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Contents

List of Figures	ix
List of Tables	xii
1. Introduction	1
1.1. Motivation	1
1.2. Outline	3
1.3. Methodological approaches	5
2. Assessing the Impact of Take-or-Pay Rates in Long-Term Contracts for Hydrogen Imports on a Decarbonized European Energy System	9
2.1. Introduction	9
2.2. Literature	12
2.3. Methodology	15
2.3.1. Model framework	15
2.3.2. The economic rationale for hydrogen imports with TOP rates	20
2.3.3. Assumptions and data	21
2.4. Results	23
2.4.1. System costs	23
2.4.2. Investment decisions under a representative weather year	25
2.4.3. Regional insights from investment decisions	28
2.4.4. Dispatch decisions under representative weather year . . .	29
2.4.5. Dispatch decisions under 35 weather years	31
2.5. Discussion	34
2.5.1. Key findings and implications	35
2.5.2. Limitations and future research	37
2.6. Conclusion	38

3. The Cost of Security: Analyzing Strategies to Hedge Hydrogen Import Disruption under Stochastic Representation of Weather	41
3.1. Introduction	41
3.2. Literature	43
3.3. Methodology	46
3.3.1. Stochastic model of the European electricity and hydrogen system	47
3.3.2. Stochastic model of hydrogen import prices	49
3.3.3. Determination of representative weather years	53
3.3.4. Assumptions and data	54
3.3.5. Scenario framework	55
3.4. Results	57
3.4.1. Hydrogen import prices	57
3.4.2. Value of the stochastic solution (VSS)	58
3.4.3. Naive planning	59
3.4.4. Diversification of hydrogen imports	61
3.4.5. Reduction of hydrogen imports	63
3.4.6. Combined strategies	65
3.4.7. Relating the cost of autarky to a perceived import disruption risk	67
3.5. Discussion	68
3.5.1. Stochastic calculation of LCOH	68
3.5.2. Stochastic optimization of European hydrogen import decisions	68
3.5.3. Mitigation strategies	69
3.5.4. Limitations	70
3.6. Conclusion	71
4. Optimal Bidding of Uncertain Renewable Electricity in Sequential Markets – Implications of Risk Aversion and Imperfect Competition	73
4.1. Introduction	73
4.2. Analytical model	75
4.2.1. Model setup	75
4.2.2. Model specification	77
4.2.3. Numerical assumptions	79

4.3.	Results	79
4.3.1.	Case 1: Risk-averse renewable oligopoly: flexible conventional production and homogeneous composition of RE producers	80
4.3.2.	Case 2: Risk-averse renewable oligopoly: inflexible conventional production and homogeneous composition of RE producers	84
4.3.3.	Case 3: Risk-averse renewable oligopoly: flexible conventional production and heterogeneous composition of RE producers	89
4.3.4.	Rents and welfare implications of Cases 1 and 2	90
4.3.5.	Rents and welfare implications of Case 3	94
4.4.	Discussion	96
4.5.	Conclusion	98
5.	Bidding Wind and Solar: A Theory of Price Premia in Sequential Electricity Markets	101
5.1.	Introduction	101
5.2.	Literature	103
5.3.	Theory	105
5.3.1.	Model	105
5.3.2.	Bidding rationales	106
5.4.	Numerical application of the theoretical model	111
5.4.1.	Observed price premia	112
5.4.2.	Data and parameterization	113
5.4.3.	Simulation of price premia	116
5.5.	Discussion	119
5.5.1.	Stylized facts	119
5.5.2.	Economic interpretation of model results	120
5.5.3.	Relation to the literature and economic implications	121
5.5.4.	Limitations and future research	122
5.6.	Conclusion	123
A.	Supplementary Material for Chapter 2	125
A.1.	Notation	126
A.2.	Assumptions	127
A.3.	Results of the investment decisions	128

B. Supplementary Material for Chapter 3	129
B.1. Capacity factors for the calculation of LCOH	129
B.2. Comparison of LCOH	130
B.3. Wind correlation before and after clustering of weather years . .	131
B.4. Assumptions	133
B.5. LTC prices	134
C. Supplementary Material for Chapter 4	137
C.1. Use of variance as a risk metric	137
C.2. Choice of lambda	137
C.3. Proofs	138
C.3.1. Proof of Proposition 2	138
C.3.2. Proof of Corollary 2	139
D. Supplementary Material for Chapter 5	141
D.1. Transformation of bid curves	141
Bibliography	143
Curriculum Vitae	156

