer-facing compliance schemes, and their associated frictions. Production-based support underwrote the sector's early growth; FITs/FIPs and capital grants provided revenue certainty and enabled project finance, which is why growth came in "waves" aligned with policy cycles (e.g., Germany and the Netherlands first, then the UK and Denmark, and more recently France). But the budgetary cost proved substantial: France's support outlays are projected to exceed €1.3 bn in 2026, prompting tariff resets, pauses, or a pivot to auctions. Several countries have also shifted from FITs to FIPs and competitive tenders in search of cost control.

As fiscal headroom tightened, policy moved toward consumption-based mechanisms that create demand obligations and certificate markets, such as national greenhouse-gas (GHG)-based quota systems (e.g., Germany's THG-Quote, the Netherlands' EREs, and France's TIRRIEGEST), which reward life-cycle emissions reductions rather than pure energy volumes. The UK RTFO similarly drives renewable fuel uptake in transport. France's CPB (Certificats de Production de Biogaz) places obligations on suppliers serving the residential and tertiary segments, effectively socialising costs through consumer bills. EU-level frameworks now matter more: the FuelEU Maritime Regulation (in force since 1 Jan 2025) creates pooling and compliance incentives that favour low-carbon intensity options such as bio-LNG, including manure-based volumes that can carry negative carbon intensity. The Commission has clarified that both subsidised and unsubsidised biomethane can be eligible—an important, and contested, design choice.

These shifts move costs from taxpayers to consumers, but they also shift risk from governments to producers and off-takers, whose revenues now hinge on volatile certificate prices and eligibility rules. This volatility, together with the market split between subsidised and unsubsidised volumes, has encouraged the exploration of Biomethane Purchase Agreements (BPAs)—gas-sector analogues of Power Purchase Agreements (PPAs). While strategically attractive, unsubsidised BPAs remain rare and, to date, have contributed only marginally to overall market growth. A second design fault line is cross-border market integration. Biomethane's "green value" is tracked through Guarantees of Origin (GOs) and Proofs of Sustainability (PoS), enabling book-and-claim or mass-balance accounting across borders. In practice, however, traded volumes remain small (approximately 5% of EU biomethane in 2024), with a handful of exporters (Denmark, the UK, and the Netherlands) and Germany being the largest importer. Debates around mass balance—including whether "virtual liquefaction" at LNG terminals should count—have produced divergent national interpretations and uncertain state-aid boundaries, particularly with respect to avoiding over-compensation when production- and consumption-side support

schemes are combined across jurisdictions.

Since REPowerEU, gas prices have been fading, and so has the emphasis on biomethane. The 2022 shock temporarily aligned energy security and climate narratives: high fossil-gas prices made biomethane look more competitive, and its domestic character promised resilience. As prices fell back towards long-run "normal", however, that alignment weakened. Policymakers are again weighing cost-effectiveness against other decarbonisation options (direct electrification, efficiency, heat pumps) and revisiting whether biogas-CHP might deliver system flexibility at lower public cost. Several Member States have explored sectoral targeting (e.g., reserving biomethane for small industrial consumers or specific end-uses) to limit impacts on consumer bills. The Commission's shift in phrasing—"biogas or its upgraded version"—is emblematic of this broader re-prioritisation. Furthermore, the political appetite for large, subsidy-intensive expansion has also been tempered by concerns over integrity (feedstocks, double counting, additionality) and distributional effects (who pays and who benefits). Without a coherent EU-wide model to reconcile producer-centric (high-integrity, circular-economy) and buyer-centric (market-driven, pan-EU trading) visions, investors and off-takers face regulatory uncertainty that depresses project pipelines and slows market integration.

The discussion surrounding biomethane deployment is not limited to Europe. The Princeton study on decarbonisation pathways in the US considers biomethane as a serious option for reaching net-zero emissions by 2050 or sooner in many scenarios.[2] Furthermore, positive externalities associated with biomethane production have been repeatedly evidenced in the literature. We now briefly present some of them. The first externality pertains to sector coupling and the interaction between gas and power systems. By providing flexibility to the power system, biomethane, serving as a partial substitute for fossil gas, may decrease investment needs in the electricity transmission grid and reduce electricity bills by up to €2/MWh in some net-zero decarbonisation scenarios in Europe by 2050.[3] Higher figures were reported for distribution grids, with savings estimated at more than €5.8/MWh on average in Germany.[4] In a similar vein, Shabazbegian et al. [2020] uses numerical simulations to estimate that the benefits of gas and electricity network coupling could decrease OPEX costs by 4%. The second positive externality relates to security-of-supply concerns, which were exacerbated by the invasion of Ukraine and the hasty reactions of European policymakers, as alluded to above. Blanco et al. [2018] estimates that the development of low-carbon gas production, such as hydrogen and biomethane, could decrease European energy-

[2]Princeton Report, Net Zero America, available at https://modelclimatelaws.org/resources/princeton-report-net-zero-america/ (accessed June 2026).

[3]See Frontier Economics [2019]: *The value of gas infrastructure in a climate-neutral Europe*, available at https://www.frontier-economics.com/uk/en/home/ (accessed June 2026).

[4]See Frontier Economics [2018]: *The importance of gas infrastructure for Germany's energy transition*, available at https://www.frontier-economics.com/uk/en/home/ (accessed June 2026).

import expenditures by €50 bn per year in a scenario with a 95% reduction in CO_2 emissions by 2050. Of course, the development of European biomethane capacity would shift fossil-gas imports towards local production, thereby reducing energy dependence. The third externality relates to the reduction of carbon emissions. Lyng et al. [2018] estimates, for instance, that replacing natural gas with biomethane may reduce GHG emissions by 0.18 tCO_2 eq/MWh in Norway. Whiting and Azapagic [2014] follows a similar endeavor while focusing on cogeneration plants in the UK and reports a reduction of 0.12 tCO_2 eq/MWh. These studies highlight that replacing natural gas with biogas or biomethane in Europe may reduce carbon emissions by 66% on average, albeit with large disparities across countries (Speirs et al. [2018]).

Having presented some of the benefits of biomethane deployment, as well as some caveats pertaining to its policy support, production costs, and operational constraints, we now turn to analysing an important driver of biomethane economics that has been largely overlooked in the literature so far, namely market risk mitigation.

1.2 The overlay of uncertainty: gas prices, geopolitics, and climate delivery risk

Looking forward, the operating environment of biomethane production is defined by three interacting uncertainties:

- Gas-price volatility. Although prices have fallen from their 2022 peaks, forward trajectories remain uncertain. Middle-East tensions, Suez and Panama routing constraints, North-African supply risks, and US LNG export dynamics can all reprice European gas markets quickly. For biomethane, this creates a two-edged incentive: high prices galvanise political support but arrive too suddenly to underwrite long-lead investments; low prices undermine competitiveness and erode policy emphasis.
- Geopolitical risk. The war in Ukraine continues; Black Sea and Eastern Mediterranean dynamics are fluid; and broader strategic competition can disrupt supply chains and capital costs. These risks reinforce the logic of domestic renewable gas, yet they do not resolve its cost gap or the need for clearer EU market rules.
- Challenged climate pathways. With 2030 targets fast approaching, permitting, system integration, and non-ETS sector decarbonisation remain behind schedule. Biomethane could help decarbonise hard-to-electrify uses and reduce agricultural emissions, but current economics, permitting timelines, and fragmented certification infrastructure limit its near-term scalability. The Union Database (UDB)—expected to improve certificate integrity and interoperability—has faced delays pending secondary legislation, prolonging uncertainty for market participants.

In combination, these uncertainties sustain the strategic case for biomethane while leaving its practical scaling pathway unsettled. Indeed, compared with natural gas, biomethane appears to exhibit a much less volatile supply cost on the one hand and a more stable carbon-emissions cost, due to its lower carbon content, on the other hand. These factors may enhance the financial attractiveness of biomethane despite its higher OPEX and operational constraints.

1.3 The research questions

We highlight the existence of a research gap in the literature analysing the benefits of biomethane inasmuch as, as explained above, existing works have so far mainly focused on co-benefits and positive externalities with respect to the electricity system (via the analysis of sector coupling), energy sovereignty, and GHG emissions, while also invoking arguments related to enhanced waste management, agricultural co-benefits, and positive externalities associated with the circular economy. The rationale has been that, compared with natural gas, the cost disadvantage and more stringent operational constraints of biomethane production could be compensated by these considerations. We argue that these are not the only rationale in favour of biomethane. Even abstracting from many of these externalities, biomethane may increase welfare because it improves the mitigation and allocation of market risk between producers and consumers. Indeed, as explained above, given the geopolitical turmoil in Russia and the Middle East, fossil-gas prices and supply are expected to display significant fluctuations in the future and, combined with uncertainty about CO_2 prices and market agents' risk aversion (Egging et al. [2017], Egging and Holz [2016]), this feature is likely to increase the financial attractiveness of domestic biomethane production relative to natural-gas imports. This discrepancy in risk profiles could then constitute an additional argument in favour of biomethane production. Our first research question can be framed as follows:

> How does gas-market risk and its allocation among market participants affect the economic and financial valuation of biomethane projects?

To answer this research question, we develop a structural model of gas trading in which gas consumers strive to minimise their risk-adjusted gas-supply costs, and a set of biomethane producers invest in production capacity subject to some operational constraints—modelled through a maximum capacity and a maximum roll-out pace—with the objective of maximising their risk-adjusted profits. Consumers and biomethane producers can engage in forward contracts (or BPAs) to hedge market risk. The model focuses primarily on financial risk trading and overlooks some of the positive externalities of biomethane production that were presented before (such as reduced capacity and network investment needs in the power system and security of supply). Regarding risk drivers, we focus on gas spot-price risk and climate risk, which we model through uncertainty in the dynamics of the carbon price. In so doing, we overlook geopolitical risk for the

simple reason that we found it extremely difficult to calibrate, even though we are aware that it constitutes a major risk driver in gas markets. Our model is dynamic, allowing us to capture the medium- to long-term evolution of market trading. Our representation of risk aversion has three advantages. First, we use a coherent risk measure, namely the good-deal bound (Cochrane and Saa-Requejo [2000]), allowing us to provide an economic intuition for risk aversion via the notions of risk-adjusted probabilities (Artzner et al. [1999]) and risk-adjusted profit, thereby easing comparisons across various benchmarks. Second, we embed this risk measure within a scenario-tree representation of time, together with the progressive revelation of uncertainty, leading to a time-consistent modelling of strategic decisions when market agents are risk-averse.[5] Third, our risk measure can be calibrated using observable market data (in our case, the acceptable Sharpe ratio of investments in the energy sector) and does not require the specific elicitation methods that one must use for other risk measures like the Conditional Value at Risk (Rockafellar and Uryasev [2000]). Our model is formulated as a tractable stochastic equilibrium problem for which we characterise the solution and offer a financial and economic interpretation of biomethane capacity investment; we also formalise the rationale for engaging in BPAs between biomethane producers and residential and industrial gas consumers.

Our second research endeavour strives to answer the following question:

> How do biomethane production and BPAs contribute to better risk allocation and higher welfare, and which counterparties are most likely to engage in BPAs?

To answer this question, we develop a detailed application of our model to the French case, France being a country in which the potential for and support of biomethane are among the highest in Europe. We calibrate the model over the 2025–2035 period using public data, except for biomethane investment and production-cost curves, for which we rely on a proprietary dataset, which is available upon request. Consumers are split into two segments: residential consumers and large industrial firms. We apply the latter segment to the case of steel producers, who use natural gas to generate heat and, in many production processes, manufacture their final product. In so doing, we are able to quantify the welfare gains (materialised through risk reduction) associated with biomethane production and BPAs.

1.4 Contributions

Long-term contracts are commonly viewed as instruments that reduce the risk associated with low-carbon investment. We show that this view is incomplete: such contracts reallocate risk between market participants, rather than eliminate it, and their value therefore depends on the

[5] We provide a formal definition of time consistency in Section 2.2 and simply note here that a time-consistent policy is one that fulfills the following property: if the policy is optimal at a given date, it remains optimal when the problem is reconsidered at future dates, provided that the information available at those dates has not changed.

pre-existing risk exposure of counterparties. Consequently, even consumers with substantial exposure to the underlying commodity (fossil gas), such as steel producers, may have no incentive to contract if spot-market purchases provide a natural hedge against other components of their profits. To demonstrate this claim, our research offers at least two noteworthy contributions to the literature.

Our first contribution is to develop, to the best of our knowledge, the first model that endogenises investment and contracting decisions in the biomethane sector while accounting for the heterogeneity of objectives and risk preferences among producers and consumers. This necessitated the development of a stochastic equilibrium formulation, which is famously challenging to solve (Abada et al. [2017a]). Thanks to this contribution, we show that the value of long-term contracts for low-carbon gas investors cannot be assessed independently of the existing risk exposures of their potential counterparties. In an incomplete market, a long-term contract does not merely reduce the risk borne by the producer: it reallocates risk between market participants whose initial exposures may differ substantially. As a result, the willingness of consumers to enter into such contracts depends on how the price of the contracted commodity covaries with the other sources of risk affecting their profits (or utility). Our equilibrium framework endogenizes this risk allocation, together with contract prices, contracted volumes, and investment decisions, thereby allowing us to identify which market participants have an economic incentive to support investment through long-term contracting. Our model is inspired by the stylised work of Abada et al. [2017b], who already endogenised time-consistent contracting decisions, albeit for fossil gas, to which we add new risk drivers (demand, the carbon price, etc.), as well as a representation of endogenous investment decisions tailored to some specificities of biomethane production. Our model strives to capture many aspects of the functioning of gas markets and the realities of biomethane economics under gas-market and climate risk. Furthermore, our modelling of risk aversion, which is benchmarked against observable market data, respects the dynamics of investment and asset operation in a time-consistent manner.

The second contribution is policy-oriented: our numerical application indicates that, in the absence of transaction costs associated with contracting, biomethane investment and BPAs increase system welfare by facilitating risk sharing between market participants. This finding is important as it identifies and quantifies a new advantage of biomethane production and BPAs—in addition to the positive externalities discussed above—namely, a reduction in market and climate risk relative to fossil gas. We also quantify the increase in installed capacity and welfare brought about by BPAs, both of which are found to be significant. Based on these findings, we recommend that European policymakers foster the exchange of risk between biomethane producers and consumers through instruments such as BPAs, as this would increase social welfare and biomethane pro-

duction simultaneously. We also strive to identify which consumer segments are more likely to engage in these contractual agreements: we find that French residential consumers have a strong incentive to enter into BPAs and contract 34% of their consumption, whereas some other industrial consumers, such as steel producers, optimally choose *not* to contract, despite their substantial exposure to fossil gas prices. The reason is that steel and gas prices are strongly positively correlated today, so purchasing gas on the spot market provides steel producers with a natural hedge against fluctuations in their output revenues, a mechanism which is absent in the case of residential consumers. Long-term biomethane contracts would therefore eliminate part of this natural hedge for steel producers, rather than simply reduce risk. This result highlights a broader implication for the design of long-term contracts supporting the energy transition: identifying suitable counterparties requires accounting for their entire risk exposure, rather than considering their demand for the contracted commodity alone.

Though the qualitative results of the second contribution are relatively intuitive, the fact that market and climate risk considerations could foster biomethane investment is not straightforward, given the strong cost disadvantage of biomethane relative to fossil gas. Furthermore, our research is, to the best of our knowledge, the first to quantify the impact of biomethane production and BPAs in terms of welfare gains, allowing policymakers to balance these gains against the possible transaction and coordination costs BPAs could entail. Finally, though our findings are encouraging for biomethane production, they should be viewed as a first step towards investigating the merits of biomethane relative to fossil gas in terms of market- and climate-risk mitigation. In particular, while our model ignores some positive externalities of this technology with respect to the electricity system and energy sovereignty, we acknowledge that it also overlooks some important operational constraints of biomethane production, such as feedstock constraints, logistics, and resource availability. These simplifications are made either because of data limitations or for computational convenience, and we leave their investigation for future research.

1.5 Structure of the paper

The remainder of the paper is organised as follows. In Section 2, we develop the stochastic equilibrium model of endogenous investment and contracting in a time-consistent, risk-averse environment. We explicitly formulate the objectives of biomethane producers and gas consumers and characterise the Nash equilibrium through a complementarity formulation. The French case study is presented in Section 3, in which we quantify the welfare gains and risk reduction generated by biomethane investments and BPAs, and undertake a robustness analysis of these findings with respect to the biomethane production cost function. Finally, we discuss our results and derive a set of policy recommendations in Section 4.

2 A stochastic equilibrium model of long-term contracting and investment in biomethane production

In this section, we present our model to capture the incentive to engage in long-term contracts between biomethane producers and gas consumers.

2.1 Premises

The dynamics and uncertainty pertaining to the evolution of gas and CO_2 markets are modelled via a scenario tree. The set of nodes in the tree is denoted by Ω (we will sometimes refer to these nodes as *scenario nodes*). The root node of the tree, denoted by ω^0, models the present situation or the first stage of the decision process. Time, indexed by t, is discretised into $N+1$ steps, $T = \{t_0, t_1, t_2, \ldots, t_N\}$, each with equal duration, which, in line with the standard frequency of clearing gas markets, we take to be one month for simplicity. The root node ω^0 occurs at the (current) time t_0; a generic node ω occurs at a time denoted by $t(\omega)$. A scenario node ω's unique predecessor (or "father") is denoted by ω_-, for $\omega \neq \omega^0$. Furthermore, the set of children nodes of a node ω is denoted by ω_+.[6] Naturally, the leaves (or end nodes) of the scenario tree are those that occur at the last period t_N. The set of leaves is denoted by Ω_l. Each node is weighted by a probability $\theta(\omega)$ with $\theta(\omega^0) = 1$ (the initial node, which models current status, is deterministic) and $\sum_{\omega' \in \omega_+} \theta(\omega') = \theta(\omega)$, $\forall \omega \in \Omega$. Finally, the set of all successors of a node ω is denoted by ω_{++} and the set of nodes defining the (unique) path from a node ω to root ω^0 is denoted by ω_{--}.

We model a set of producers $i \in \mathcal{I}$ endowed with biomethane projects in which they can invest, and subsequently produce. Each project has a maximum capacity of K_i (expressed in MWh/year), which may represent a constraint on the available farming surface for waste production or limited social acceptance. A project i has a constant marginal investment cost (or Capital Expenditure, CAPEX) of ci_i (expressed in €/MW/year) and a constant marginal operational cost (or Operating Expenses, OPEX) of $co_i(\omega)$ (expressed in €/MWh). We also model heterogeneous segments of consumers, indexed by $e \in \mathcal{E}$. A consumer segment e has a demand $d_e(\omega)$; naturally, we make demand node-dependent to reflect the fact that it is random and dynamic inasmuch as it can fluctuate with market conditions—for instance, for industrial consumers who can adjust their consumption schedules with respect to gas prices—or meteorological conditions—for instance, for residential consumers who may use natural gas for space heating. We assume the existence of alternatives to biomethane for consumers, such as fossil gas for industrial users or heat pumps for residential ones. These alternatives are available at prices that, for ease of exposition, are aggregated under the label "spot market price" (for natural gas). The spot market gas price is $p_g(\omega)$

[6] Therefore, by a slight abuse of notation in which we identify time index t_i to i, we have that $t(\omega_-) = t(\omega) - 1$, $\forall \omega \neq \omega^0$ and $t(\omega') = t(\omega) + 1, \forall \omega' \in \omega_+$.

(€/MWh). Moreover, consumer segment e values its consumption according to a marginal value $p_e(\omega)$ (€/MWh). For instance, if e is the segment of residential consumers, this parameter could correspond to the Value of Lost Load ($VOLL_e$); alternatively, if e is an industrial gas consumer using natural gas to produce, say, steel, then $p_e(\omega)$ could represent the steel market price—adjusted by an efficiency parameter. In its consumption process, consumer segment e incurs a constant marginal cost $cd_e(\omega)$ (expressed in €/MWh when adjusted by an efficiency parameter of the consumption process) and has a consumption limit $K_e(\omega)$ (MWh/year). Taking again the example of a steel producer, this cost parameter could represent the combined production and transportation costs of steel, and this limit could model a steel production capacity constraint. For residential consumers using natural gas for space heating, the cost parameter can be set to zero, and the limit can represent gas demand. Turning to emissions accounting, in line with how many countries regulate greenhouse gas emissions, we focus on carbon dioxide and assume that it is taxed at a rate $p_{CO_2}(\omega)$ (expressed in €/ton). This parameter may represent a specific Pigouvian tax, a centralised carbon market price (such as that derived from the Emissions Trading System), or a combination of both. For ease of notation, we consider throughout the remainder of the paper that the carbon cost is already included in the marginal operational cost $co_i(\omega)$.[7]

Our model is general enough to accommodate the existence of a set of risk-mitigating instruments that can be traded in a financial market. These could represent, for instance, forward contracts or oil-indexed long-term contracts. The set of available risk-mitigating or risk-sharing instruments is $\mathcal{C}$, and each contract c is assumed to provide a dynamic and stochastic marginal remuneration $p_c(\omega)$ (€/MWh). For an oil-indexed long-term contract, for instance, $p_c(\omega)$ may be the oil price at node ω of the scenario tree. All market agents are price-takers, insofar as both the spot market for natural gas and the financial market for hedging securities are competitive.

To clarify, Figure 1 illustrates the scenario tree that we will use in our numerical application, which is inspired by the French biomethane investment context we will detail in Section 3. We model an investment and contracting process that spans the period 2025-2035 in three stages: t_0, t_1, and t_2. The first stage, t_0, represents initial conditions (2025); it corresponds to the deterministic node ω^0 in the tree. In the second stage, t_1, which models the evolution of markets until 2030, we simulate 20 scenarios to account for fluctuations in commodities' prices (steel, natural gas, and CO_2) as well as demand: $\omega^1, \omega^2, \ldots, \omega^{20}$. These scenarios are generated using statistical bootstrapping of market data obtained from 2023 to 2025 (with a monthly granularity) to capture correlations among all random parameters. Starting from 2030 and the beginning of the third

[7] In other words, the marginal operational cost $co_i(\omega)$ is calculated as the sum of the OPEX marginal cost (including operation and maintenance [O&M] costs) and the carbon price p_{CO_2} multiplied by the carbon content of biomethane (expressed in $kgCO_2$-eq/MWh).

stage, t_2, each second-stage node of the scenario tree follows either a high, medium, or low trajectory, while preserving current correlations until 2035. This leads to 60 nodes in the third stage: $\omega^{21}, \omega^{22}, \ldots, \omega^{80}$. We proceed in this way because current market data can hardly be used to infer their probability distribution in ten years from now. To provide a better understanding of our notation, we have, for instance, that:

$$\begin{aligned} \omega_{+}^{0} &= \{\omega^1, \omega^2, \ldots, \omega^{20}\}, & \omega_{-}^{18} &= \omega^0, \\ \omega_{+}^{20} &= \{\omega^{78}, \omega^{79}, \omega^{80}\}, & t(\omega^{25}) &= t_2, \\ \omega_{++}^{0} &= \{\omega^1, \omega^2, \ldots, \omega^{80}\}, & \omega_{--}^{80} &= \{\omega^0, \omega^{20}, \omega^{80}\}, \\ \Omega_l &= \{\omega^{21}, \ldots, \omega^{80}\}, & \theta(\omega^{24}) &= \tfrac{1}{60}. \end{aligned} \tag{1}$$