List of Figures

2.1. Schematic representation of the model HYEBRID.	16
2.2. Fundamental two-stage modeling approach.	16
2.3. Increase in total system costs with TOP rates for the representative weather year (left) and schematic illustration of the relationship between benchmark and individual solutions regarding total system costs (right).	24
2.4. Maximum price premium for hydrogen imports as a function of TOP rates, illustrating a theoretical cost trade-off between flexibility and contractual obligations.	25
2.5. Relative change in investment decisions as a function of TOP rates.	27
2.6. Regional shifts in investment decisions from 0% TOP rate to 100% TOP rate.	29
2.7. Aggregated European hydrogen storage levels, demand, and supply profiles for the representative weather year 1989 and the TOP rates 0% (left) and 100% (right).	31
2.8. System response to variability of 35 weather years.	32
2.9. Sorted H ₂ terminal utilization for selected TOP rates on average (blue) and for all underlying weather years (grey).	34
3.1. Overview of the two-step stochastic modeling approach.	46
3.2. Schematic model overview: stochastic determination of LTC prices and the European energy system.	47
3.3. Exemplified LCOH of Morocco (MA) for single years and stochastic optimization in the target year 2050.	52
3.4. Comparison of stochastic LCOH and probability-weighted mean LCOH for onshore wind across various exporting countries. Percentages indicate the differences between both methodological approaches.	52
3.5. Relative deviation in total system costs of single weather years from the average of 27 weather years computed with the model HYEBRID.	53

3.6.	LTC prices including transport to Germany from various exporters.	58
3.7.	Comparison of total system costs from the stochastic and deterministic modeling approaches, assuming a VOLL of 5,000 EUR/MWh.	59
3.8.	Overview of investment (blue) and dispatch (yellow) results for the scenario <i>naive planning</i> .	61
3.9.	Average annual hydrogen trade flows in the scenario <i>naive planning</i> .	61
3.10.	Impact of diversification of hydrogen imports by HHI targets on total system costs and number of exporters.	62
3.11.	Volume-weighted European hydrogen import prices by exporter and HHI target (left axis), and average export volumes (right axis).	63
3.12.	Impact of reduction of hydrogen imports by import share targets on total system costs and number of exporters.	64
3.13.	Sensitivity of additional system costs for autarky as a function of the WACC spread between exporters and Europe.	65
3.14.	Impact of <i>combined diversification</i> and <i>reduction</i> of hydrogen imports on total system costs and number of exporters.	66
3.15.	Disruption probability by exporter required to justify the cost of full autarky as a function of the Value of Lost Load.	67
4.1.	Results under identical supply curve slopes in stage one and two for risk-averse and risk-neutral producers: bids, prices, and forward premium	83
4.2.	Numerical assessment of inequality 4.33.	87
4.3.	Results under risk aversion and inflexible supply curve: bids, prices, and forward premium.	88
4.4.	Results under risk aversion and (in)flexible supply curve: producer surplus, consumer surplus, and welfare.	93
4.5.	Results under risk aversion, flexible supply curve, and heterogeneous RE producers: producer surplus, consumer surplus, and welfare.	96
5.1.	Hourly price premium (day-ahead – ID3) in Germany for the period January 2024 to August 2025. Boxes represent the interquartile range (25th–75th percentile), while whiskers extend to the 10th and 90th percentiles. The sample is restricted to the 1st–99th percentiles to exclude extreme outliers.	103

5.2.	Schematic marginal cost curve, RE production, and profit distribution of RE producers. Assumptions: $a=0.01$, $b=0.01$, $c=0$, $d=100$	108
5.3.	Hourly means of RE forecast (μ_{RE}), RE standard deviation (σ_{RE}), wind forecast (μ_{wind}), wind standard deviation (σ_{wind}), PV forecast (μ_{PV}), PV standard deviation (σ_{PV}), and load forecast (d) from January 2024 to August 2025.	113
5.4.	Original and transformed day-ahead bid curves from 11/18/2024 at 9 p.m. and derived slopes.	115
5.5.	Hourly slope ratios a_h^{linear} from January 2024 to August 2025 of the day-ahead auction.	116
5.6.	Simulated price premia relative to average day-ahead prices for homogeneous bidding rationales among RE producers.	117
5.7.	Simulated price premia relative to average day-ahead prices for separate bidding rationales between wind and PV producers, and mean observed price premia.	118
B.1.	Comparison of stochastic LCOH and probability-weighted mean LCOH for wind offshore across various exporting countries. Percentages indicate the differences between both methodological approaches.	130
B.2.	Comparison of stochastic LCOH and probability-weighted mean LCOH for PV across various exporting countries. Percentages indicate the differences between both methodological approaches.	131
B.3.	Correlation of wind onshore capacity factors between Europe and exporters.	132
C.1.	Variance of RE producer profits	137
C.2.	Conditional Value at Risk of RE producer profits	137

List of Tables

4.1. Overview of modeled cases.	77
4.2. Numerical assumptions of parameters.	79
A.1. Model sets, parameters, variables, and indices.	126
A.2. Techno-economic assumptions as inputs for the energy system model.	127
A.3. Investment decisions under varying TOP rates for the representa- tive weather year 1989.	128
B.1. Techno-economic assumptions as inputs for the energy system model.	133
B.2. LCOH including transport costs (EUR/MWh) to selected Euro- pean countries from various exporters.	134