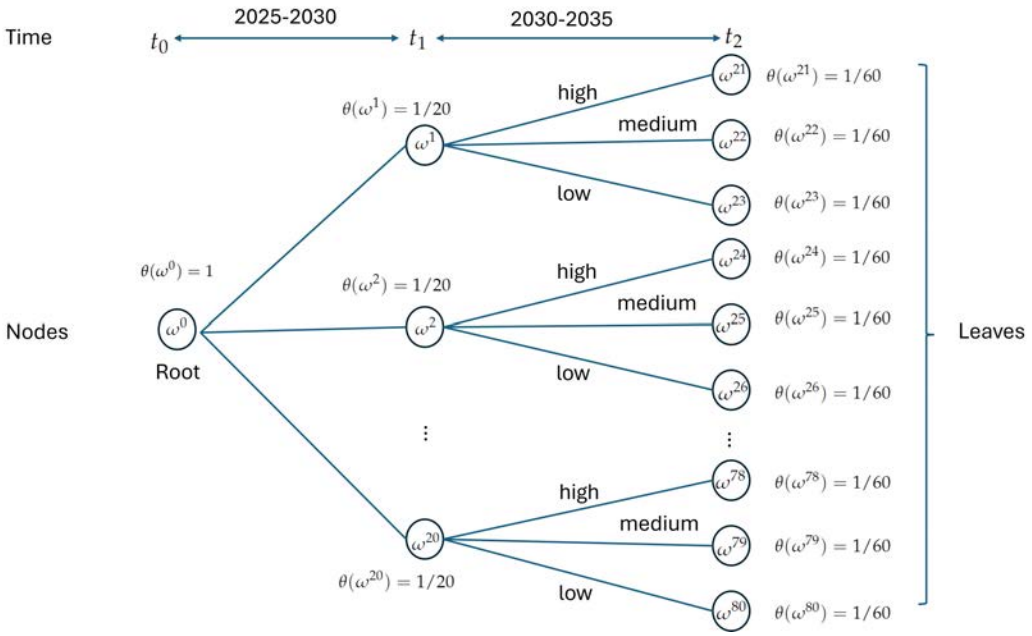


Figure 1: The scenario tree

2.2 Modelling risk aversion with time-consistent and coherent risk measures

We model aversion to risk via coherent and time-consistent risk measures. The theory of coherent risk measures was introduced in Artzner et al. [1999] as an alternative to the theory of expected concave utility functions for modelling aversion to risk. Coherent risk measures offer several advantages. First, they align with how companies value the riskiness of investments as exemplified by the Conditional Value at Risk—a particular instance of coherent risk measures—which, as argued in Wang and Zitikis [2021], has been adopted by the Basel Accords as a standard method for assessing market risk. Second, coherent risk measures offer computational tractability as well as appreciable convexity properties making them suitable for use in a multi-stage investment or contracting decision process. Finally, these measures yield valuable economic interpretations

of project risk through certainty equivalence, and they allow us to account for risk-mitigating schemes such as long-term forward contracts or options seamlessly. Mathematically, a coherent risk measure assesses the risk of a stochastic profit (or any other utility, such as consumer surplus or social welfare), U, as:

$$\text{Max}_{\zeta \in \mathcal{M}} \mathbb{E}_{\zeta} \left[-U \right], \tag{2}$$

where $\mathcal{M}$ is a compact and convex set of probability measures, referred to as the risk set, and $\mathbb{E}_{\zeta}[.]$ denotes the expectation under distribution ζ. In other words, a coherent risk measure defines risk as the worst expected value of the loss when the probability measure belongs to the risk set.

In a multi-stage setting, a coherent risk measure can be generalised to fulfill time-consistency (Riedel [2004]) as proposed in Shapiro et al. [2021], for instance. As explained in Boda and Filar [2006], pp. 2-3, *"Time consistency of a risk measure means that if a decision-maker uses a risk measure minimising policy for the n-stage problem, then the component of that multi-stage policy from the t th-stage to the end should be a risk measure minimising policy in the remaining $(n - t + 1)$-stage problem, for every $t = 1, 2, \ldots, n$. In common sense terms, a decision maker needs to be constantly concerned about optimising his or her decisions for the remaining portion of the time horizon. That is, current optimal decisions must look to the future, rather than the past."* A time-consistent and coherent risk measure can be computed via a scenario-tree representation in a recursive form (see, for instance, Ferris and Philpott [2021]).[8] Consider a stochastic and dynamic profit that a project is expected to deliver and which is defined over the scenario tree, $U(\omega)$, $\omega \in \Omega$. We need to capture how a risk-averse investor assesses the project's risk in the investment phase, that is, at the (initial) node ω^0. To do so, we consider a sequence of risk sets $\mathcal{M}(\omega)$ that allow us to evaluate the risk of profits accrued at successor nodes of ω. More precisely, the risk $\rho(\omega)$ of all future profits generated from node ω is expressed recursively, starting from leaves of the tree, as:

$$\rho(\omega) = \begin{cases} -U(\omega) & \text{if } \omega \in \Omega_l \\ \text{Max}_{\zeta \in \mathcal{M}(\omega)} \sum\limits_{\omega' \in \omega_+} \zeta(\omega') \left[-U(\omega') + \rho(\omega') \right] & \text{otherwise.} \end{cases} \tag{3}$$

The intuition behind this expression is that, when viewed from a node ω of the tree, the risk measure provides a certainty equivalent of the stochastic and dynamic profits that accrue in all future nodes of the sub-tree rooted at ω, and composed of its successor nodes ω_{++}. Therefore, viewed from root node ω^0, the investor values the riskiness of the project as:

$$\rho(\omega^0). \tag{4}$$

[8] The notions developed in this section, now standard in the operations research literature, are inspired by the work of Ferris and Philpott [2021].

Barring special cases of data degeneracy, the optimal solutions to Problems (3) are unique. For ease of exposition, we assume, henceforth, that this is the case and denote these optimal solutions as $\zeta^*(\omega)$; by convention, we also set $\zeta^*(\omega^0) = 1$. Therefore, the reader can verify that risk can be expressed as:

$$\rho(\omega^0) = -\sum_{\omega \in \Omega} \phi(\omega) U(\omega), \tag{5}$$

where

$$\phi(\omega) = \prod_{\omega' \in \omega_{--}} \zeta^*(\omega'), \quad \forall \omega \in \Omega, \tag{6}$$

and where, we remind the reader, ω_{--} is the set of nodes along the path linking ω to the root of the tree ω^0. These variables $\phi(\omega)$ are the so-called *time-consistent risk-adjusted probabilities* because, instead of using the natural probability distribution $\theta(\omega)$, as a risk-neutral investor would, they allow us to express project risk as the *risk-adjusted* expectation of its loss. This approach provides a certainty equivalent valuation of a project. Naturally, we can define the risk-adjusted profit of the project as:

$$\text{Risk-adjusted profit} = \sum_{\omega \in \Omega} \phi(\omega) U(\omega). \tag{7}$$

In the remainder of the paper, we will frequently refer to risk-adjusted profits or surplus: however, the reader should bear in mind that risk-adjusted probabilities are endogenous to our model, as they are derived from a sequence of optimisation problems of the form given in (3). We now continue the analysis by providing an example of time-consistent and coherent risk measures.

2.3 The good-deal risk measure

The most famous (two-stage) coherent risk measure is certainly the conditional value at risk (CVaR), which, according to the seminal work of Rockafellar and Uryasev [2000], can be expressed as in (2), in a two-stage setting for uncertainty (a tree involving only two time periods). Despite its extensive use in the literature on investment decisions under risk and risk aversion (see, for instance, Downward et al. [2016], de Maere d Aertrycke et al. [2017], Ferris and Philpott [2021], Mays and Jenkins [2022], and Dimanchev et al. [2024]), the CVaR has, alas, two fundamental shortcomings: the first is that although some elicitation methods exist for determining levels of risk aversion when the CVaR is applied to individuals (see, for instance, Fissler and Ziegel [2021]), we are not aware of any applications in the context of firm-level investment decisions related to natural gas or other commodities. This makes it difficult to determine an appropriate level of risk aversion of the CVaR and, indeed, a review of the literature reveals that a wide range of values is used. The second shortcoming pertains to its generalization to a multi-stage setting. Indeed, it is possible to embed the CVaR in a sequence of optimisation problems of the form given in (3) to make this risk measure time-consistent, but doing so precludes any meaningful economic

or financial interpretation of the obtained expression. In other words, the CVaR of a two-stage payoff is not the CVaR of the sum of the first-stage payoff and the CVaR of that of the second stage. Therefore, our research will use another coherent and time-consistent measure that is very popular in finance: the good-deal risk measure (GD hereafter), allowing us to overcome both shortcomings, as we explain shortly.

The GD was introduced by Cochrane and Saa-Requejo [2000] in both its single and multi-stage forms. For ease of exposition, we now directly present its adaptation to a stochastic tree representation of randomness, as elaborated in Abada et al. [2017b]. Given a stochastic and dynamic revenue whose payoff in node ω is $U(\omega)$, its GD risk is expressed as:

$$\rho^{GD}(U) := \text{Max}_{\zeta(\omega)} \quad -\sum_{\omega\in\Omega}\theta(\omega)\left(\prod_{\omega'\in\omega_{--}}\zeta(\omega')\right)U(\omega) \tag{8}$$

$$\text{s.t} \quad \sum_{\omega'\in\omega_+}\frac{\theta(\omega')}{\theta(\omega)}\zeta(\omega')p_c(\omega') = p_c(\omega) \qquad \forall(\omega,c)\in(\Omega/\Omega_l)\times\mathcal{C} \tag{9}$$

$$\sum_{\omega'\in\omega_+}\frac{\theta(\omega')}{\theta(\omega)}\zeta^2(\omega') \leq A^2 \qquad \forall\omega\in\Omega/\Omega_l \tag{10}$$

$$\zeta(\omega) \geq 0 \qquad \forall\omega\in\Omega. \tag{11}$$

This expression makes use of the notion of *stochastic discount rates* from the theory of asset pricing: each profit $U(\omega)$ is discounted by the one-step discount rate $\zeta(\omega)$ and then valued in expectation from the root node ω^0. Therefore, the GD provides a valuation of the risk as the worst stochastically discounted expectation of a project. Relation (9) is the classical no-arbitrage condition of asset pricing, expressed from period to period: the price of a traded financial contract c at node ω must be equal to the discounted expectation of its revenues in the successor nodes ω_+—otherwise, the contract offers an arbitrage opportunity and would be immediately grabbed by traders. Constraint (10) imposes a limit on the Sharpe ratio generated by the project, as demonstrated in Cochrane and Saa-Requejo [2000].[9] Indeed, in standard financial theory, projects with too high Sharpe ratios are considered unsustainable because investors would quickly exploit such opportunities. The relationship between the Sharpe ratio h and our parameter A is given by:

$$A := \sqrt{1+h^2}\,R \tag{13}$$

where R is the risk-free rate of the financial market. Typically, a Sharpe ratio of 1 or higher is

[9] Given a random payoff of a project, $U(\omega)$, the Sharpe ratio h is defined as:

$$h = \frac{\mathbb{E}[U]-R}{\sigma[U]}, \tag{12}$$

where R is the risk-free return, $\mathbb{E}[U]$ is the expected value of U and $\sigma[U]$ its standard deviation. The higher the Sharpe ratio, the more attractive the project, as it indicates high profitability relative to risk.

considered good in the market, which corresponds to $A \approx 1.4$ for a risk-free interest rate of 5%. A Sharpe ratio of 0.8, which is acceptable, corresponds to $A \approx 1.3$. Parameter A has another valuable interpretation as it also represents the level of aversion to risk: for the same random payoff U, a higher value of A implies that the player perceives greater risk as this increases the size of the feasibility set of Problem (8).

Introducing notation

$$\phi(\omega) = \begin{cases} \theta(\omega) \prod_{\omega' \in \omega_{--}} \zeta(\omega') & \text{if } \omega \neq \omega^0 \\ 1 & \text{otherwise,} \end{cases} \tag{14}$$

we can re-express the GD risk measure as (with some useful dual variables written between parenthesis next to their constraints):

$$\begin{aligned} \rho^{GD}(U) := \text{Max}_{\phi(\omega)} \quad & -\sum_{\omega \in \Omega} \phi(\omega) U(\omega) \\ \text{s.t} \quad & \sum_{\omega' \in \omega_+} \phi(\omega') p_c(\omega') = \phi(\omega) p_c(\omega) \quad (W_c(\omega)) \quad \forall (\omega, c) \in (\Omega / \Omega_l) \times \mathcal{C} \\ & \sqrt{\sum_{\omega' \in \omega_+} \frac{\theta(\omega')}{\theta(\omega)} \phi^2(\omega')} \leq A \phi(\omega) \qquad \forall \omega \in \Omega / \Omega_l \\ & \phi(\omega) \geq 0 \qquad \forall \omega \in \Omega. \end{aligned} \tag{15}$$

This latter expression, when compared to relations (3) and (5), shows that the GD is a time-consistent coherent risk measure. Moreover, the nested formulation of the GD provided in (8) shows that the multi-stage form of this risk measure has a consistent interpretation over time: the GD of a two-stage payoff is equal to the GD of the sum of the first-stage payoff and the GD of the second stage—a useful property that the CVaR lacks. Furthermore, this expression shows that the GD risk measure can be computed via a conic—and hence convex—optimisation problem. Finally, the level of risk aversion, which is derived from (13), can be readily elicited given that acceptable levels of the Sharpe ratio can be derived from market information, and are publicly known across many industries.

In a nutshell, the GD risk measure is coherent, time-consistent, has a natural interpretation in terms of stochastic discount rates, and allows us to benchmark its level of risk aversion based on observable market data (the Sharpe ratio). The formulation of the GD also offers an appealing interpretation of the dual variables $W_c(\omega)$, which price the no-arbitrage conditions of traded products $\mathcal{C}$ along the scenario tree. Indeed, when agents are price-takers, $W_c(\omega)$ quantifies the volume of contract c traded in the financial market at node ω (a positive value indicates a sale,

a purchase otherwise). In Appendix A, we provide a useful reformulation of the GD that can readily be embedded into investment decision problems.

2.4 Forward contracts and BPAs

Many risk-hedging contracts have been developed in the past to support natural gas production, including oil-indexed contracts, gas spot-indexed contracts, and forward contracts (see Stern and Rogers [2014], Chyong [2015], and Abada et al. [2017b]). While gas spot and oil-indexed contracts can be directly embedded in the formulation of the GD risk measure, as discussed in the preceding sections, forward contracts can be modelled explicitly within the optimisation problems of market participants. We focus on their simplest from. The volume sold through the forward contract by a biomethane producer i to a consumer segment e is denoted by $y_{i,e}$ in our model, and the volume purchased by consumer segment e from i is denoted by $x_{i,e}$. The contract price, which is agreed upon by market agents e and i in the first stage, is denoted by $\pi_{i,e}$. These variables are deterministic, as they must be estimated by market agents in the first stage, prior to the progressive revelation of uncertainty and the unfolding of the scenario tree—some authors refer to them as *here-and-now* variables. Forward contracts are designed so that their volumes remain constant, and must be exchanged at each time step between counterparties. As such, this condition is similar to the classical Take-Or-Pay clause in historical fossil gas long-term contracts, which stipulated that the consumer still had to pay the contract price even when it did not need the contracted gas (for instance, when the spot market offered more economical purchase conditions, which happened between 2011 and 2014 in Europe for instance). These forward contracts are also aligned, in their functioning (and modelling), with Biomethane Purchase Agreements that are (marginally) traded in Europe today.

Naturally, once investments are made and contracts signed, recourse actions are possible, since market agents can trade natural gas in the spot market at subsequent stages of the decision process. This way of modelling forward contracts and BPAs has two advantages: it allows us to explicitly represent the revenues and costs of contracts directly in the objective functions of market participants on the one hand, and, on the other hand, it makes it possible to model the price of the contract $\pi_{i,e}$ as an endogenous variable, mimicking the negotiation process between each producer/consumer pair, (i, e), in the contracting stage. We elaborate further on this point in the coming section.

2.5 The equilibrium formulation

In this section, we present the equilibrium problem that captures the contracting and investment processes. We first delineate the optimisation problems of the biomethane producers in Section 2.5.1, and of the consumers in Section 2.5.2, before formulating the spot and financial market

clearing conditions in Section 2.5.3.

2.5.1 Modelling the biomethane producers

We first turn to formulating the strategic investment and contracting processes of a biomethane producer. Consider then a producer $i \in \mathcal{I}$ willing to invest in its biomethane field endowed with a maximum capacity of K_i. The investment decision on nominal capacity, denoted κ_i, is made at the initial stage of the decision process, i.e., at node ω^0. Volumes of forward contracts (or BPAs) $y_{i,e}$ are also signed with consumers in the first stage. At each node ω, production is $z_i(\omega)$ and sales to the natural gas spot market are $y_i^s(\omega)$. We assume a progressive increase in available capacity upon investment: at stage t, production in a scenario node ω occurring at time t, $z_i(\omega)$, cannot exceed a fraction $\gamma_i(t)$ of the invested capacity κ_i, with $\gamma_i(t) \in [0,1]$ increasing over time. This models possible lags in biomethane deployment. At a scenario node ω, the producer seeks to maximise its *short-term* profit, expressed as:

$$
\begin{aligned}
U_i(\omega) := \text{Max}_{z_i(\omega)\geq 0, y_i^s(\omega)\geq 0} \quad & y_i^s(\omega) p_g(\omega) - co_i(\omega) z_i(\omega) \\
\text{s.t} \quad & z_i(\omega) \leq \gamma_i\left(t(\omega)\right) \kappa_i \\
& \sum_{e\in\mathcal{E}} y_{i,e} + y_i^s(\omega) - z_i(\omega) = 0.
\end{aligned} \tag{16}
$$

The objective function comprises revenues accrued from the spot market—valued at the spot market price, and the costs of production. Revenues from forward contracts, which are absent from (16) because we focus on short-term profits for the time being, will be discussed shortly. The first constraint in Problem (16) enforces that production does exceed the invested capacity (adjusted by the availability rate) while the second constraint equates total sales (to the spot market and through contracts) to production.

Viewed from the first stage, the producer values its risky short-term profit $U_i(\omega)$ through the lens of the GD risk measure, denoted as $\rho_i^{GD}(U_i)$ and associated with a level of risk aversion A_i. Therefore, in the first stage, the producer will seek to maximise its *risk-adjusted profit*, net of the investment cost, by determining its optimal investment and contracting variables. We assume that the risk-adjusted profit takes the form

$$
\alpha_i \mathbb{E}_\theta\left[U_i\right] - (1-\alpha_i)\rho_i^{GD}(U_i), \tag{17}
$$

where $\mathbb{E}_\theta\left[.\right]$ is the expectation under the empirical (natural) probability θ and $\alpha_i \in (0,1)$ is a parameter that tunes how strongly risk affects the valuation of a project in the eyes of producer i. This approach, standard in modelling investment decisions under uncertainty in energy systems (Downward et al. [2012]; Abada and Ehrenmann [2025]), is akin to the mean-variance approach

of the theory of portfolio optimisation (Markowitz [2014]). Therefore, the first-stage optimisation problem of the producer is:

$$\begin{aligned} \text{Max}_{\kappa_i \geq 0, y_{i,e} \geq 0} \quad & N \sum_{e \in \mathcal{E}} y_{i,e} \pi_{i,e} - ci_i \kappa_i + \alpha_i \sum_{\omega \in \Omega} \theta(\omega) U_i(\omega) - (1 - \alpha_i) \rho_i^{GD}(U_i) \\ \text{s.t.} \quad & \kappa_i \leq K_i. \end{aligned} \tag{18}$$

Constraint $\kappa_i \leq K_i$ limits investment by the available capacity. The term $N \sum_{e \in \mathcal{E}} y_{i,e} \pi_{i,e}$ models the revenues from long-term contracts—which accrue at each of the N periods $t_1, t_2, \ldots, t_N$ of the time set—and $ci_i \kappa_i$ is the investment cost. Despite its conciseness, this optimisation problem contains two nested optimisation levels, since the GD risk measure is itself computed through another optimisation problem (relation (15)), which in turn involves the outcomes of other optimisation problems obtained from short-term trading (Problems (16), estimated for all nodes ω). This results in a complex Max-Min-Max optimisation problem. Fortunately, by using reformulation (26) of the GD risk measure provided in Appendix A, we can show that the resulting optimisation problem is convex on the one hand, and can still be written as a maximisation problem on the other. The immediate consequence is that the investment and contracting problem (18) can be tackled through its first-order Karush Khun and Tucker (KKT) conditions, which we report in Appendix B.1 for the interested reader. In particular, we explain in this appendix the formation process of risk-adjusted probabilities and offer a clear rationale for investment and long-term contracting: first a producer will enter a forward contract only when its price matches the *risk-adjusted* expectation of the spot market price, thereby ensuring a no-arbitrage condition between the spot and forward markets. Second, a producer invests only if it trusts it recoups the capital cost via its *risk-adjusted* short-term profits.

2.5.2 Modelling consumers

We now focus on the modelling of biomethane consumers. Consumer e engages in forward contracts with biomethane producers; we remind the reader that the volumes of these contracts are denoted as $x_{i,e}$ and are agreed upon at root scenario node ω^0. The consumer can also purchase volumes $x_e^s(\omega)$ from the spot market. At a scenario node ω, the consumer seeks to maximise its *short-term* profit, expressed as:

$$\begin{aligned} U_e(\omega) := \text{Max}_{x_e^s(\omega) \geq 0} \quad & \left(x_e^s(\omega) + \sum_{i \in \mathcal{I}} x_{i,e}^s \right) \left(p_e(\omega) - cd_e(\omega) \right) - x_e^s(\omega) p_g(\omega) \\ \text{s.t} \quad & x_e^s(\omega) + \sum_{i \in \mathcal{I}} x_{i,e} \leq K_e(\omega). \end{aligned} \tag{19}$$

The objective function comprises the net utility derived from consuming or transforming natural gas, $\left(x_e^s(\omega) + \sum_{i \in \mathcal{I}} x_{i,e}^s \right) \left(p_e(\omega) - cd_e(\omega) \right)$, from which we substract the spot purchases cost.

Viewed from the first stage, the consumer values its risky short-term profit $U_e(\omega)$ via the GD risk measure, $\rho_e^{GD}(U_e)$, which is associated with a level of risk aversion A_e. Therefore, in the first stage, the consumer will seek to maximise its *risk-adjusted profit* by determining its optimal contracting variable. Here again, the risk-adjusted profit takes the form

$$\alpha_e \mathbb{E}_\theta [U_e] - (1-\alpha_e)\rho_e^{GD}(U_e), \tag{20}$$

with $\alpha_e \in (0,1)$. The first-stage optimisation problem of the consumer is:

$$\text{Max}_{x_{i,e}\geq 0} \qquad -N\sum_{i\in\mathcal{I}} x_{i,e}\pi_{i,e} + \alpha_e \sum_{\omega\in\Omega} \theta(\omega)U_e(\omega) - (1-\alpha_e)\rho_e^{GD}(U_e). \tag{21}$$

The term $N\sum_{e\in\mathcal{E}} y_{i,e}\pi_{i,e}$ accounts for purchases from long-term contracts, which accrue in each of the N periods of the time set. Here again, we can show that the resulting optimisation problem (21) is convex and can be written as a maximisation problem. Appendix B.2 reports its equivalent KKT conditions; the appendix also highlights that the consumer, very much like producers, will sign a forward contract only when its price equals the *risk-adjusted* expectation—as estimated by the consumer—of the spot market price, thereby ensuring a no-arbitrage condition between the spot and forward markets.

2.5.3 Market clearing constraints

We now explain the process of forward contract price formation. We do so by writing a financial market clearing constraint for all forward contracts (in the remainder of the paper, $a \perp b$ means that $a.b = 0$ for any real numbers a and b):

$$\pi_{i,e} \quad \perp \quad \left(x_{i,e} - y_{i,e}\right) = 0 \quad \forall (i,e) \in \mathcal{I}\times\mathcal{E}. \tag{22}$$

Equation (22) equates demand and supply for each forward contract. In the absence of market power, the dual variable associated with this constraint, $\pi_{i,e}$, represents the price of the contract exchanged between i and e. In this way, one can make each contract's price endogenous to the model.

2.5.4 Framing and solving the equilibrium

Concatenating the KKT conditions of the objectives of biomethane producers, (29) in Appendix B.1, and those of consumers, (34) in Appendix B.2, along with the market clearing conditions (22), frames the equilibrium problem of investment and long-term contracting. In Appendix C, we prove that the problem always has a solution. The Nash equilibrium is computed by formulating

the model as a mixed complementarity problem (MCP) and solving the KKT conditions of all market agents together with the market clearing constraints. Once the equilibrium is calculated, we can easily derive a set of relevant economic indicators. First, we compute the risk-adjusted profit of the biomethane production industry, which we derive from (18):

$$RAP_{\text{biomethane}} = \sum_{i\in\mathcal{I}} \Big(N \sum_{e\in\mathcal{E}} y_{i,e}\pi_{i,e} - ci_i\kappa_i + \alpha_i \sum_{\omega\in\Omega} \theta(\omega)U_i(\omega) - (1-\alpha_i)\rho_i^{GD}(U_i) \Big). \tag{23}$$

Similarly, we define the risk-adjusted consumer surplus from (21):

$$RAP_{\text{consumers}} = \sum_{e\in\mathcal{E}} \Big(-N \sum_{i\in\mathcal{I}} x_{i,e}\pi_{i,e} + \alpha_e \sum_{\omega\in\Omega} \theta(\omega)U_e(\omega) - (1-\alpha_e)\rho_e^{GD}(U_e) \Big). \tag{24}$$

Finally, we measure risk-adjusted social welfare, which is an indicator of system efficiency, as:

$$RAW = RAP_{\text{biomethane}} + RAP_{\text{consumers}}. \tag{25}$$

3 A case study in France

In this section, we apply our model to the case of biomethane production in France. France offers a compelling case study because it has a significant exploitable biomethane potential—between 100 and 170 TWh/year on the one hand—and official decarbonization scenarios for the country account for at least 95 TWh/year of biomethane production on the other, to achieve carbon neutrality by 2050 (Bouacida and Aubert [2025]). With 12 TWh of biomethane injected in 2024, these figures imply that production capacity must increase eightfold to reach carbon neutrality in some scenarios, possibly calling for massive investments in the coming decade. We first present the data collection process in detail before discussing the main insights of the case study.

3.1 Data collection

The scenario tree We focus on the 2025–2035 period using a three-stage framework. The first stage represents current conditions (2025) and corresponds to the deterministic node ω^0 of the scenario tree. The second stage captures market evolution up to 2030 and includes 20 scenarios representing fluctuations in commodity prices and demand. These scenarios are generated via statistical bootstrapping of market data from 2023–2025 with monthly granularity; this process allows us to preserve correlations among all random variables. From 2030 onward, in the third stage, each second-stage node evolves along one of three possible trajectories—high, medium, or low—until 2035. More precisely, we assume that, between stage 2 and stage 3:

- The gas price either increases by 30%, remains constant, or decreases by 20%.
- The steel price either remains constant, decreases by 20%, or by 30%. (As we explain shortly, we model steel producers as a segment of gas consumers.) This reflects forecasts of future

steel price trends in Europe, which anticipate a decrease in steel demand and prices in Europe (OECD [2025]).

- The CO_2 price either remains constant, increases by 25%, or by 50%. This setup ensures that the CO_2 price could reach €141/ton by 2035, a value consistent with standard forecasts of the evolution of the European Emissions Trading System, which aligns with Europe's decarbonization targets by 2035 (Enerdata [2023]).
- Demand for residential and tertiary consumers either decreases by 10%, increases by 20%, or by 50%. This wide range of demand fluctuations is intentional, reflecting the high uncertainty pertaining to renovation and electrification policies for housing in France.

Overall, this procedure results in a total of 81 nodes in the scenario tree. At each stage, all scenarios are drawn from a uniform distribution—in line with the bootstrapping philosophy. The resulting scenario tree is depicted in Figure 1.

Additional data The rest of the data are calibrated using publicly available 2025 French datasets for natural gas demand, steel production, and commodity prices. Consumers are split into two segments: residential/tertiary consumers who use natural gas for space heating and steel producers using Direct Reduced Iron with Electric Arc Furnace technology. Biomethane supply curves are constructed from a proprietary Geographical Information System-based assessment of France's production potential and validated against International Energy Agency and official French projections. Because the study relies on proprietary data, we are unfortunately unable to share the complete dataset. Instead, we provide the aggregated country-level biomethane cost curve in Figure 2, along with a few descriptive statistics in Table 1 for 2030. The number of biomethane projects being very large (1,972 in 2030), we had to aggregate the supply curves to ensure numerical tractability. We did so using the K-means clustering method, grouping biomethane fields into 50 clusters, based on their (OPEX,CAPEX) characteristics. We verified, at the end of this procedure, that the obtained aggregated supply curve closely matches the original one. Risk aversion parameters are calibrated using a standard value of the maximum Sharpe ratio in the energy industry (0.8). All calibration details are provided in Appendix D.

Year	2030
Number of projects	1,972
Min OPEX (€/MWh)	57.9
Max OPEX (€/MWh)	120.1
Capacity-weighted OPEX (€/MWh)	67.5
Min CAPEX annuity (€/kW/year)	45.2
Max CAPEX annuity (€/kW/year)	99.6
Capacity-weighted CAPEX annuity (€/kW/year)	52.6
Total capacity (TWh)	43.6

Table 1: Basic descriptive statistics of the biomethane cost curve in 2030

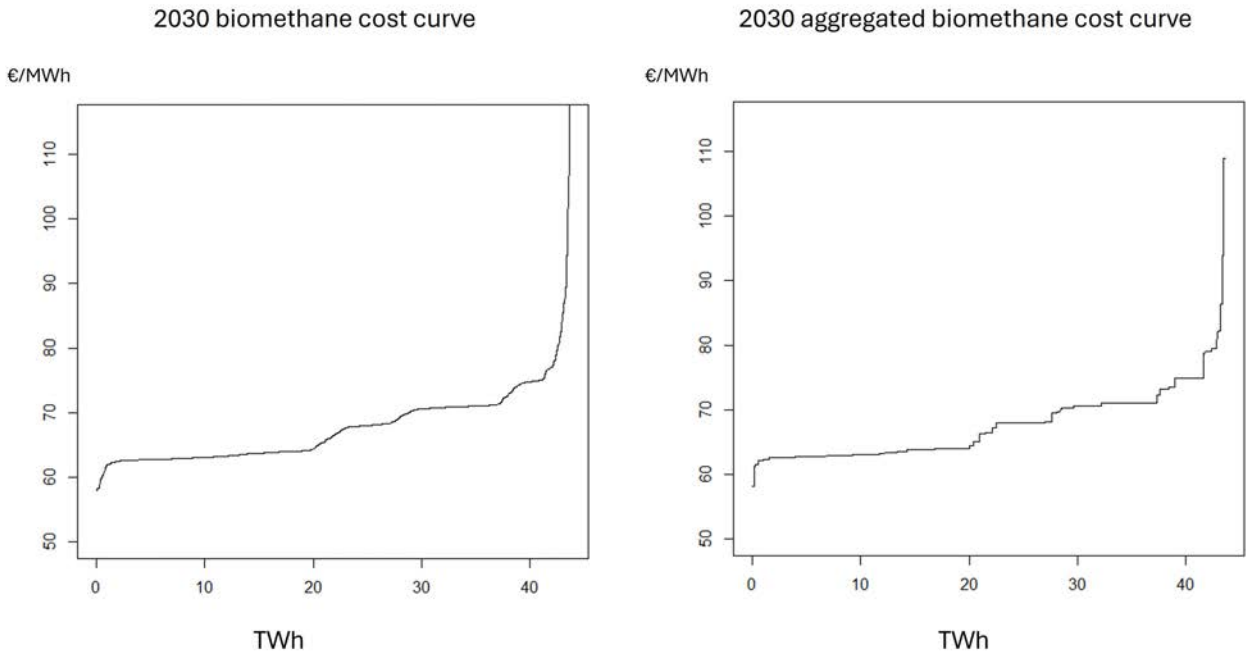


Figure 2: The biomethane cost curve in 2030

3.2 Base results

We now present our main results, which rely on the biomethane cost curve for 2030 in France. We begin with social welfare, which is a measure of system efficiency—where the system consists of biomethane producers, residential consumers, and steel producers. More precisely, we evaluate welfare under three cases. In the first case, no contracts are signed between producers and consumers. In the second case, forward contracting is allowed. In the third case, we assume the existence of a complete market for risk: in this theoretical benchmark, there are enough risk-mitigating instruments to hedge any revenue risk. In other words, the set of contracts $\mathcal{C}$ is rich enough to generate payoffs $p_c(\omega)$ that can replicate any stochastic payoff defined on the scenario tree. This would require as many contracts as the number of nodes in the scenario tree, a situation that is unrealistic in practice.

Figure 3 shows social welfare in these benchmarks. Two observations are worth making. First,

social welfare is the highest under market completeness. This is a natural and reassuring result, as it is now well established that a complete market for risk, combined with a perfectly competitive spot market, maximises social welfare (see Ehrenmann and Smeers [2013] and related works). This result generalizes the classical welfare theorem—according to which perfectly competitive markets yield optimal welfare—to the case where market agents are risk-averse toward uncertainty. Unfortunately, this situation is but a theoretical chimera, as no such thing as a fully complete market exists. As explained before, completeness would require an overly large amount of financial instruments to exchange risk among market participants—in our case, 81—and this does not even account for additional transactional costs they would entail (such as default risk or administrative costs related to contract monitoring and management to cite only a few; see, for instance, Barthélemy and Quélin [2006] and Seggie [2012]). Second, long-term forward contracts enhance welfare: we estimate that their introduction is beneficial to the system as they increase welfare by €1.9 bn/year (as compared to the case in which they are absent). This outcome is driven by the fact that, by allowing producers and consumers to trade risk, forward contracts encourage producers to invest in biomethane capacity. This increases their risk-adjusted profit and also raises consumer surplus, since consumers have the option to obtain part of their natural gas supply through contracts at a price that is, in some scenarios, lower than the market price. In the presence of contracts for biomethane, welfare remains lower than in the complete market case. This does not imply that contracts are undesirable, since the complete market only provides a theoretical upper bound on welfare. The finding does indicate, however, that additional risk-mitigation schemes could be considered to further foster biomethane production and enhance welfare.

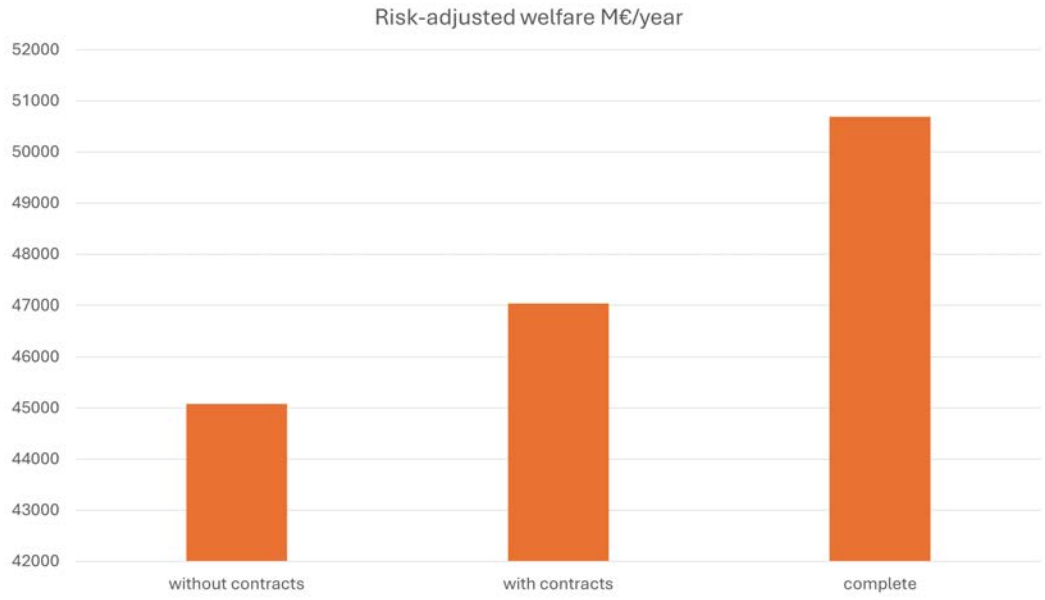


Figure 3: Social welfare

We now investigate biomethane investment, expressed in TWh/year, in the three benchmarks, which we depict in Figure 4. The first result is that biomethane investment is quite low without contracts: only 76% of the available capacity is exploited. The main reason is that biomethane projects are too expensive in 2030 when compared with alternatives available on the spot market, on the one hand, and that their revenues are overly risky for investors, on the other. When producers can secure contracts, biomethane production reach 95% of its potential, according to the cost curve in Figure 2. This is slightly lower than in the complete market case—which allows quasi-full development of projects—but our findings further highlight the importance of long-term contracts for biomethane: not only do they make investments financially feasible, they also increase system welfare, which makes them beneficial for consumers as well.

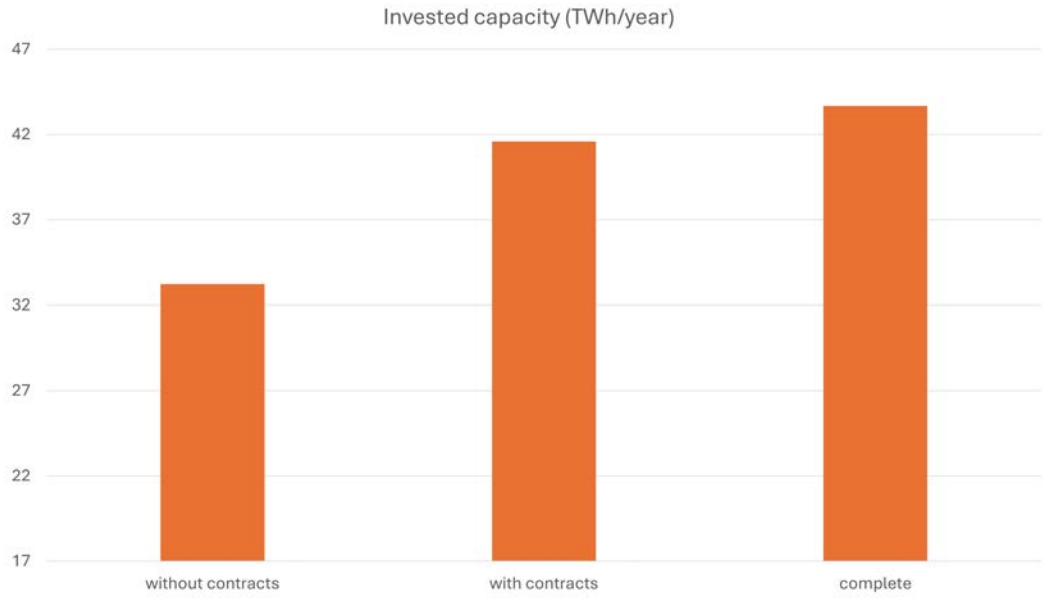


Figure 4: Biomethane production

We now turn to analyzing the contracting strategy at equilibrium. We report in Table 2 the contracted volumes and their share in average consumption per consumer segment. We observe that steel producers do not have an incentive to sign long-term contracts with biomethane producers. The main reason of this phenomenon is that gas and steel market prices are highly correlated. Indeed, the Kendall correlation coefficient between these two parameters, estimated over the 2023-2025 period, is 0.73. This strong correlation implies that gas, when purchased on the spot market, offers a natural financial hedge for profits accrued from the steel market. The dynamics of this hedge is quite straightforward: in scenarios where the steel price is low, reducing the steel producer's revenue, the gas purchase price in the spot market is also low, thereby mitigating losses. Thus, this dynamics induces stability in the steel producer's profit, which limits its incentive to engage in long-term contracts with biomethane producers. Residential consumers, meanwhile, do have an interest in signing contracts with biomethane producers, as their demand

Consumer segment	Residential	Steel producers
Volume of contracts signed (TWh/year)	52	0
Share of contracts in average consumption (%)	34%	0%

Table 2: Contracted volumes

is also positively correlated with the spot gas price—with a Kendall correlation coefficient of 0.13. Because the supply cost for residential consumers is the product of the gas price and demand, this positive correlation increases the risk to their utility, making long-term contracts particularly appealing. As a result, we find that residential consumers would contract 34% of their demand with biomethane producers, the rest being provided by alternatives such as heat pumps.

To conclude this section, we quantify the reduction in CO_2 emissions brought about by biomethane production and BPA contracts in France by 2030, which our model estimates at 7.7 $MtCO_2e$/year, thereby highlighting an additional benefit of BPAs.

3.3 Robustness checks

Because the development of biomethane projects is subject to uncertainty (stemming, for instance, from regulatory constraints and social acceptance), it is important to assess the robustness of our findings with respect to the assumed biomethane cost curves. In this section, we do so by conducting two sensitivity analyses.

In the first analysis, we explore the possibility that biomethane projects benefit from public and political support, leading to a faster pace of development. We do so by undertaking the same analysis as in our base case while changing only the cost curve, which we take for the year 2050 instead of 2030. This new biomethane cost curve is graphed in Figure 5, and some of its basic descriptive statistics are provided in Table 3. A comparison between Tables 1 and 3 reveals that biomethane production is more substantial and economical in 2050. Figure 6 shows our results for biomethane production and social welfare in this first senstivity analysis. Our findings remain qualitatively unchanged: adding contracts increases welfare—by €2.2 bn/year—and biomethane production at the same time. In this case, biomethane investment could reach 109.2 TWh/year with contracts, against 41 TWh/year with the 2030 cost curve. Contracted volumes are reported in Table 4: they are slightly higher than those obtained with the 2030 cost curve and could account for 37% of heating demand for housing. Here again, we find no incentive for steel producers to sign long-term contracts because of the strong correlation between spot gas and steel prices. Finally, we quantify the reduction in CO_2 emissions brought about by biomehtane production and BPA contracts in France by 2050, which we estimate at 8.6 $MtCO_2e$/year.

Year	2050
Number of projects	3,975
Min OPEX (€/MWh)	54.6
Max OPEX (€/MWh)	120.1
Capacity-weighted OPEX (€/MWh)	65.5
Min CAPEX annuity (€/kW/year)	14.3
Max CAPEX annuity (€/kW/year)	75.9
Capacity-weighted CAPEX annuity (€/kW/year)	37.0
Total capacity (TWh)	127.9

Table 3: Basic descriptive statistics of the biomethane cost curve in 2050, sensitivity analysis 1

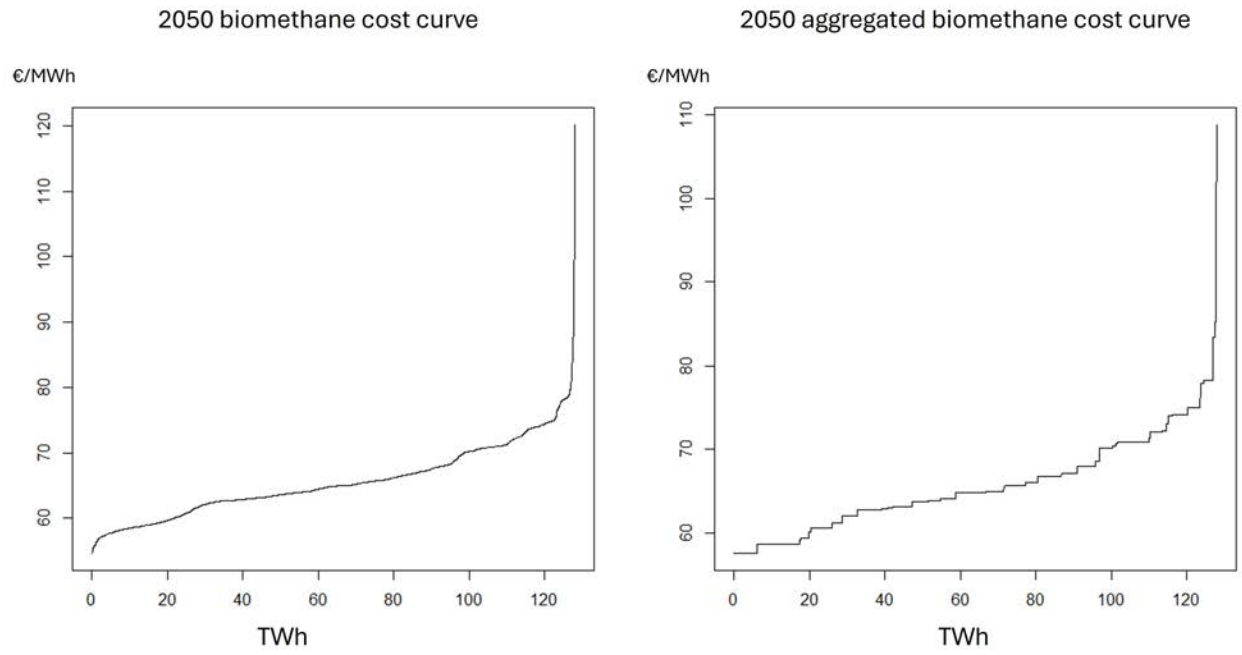


Figure 5: The biomethane cost curve in 2050

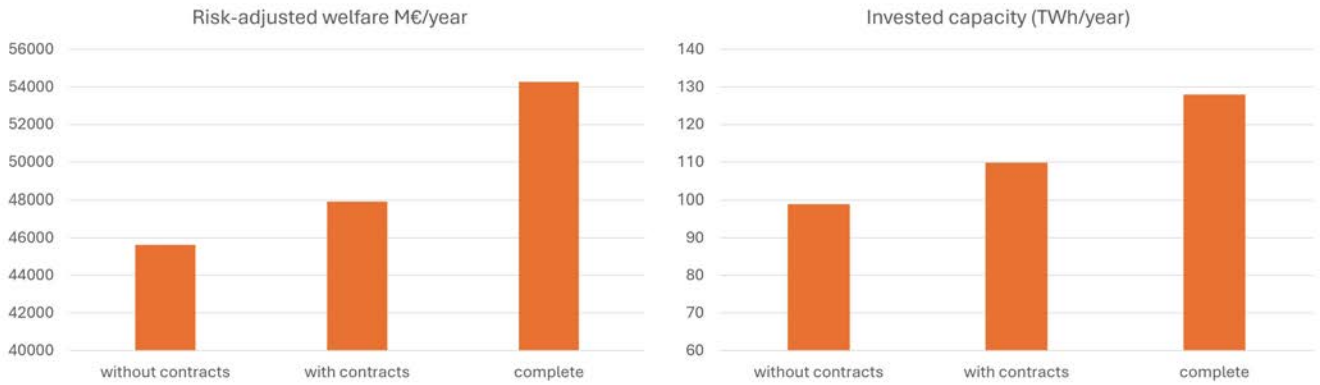


Figure 6: Biomethane production and social welfare with the cost curve in 2050, sensitivity analysis 1

In the second sensitivity analysis, we explore the possibility that biomethane development is more costly than assumed in the base case of Section 3.2. To do so, we add a fixed markup to the biomethane production cost curve, expressed in €/MWh, which we progressively increase

Consumer segment	Residential	Steel producers
Volume of contracts signed (TWh/year)	57.5	0
Share of contracts in average consumption (%)	37%	0%

Table 4: Contracted volumes in sensitivity analysis 1

until our qualitative results no longer hold. Our numerical simulations show that our qualitative results remain unchanged as long as the markup remains below €20/MWh: social welfare increases with the introduction of biomethane production and contracts, with residential consumers remaining the most likely to engage in BPAs. For instance, when the markup is €15/MWh, we estimate that biomethane production with contracts increases social welfare by €146 m/year, leading to biomethane production of 3.1 TWh/year. Overall, these results indicate that our qualitative results are robust to the choice of biomethane production cost curve, provided that OPEX does not increase by more than €20/MWh.

4 Discussion and concluding remarks

Long-term contracts have long been the backbone of the gas production industry around the world. They constituted an efficient means to share the risk of a CAPEX-intensive activity between investors and consumers. Even after the liberalization of gas markets in the 1990s, they have remained the main source of gas supply in Europe. Many of the drivers that led to their development for fossil gas persist today for biomethane as well: high investment costs, uncertain demand, volatile gas and carbon prices, and the scarcity of liquid risk-hedging instruments. Yet, biomethane could serve as a promising insurance technology in our decarbonization effort.

Our results for the French case underscore the importance of developing long-term contracts for biomethane production. We find that such contracts increase invested capacity, reduce project risk, and enhance consumer surplus and social welfare. Our first policy recommendation is therefore to foster the development of long-term Biomethane Purchase Agreements (BPAs). However, choosing the appropriate counterparties is crucial. While residential consumers have strong financial incentives to engage in such contracts, steel producers may not, because the price of their output is naturally correlated with the price of natural gas. Our second policy recommendation is therefore to carefully select the counterparties to these long-term contracts. While the welfare gains associated with biomethane production and long-term contracts appear substantial, policymakers must ensure that additional production or transaction costs do not offset them. To limit contracting costs, a central entity could represent consumers, much like Contracts for Difference have been used in electricity markets. This approach is particularly relevant for residential consumers, who have limited understanding of market risk and price volatility. Our third policy recommendation is therefore that the State sign long-term contracts on behalf of residential con-

sumers in a centralized manner with biomethane developers.

While we have strived to make our structural model realistic in its representation of risk valuation and biomethane production, our work nevertheless grapples with some inevitable limitations. From a modelling perspective, we acknowledge that calibrating a 10-year model with current gas system, market, and financial data might be overly ambitious, even if we incorporated a set of assumptions to mimic future uncertainty about demand, prices, etc. Many unanticipated technological, regulatory, and environmental changes are likely to occur by 2035, making prospects for industrial steel production or residential heating overly uncertain. That said, policymakers and investors face that very same problem when analyzing the future of the gas system, making our approach, albeit imperfect, relatively realistic in mimicking how investment and contracting decisions are made. Furthermore, other simplifications exist in our analysis, such as considering only two consumer segments—which is likely to make our investment results conservative—, assuming that consumption remains inelastic, excluding other risk-hedging instruments, and overlooking some operational constraints of biomethane production. Besides, shorter time steps could better capture seasonal demand patterns. All these aspects deserve further investigation.

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A The dual reformulation of the GD

In this appendix, we present a useful reformulation of the GD that can readily be embedded into investment decision problems. Taking the dual of optimisation problem (15), which, as alluded to before, is a particular instance of a conic optimisation problem—and hence convex and fulfills standard constraint qualification conditions—one obtains (we refer to Abada et al. [2017b] for a full derivation):

$\rho^{GD}(U) =$

$$\begin{aligned}
\text{Min}_{\eta(\omega),\, W_c(\omega)} \quad & -U(\omega^0) - \sum_{c\in\mathcal{C}} W_c(\omega^0)p_c(\omega^0) + A\sqrt{\sum_{\omega'\in\omega^0_+}\theta(\omega')\eta^2(\omega')} \\
\text{s.t} \quad & U(\omega) + \eta(\omega) + \sum_{c\in\mathcal{C}}\Big(W_c(\omega) - W_c(\omega_-)\Big)p_c(\omega) - A\sqrt{\sum_{\omega'\in\omega_+}\frac{\theta(\omega')}{\theta(\omega)}\eta^2(\omega')} \geq 0 \quad \forall\omega\in\Omega/\omega^0 \\
& \eta(\omega) \geq 0 \qquad\qquad \forall\omega\in\Omega.
\end{aligned} \tag{26}$$

This latter expression is obtained through the primal-dual equivalence of conic optimisation problems.

B Expressing the equilibrium problem

B.1 The producers

In this section, we derive the KKT conditions of optimisation problem (18). Combining relation (26) and the expression of the short-term profit (16), one can re-write Problem (18) as follows:

$$
\begin{aligned}
\underset{\substack{\eta_i(\omega)\geq 0,\, W_{i,c}(\omega)\\ \kappa_i\geq 0, y_{i,e}(\omega)\geq 0\\ z_i(\omega)\geq 0, y_i^s(\omega)\geq 0}}{\text{Min}} \quad & -N\sum_{e\in\mathcal{E}} y_{i,e}\pi_{i,e} + ci_i\kappa_i - \alpha_i\sum_{\omega\in\Omega}\theta(\omega)U_i(\omega)\\
& +(1-\alpha_i)\left[-\sum_{c\in\mathcal{C}} W_{i,c}(\omega^0)p_c(\omega^0) + A_i\sqrt{\textstyle\sum_{\omega'\in\omega_+^0}\theta(\omega')\eta_i^2(\omega')}\right]\\
\text{s.t} \quad & U_i(\omega) + \eta_i(\omega) + \sum_{c\in\mathcal{C}}\Big(W_{i,c}(\omega) - W_{i,c}(\omega_-)\Big)p_c(\omega)\\
\forall\omega\in\Omega/\omega^0, \quad & -A_i\sqrt{\sum_{\omega'\in\omega_+}\frac{\theta(\omega')}{\theta(\omega)}\eta_i^2(\omega')} \geq 0 \qquad (\nu_i(\omega))\\
\forall\omega\in\Omega/\omega^0, \quad & z_i(\omega)\leq\gamma_i\left(t(\omega)\right)\kappa_i \qquad (\mu_i(\omega))\\
\forall\omega\in\Omega/\omega^0, \quad & \sum_{e\in\mathcal{E}} y_{i,e} + y_i^s(\omega) - z_i(\omega) = 0 \qquad \Big(\sigma_i(\omega)\nu_i(\omega)\Big)\\
& \kappa_i\leq K_i \qquad (\xi_i),
\end{aligned}
\tag{27}
$$

where some (normalised) dual variables are written next to their constraints and where, by a slight abuse of notation, $U_i(\omega)$ is the expression of the short-term profit

$$
U_i(\omega) = y_i^s(\omega)p_g(\omega) - co_i(\omega)z_i(\omega). \tag{28}
$$

Using the primal-dual equivalence of Problems (15) and (26), we can demonstrate that variables $\nu_i(\omega)$ are the risk-adjusted probabilities (with the convention that $\nu_i(\omega^0) = 1$). optimisation problem (27) being convex and satisfying classical constraint qualification conditions, it is equivalent to its KKT conditions, which are:

$$\kappa_i \perp \quad -ci_i + \xi_i - \sum_{\omega \in \Omega/\omega^0} \mu_i(\omega)\gamma_i\left(t(\omega)\right) \leq 0 \tag{29a}$$

$$y_{i,e} \perp \quad N\pi_{i,e} - \sum_{\omega \neq \omega^0} \sigma(\omega)\nu_i(\omega) = 0 \qquad \forall e \in \mathcal{E} \tag{29b}$$

$$0 \leq y_i^s(\omega) \perp \quad -p_g(\omega) + \sigma_i(\omega) \geq 0 \qquad \forall \omega \in \Omega/\omega^0 \tag{29c}$$

$$0 \leq z_i(\omega) \perp \quad -\nu_i(\omega)\Big(co_i(\omega) - \sigma_i(\omega)\Big) + \mu_i(\omega) \leq 0 \qquad \forall \omega \in \Omega/\omega^0 \tag{29d}$$

$$W_{i,c}(\omega) \perp \quad p_c(\omega)\nu_i(\omega) - \sum_{\omega' \in \omega_+} p_c(\omega')\nu_i(\omega') = 0 \qquad \forall (\omega, c) \in \Omega/\Omega_l \times \mathcal{C} \tag{29e}$$

$$0 \leq \eta_i(\omega) \perp \quad \nu_i(\omega) - \nu_i(\omega_-)A_i \frac{\eta_i(\omega)\frac{\theta(\omega)}{\theta(\omega_-)}}{\sqrt{\sum_{\omega'/\omega'_- = \omega_-} \eta_i^2(\omega')\frac{\theta(\omega')}{\theta(\omega_-)}}} \leq 0 \qquad \forall \omega \in \Omega/\omega_0 \tag{29f}$$

$$0 \leq \nu_i(\omega) \perp \quad y_i^s(\omega)p_g(\omega) - co_i(\omega)z_i(\omega) + \eta_i(\omega) + \sum_{c \in \mathcal{C}} \Big(W_{i,c}(\omega) - W_{i,c}(\omega_-)\Big)p_c(\omega) - A_i\sqrt{\sum_{\omega' \in \omega_+} \frac{\theta(\omega')}{\theta(\omega)}\eta_i^2(\omega')} \geq 0 \qquad \forall \omega \in \Omega/\omega_0 \tag{29g}$$

$$0 \geq \mu_i(\omega) \perp \quad z_i(\omega) - \kappa_i \leq 0 \qquad \forall \omega \in \Omega/\omega_0 \tag{29h}$$

$$\sigma_i(\omega) \perp \quad \sum_{e \in \mathcal{E}} y_{i,e} + y_i^s(\omega) - z_i(\omega) = 0 \qquad \forall \omega \in \Omega/\omega_0 \tag{29i}$$

$$0 \geq \xi_i \perp \quad \kappa_i - K_i \leq 0. \tag{29j}$$

Combining expressions (29a), (29c), and (29d) shows that when $\kappa_i > 0$, then:

$$ci_i = \xi_i + \sum_{\omega \neq \omega^0} \nu_i(\omega)\Big(p_g(\omega) - co_i(\omega)\Big)\gamma_i\left(t(\omega)\right)\mathbb{1}_{z_i(\omega)>0}, \tag{30}$$

which yields a valuable financial and economic interpretation of the investment criterion. If the available capacity K_i is not binding (and hence $\xi_i = 0$), then the biomethane producer invests only if it trusts, in a risk-adjusted way, it recoups its investment cost from revenues in subsequent stages and at scenario nodes where it produces from its field, considering its availability rate. When the available capacity K_i becomes biding, its shadow price, $-\xi_i$, has to be added to the investment cost. Furthermore, combining (29b) with (29c) gives:

$$\pi_{i,e} = \frac{1}{N} \sum_{\omega \neq \omega^0} \nu_i(\omega)p_g(\omega) \quad \forall e \in \mathcal{E}. \tag{31}$$

This provides a rationale for engaging in long-term contracts: the producer signs a forward contract only when the contract price equals the risk-adjusted expectation of the spot market price.

This reflects a no-arbitrage condition between the spot and forward markets, as perceived by the producer.

B.2 The consumers

In this appendix, we derive the KKT conditions of optimisation problem (21). Combining relation (26) and the expression of the short-term profit (19), one can re-write Problem (21) as:

$$
\begin{aligned}
\underset{\substack{\eta_e(\omega)\geq 0,\, W_{e,c}(\omega) \\ x_{i,e}(\omega)\geq 0, x_e^s(\omega)\geq 0}}{\text{Min}} \quad & N\sum_{i\in\mathcal{I}} x_{i,e}\pi_{i,e} - \alpha_e \sum_{\omega\in\Omega}\theta(\omega)U_e(\omega) \\
& +(1-\alpha_e)\left[-\sum_{c\in\mathcal{C}} W_{e,c}(\omega^0)p_c(\omega^0) + A_e\sqrt{\textstyle\sum_{\omega'\in\omega_+^0}\theta(\omega')\eta_e^2(\omega')}\right] \\
\text{s.t} \quad & U_e(\omega) + \eta_e(\omega) + \sum_{c\in\mathcal{C}}\Big(W_{e,c}(\omega) - W_{e,c}(\omega_-)\Big)p_c(\omega) \\
\forall \omega\in\Omega/\omega^0, \quad & -A_e\sqrt{\sum_{\omega'\in\omega_+}\frac{\theta(\omega')}{\theta(\omega)}\eta_e^2(\omega')} \geq 0 \qquad (\nu_e(\omega)) \\
\forall \omega\in\Omega/\omega^0, \quad & x_e^s(\omega) + \sum_{i\in\mathcal{I}} x_{i,e} \leq K_e(\omega) \qquad \Big(\psi_e(\omega)\nu_e(\omega)\Big),
\end{aligned}
\tag{32}
$$

where some (normalised) dual variables are written next to their constraints and where, by a slight abuse of notation, $U_e(\omega)$ is the expression of the short-term profit

$$
U_e(\omega) = \Big(x_e^s(\omega) + \sum_{i\in\mathcal{I}} x_{i,e}^s\Big)\Big(p_e(\omega) - cd_e(\omega)\Big) - x_e^s(\omega)p_g(\omega). \tag{33}
$$

The KKT conditions are:

$$x_{i,e}\perp \quad -N\pi_{i,e} + \sum_{\omega\neq\omega^0} \nu_e(\omega)\Big(p_e(\omega) - cd_e(\omega)\Big) - \sum_{\omega\neq\omega^0} \nu_e(\omega)\psi_e(\omega) = 0 \qquad \forall i \in \mathcal{I} \tag{34a}$$

$$0 \leq x_e^s(\omega)\perp \quad p_g(\omega) - \Big(p_e(\omega) - cd_e(\omega)\Big) + \psi_e(\omega) \geq 0 \qquad \forall \omega \in \Omega/\omega^0 \tag{34b}$$

$$W_{e,c}(\omega)\perp \quad p_c(\omega)\nu_e(\omega) - \sum_{\omega'\in\omega_+} p_c(\omega')\nu_e(\omega') = 0 \qquad \forall (\omega, c) \in \Omega/\Omega_l \times \mathcal{C} \tag{34c}$$

$$0 \leq \eta_e(\omega)\perp \quad \nu_e(\omega) - \nu_e(\omega_-)A_e \frac{\eta_e(\omega)\frac{\theta(\omega)}{\theta(\omega_-)}}{\sqrt{\sum_{\omega'/\omega'_-=\omega_-} \eta_e^2(\omega')\frac{\theta(\omega')}{\theta(\omega_-)}}} \leq 0 \qquad \forall \omega \in \Omega/\omega_0 \tag{34d}$$

$$0 \leq \nu_e(\omega)\perp \quad \Big(x_e^s(\omega) + \sum_{i\in\mathcal{I}} x_{i,e}^s\Big)\Big(p_e(\omega) - cd_e(\omega)\Big) - x_e^s(\omega)p_g(\omega) + \eta_e(\omega)$$
$$+ \sum_{c\in\mathcal{C}} \Big(W_{e,c}(\omega) - W_{e,c}(\omega_-)\Big)p_c(\omega) - A_e\sqrt{\sum_{\omega'\in\omega_+} \frac{\theta(\omega')}{\theta(\omega)}\eta_e^2(\omega')} \geq 0 \qquad \forall \omega \in \Omega/\omega_0 \tag{34e}$$

$$\psi_e(\omega)\perp \quad \sum_{i\in\mathcal{I}} x_{i,e} + x_e^s(\omega) - K_e(\omega) \leq 0 \qquad \forall \omega \in \Omega/\omega_0. \tag{34f}$$

The risk-adjusted probabilities are $\nu_e(\omega)$. Combining relations (34a) with (34b) proves the relation:

$$\pi_{i,e} = \frac{1}{N}\sum_{\omega\neq\omega^0} \nu_e(\omega)p_g(\omega) \quad \forall i \in \mathcal{I}, \tag{35}$$

which entails a no-arbitrage condition between the financial and spot markets for natural gas, as perceived by the consumer.

C Existence of equilibria

We can prove that our equilibrium problem always has a solution by invoking standard fixed-point arguments applied to risked-based equilibria (Ralph and Smeers [2015]). More precisely, let $\mathcal{M}_i$ denote the risk set of producers i, $i \in \mathcal{I}$, which we derive from the primal formulation of the GD (15),

$$\mathcal{M}_i := \left\{ \begin{array}{lll} \phi(\omega) \geq 0 & \text{such that} & \forall (\omega, c) \in (\Omega/\Omega_l) \times \mathcal{C}, \\ & \text{and} & \forall \omega \in \Omega, \end{array} \begin{array}{l} \sum_{\omega'\in\omega_+} \phi(\omega')p_c(\omega') = \phi(\omega)p_c(\omega) \\ \sqrt{\sum_{\omega'\in\omega_+} \frac{\theta(\omega')}{\theta(\omega)}\phi^2(\omega')} \leq A_i\phi(\omega) \end{array} \right\},$$

and let $\mathcal{M}_e$ denote the risk set of consumers e, $e \in \mathcal{E}$,

$$\mathcal{M}_e := \left\{ \begin{array}{lll} \phi(\omega) \geq 0 & \text{such that} & \forall (\omega, c) \in (\Omega/\Omega_l) \times \mathcal{C}, \\ & \text{and} & \forall \omega \in \Omega, \end{array} \begin{array}{l} \sum_{\omega'\in\omega_+} \phi(\omega')p_c(\omega') = \phi(\omega)p_c(\omega) \\ \sqrt{\sum_{\omega'\in\omega_+} \frac{\theta(\omega')}{\theta(\omega)}\phi^2(\omega')} \leq A_e\phi(\omega) \end{array} \right\}.$$

It can then be shown that the problem admits a Nash equilibrium if the risk sets are sufficiently similar, that is, when the set:

$$\left(\cap_{i\in\mathcal{I}}\,\mathcal{M}_i\right)\cap\left(\cap_{e\in\mathcal{E}}\,\mathcal{M}_e\right) \tag{36}$$

has a non-empty interior; see de Maere d Aertrycke and Smeers [2013]. In particular, this always holds if levels of risk aversion A_i, $i \in \mathcal{I}$ and A_e, $e \in \mathcal{E}$, are positive.

D Additional data

Consumers Consumers are separated into two segments. The first segment comprises residential and tertiary consumers who use natural gas for space heating. Their demand (in 2025) is taken from the French official database platform for transport, energy, and housing.[10] The second segment represents steel producers using Direct Reduced Iron with Electric Arc Furnace technology; their demand (in 2025) is taken from INSEE (Institut National de la Statistique et des Etudes Economiques).[11] These producers rely on natural gas in the chemical process used to produce steel (Souza et al. [2023]). We use a gas-to-steel efficiency of 0.34 t/MWh.[12] Regarding the calibration of costs cd_e, we assume that residential consumers do not incur operational costs whereas steel producers have an OPEX of €461/ton.[13] France's steel production capacity is taken at its current level of 15 million tons per year.[14]

Commodity prices All data pertaining to commodity prices are derived from public sources (in 2025). Gas prices are extracted from the database of the Comité National Routier.[15] Steel prices are taken from the INSEE database.[16] Carbon dioxide prices are extracted from Statista.[17] Finally, the Value Of Lost Load for residential consumers of natural gas is €750/MWh.

Biomethane producers We rely on an internal study to construct production cost curves for biomethane in France by 2050. The study undertakes a detailed Geographical Information System (GIS)-based analysis of the entire country, at a one-square-kilometer resolution, to quantify the potential of agricultural waste along with the capacity to transform it into biomethane and inject

[10] See https://www.statistiques.developpement-durable.gouv.fr/catalogue?page=dataset&datasetId=631b03afb61e5c6479370169&tab=download (accessed October 2025).
[11] See https://www.insee.fr/fr/statistiques/serie/010534266#Telechargement (accessed October 2025).
[12] See https://www.steelonthenet.com/resources/cost-models/eaf.html (accessed October 2025). Steel production is measured in tons.
[13] See Souza et al. [2023].
[14] See https://www.ademe.fr/ (accessed October 2025).
[15] See https://www.cnr.fr/datas/all (accessed October 2025).
[16] See https://www.insee.fr/fr/statistiques/serie/010534266#Telechargement (accessed October 2025).
[17] See https://www.statista.com/statistics/1322214/carbon-prices-european-union-emission-trading-scheme/ (accessed October 2025).

it into the distribution or transportation grids. Because the study relies on proprietary data, we are unfortunately unable to share the complete dataset. Instead, we provide the aggregated country-level biomethane cost curves in Figure 2, along with a few descriptive statistics in Table 1 for 2030. Most importantly, we verified that the biomethane cost curves obtained for France are closely aligned with the results of the recent International Energy Agency study on the outlook for biomethane development through 2050 (IEA [2025]). (The aggregated data used to construct the country-level cost curves are available upon request.) The number of biomethane projects being very large (1,972 in 2030), we had to aggregate the supply curves to ensure numerical tractability. We did so using the K-means clustering method, grouping biomethane fields into 50 clusters, based on their (OPEX,CAPEX) characteristics. We verified, at the end of this procedure, that the obtained aggregated supply curve closely matches the original one.[18] We also verified that our supply curve is aligned with French official forecasts.[19] The CO_2 content of fossil gas is 243 kgCO_2-eq/MWh and that of biomethane is 23.4 kgCO_2-eq/MWh.[20]

Risk aversion and hedging contracts The maximum Sharpe ratio is set to 0.8, which corresponds to the five-year expected Sharpe ratio in the energy sector (MSCI [2025]). Furthermore, we assume that agents assign a 70% weight to risk in their valuation of a project's profitability:

$$\alpha_e = \alpha_i = 0.3, \quad \forall (e,i) \in \mathcal{E} \times \mathcal{I}. \tag{37}$$

This parameter is aligned with standard values found in the literature on investment decisions under risk aversion. Finally, we assess the potential for signing long-term forward contracts that span the full horizon of the case study, that is, until 2035, as explained in Section 2.4. Therefore, in the base case, the set $\mathcal{C}$ that intervenes in the definition of the GD risk measure comprises only to so-called *risk-free* asset, whose price is constant across all nodes of the scenario tree. This instrument makes it possible to define risk-adjusted probabilities as actual probability distributions, meaning that they are non-negative and sum to one at every stage.

[18] This verification is done via the elbow method to estimate the optimal number of clusters with K-means.

[19] See Agence de l Environnement et de la Maîtrise de l'Energie (ADEME): https://librairie.ademe.fr/energies/6503-avis-technique-methanisation.html# (accessed October 2025).

[20] See the publications of the French distribution system operator at https://www.grdf.fr/gaz-vert/energie-transition-ecologique/reduction-gaz-effet-serre (accessed October 2025).