1. Introduction

1.1. Motivation

The transition to a climate-neutral energy system fundamentally alters the economic environment of energy supply. In Europe, this shift is characterized by the rapid expansion of weather-dependent renewable generation and the anticipated scale-up of hydrogen as a complementary energy carrier (IEA, 2025). Together, these developments increase the exposure of the energy system to uncertainty and risk. In the Knightian sense, uncertainty refers to developments for which reliable probability distributions are unavailable, such as potential hydrogen import disruptions, while risk describes uncertain but probabilistically quantifiable outcomes, such as weather-driven renewable generation (Knight, 1921).

A central implication is that uncertainty and risk become first-order determinants of economic outcomes, so that efficient outcomes depend not only on expected conditions but on how this exposure is internalized in decision-making. Internalizing it is inherently costly and redistributes costs across actors and time horizons. Instruments such as long-term contracts, hedging strategies, or risk-adjusted bidding behavior do not eliminate uncertainty and risk but transform them into additional system investments, contractual rigidities, or price premia. As a result, an inefficient handling of uncertainty and risk leads to a misallocation of resources.

These challenges manifest differently across time horizons. In the long run, uncertainty complicates the coordination of investments in an increasingly integrated energy system. Investment decisions must be taken before key uncertainties are resolved and require trading off cost efficiency against robustness to adverse states of the world. Accounting for these sources of uncertainty can substantially alter optimal system design and has important implications for policy, as regulatory frameworks shape the trade-off between system costs and security of supply.

In the short run, uncertainty shapes market outcomes in sequential electricity markets, where trading takes place both before and after the realization of uncertain renewable supply. This structure exposes market participants to risk, as positions are taken under incomplete information and adjusted as uncertainty resolves. While sequential trading allows agents to update decisions over time, it also creates scope for strategic behavior in the presence of uncertainty. In this context, risk preferences, market structure, and system flexibility jointly determine how uncertainty is translated into prices and dispatch decisions. These

1. Introduction

mechanisms have important implications for efficiency and welfare and provide a basis for assessing potential inefficiencies in market design and regulatory frameworks.

This dissertation studies how uncertainty and risk affect economic outcomes along these two dimensions. The first part analyzes long-term system design in integrated electricity and hydrogen systems. The second part examines short-term market behavior in sequential electricity markets, focusing on how risk and uncertainty shape bidding and price formation. The dissertation focuses on the European energy system and German power markets. The research develops and applies numerical optimization methods and analytical approaches. Each chapter is based on a standalone research paper to which all authors contributed equally:

- Chapter 2: Assessing the Impact of Take-or-Pay Rates in Long-Term Contracts for Hydrogen Imports on a Decarbonized European Energy System. Joint work with Jan Kopp, *EWI Working Paper 24/07* and published in *Applied Energy* (Keutz and Kopp, 2025a).
- Chapter 3: The Cost of Security: Analyzing Strategies to Hedge Hydrogen Import Disruption under Stochastic Representation of Weather. Joint work with Jan Kopp, *EWI Working Paper 25/12* (Keutz and Kopp, 2025b).
- Chapter 4: Optimal Bidding of Uncertain Renewable Electricity in Sequential Markets – Implications of Risk Aversion and Imperfect Competition. Joint work with Amir Ashour Novirdoust and Pia Hoffmann-Willers, *EWI Working Paper 25/10* (Ashour Novirdoust et al., 2025).
- Chapter 5: Bidding Wind and Solar: A Theory of Price Premia in Sequential Electricity Markets. *EWI Working Paper 26/02* (Keutz, 2026).

The following section provides an outline of the individual chapters and discusses the methodological approaches, limitations, and opportunities for future research.

1.2. Outline

Assessing the Impact of Take-or-Pay Rates in Long-Term Contracts for Hydrogen Imports on a Decarbonized European Energy System

Climate-neutral hydrogen is expected to play a central role in decarbonizing Europe by 2050. However, existing studies often assume fully flexible hydrogen imports and neglect contractual constraints such as Take-or-Pay (TOP) clauses in long-term contracts, which limit import flexibility. Chapter 2 develops a numerical optimization model of a coupled European power and hydrogen system in 2050, explicitly incorporating TOP constraints in hydrogen imports. The model co-optimizes investment and dispatch decisions under different levels of import rigidity.

The results reveal that higher TOP rates significantly alter cost-optimal system configurations: reduced import flexibility is mainly balanced by increased hydrogen storage, while import capacity declines. Moreover, systems planned under high TOP rates exhibit lower reliability when evaluated across multiple weather years. Overall, the findings highlight the importance of accounting for contractual constraints in hydrogen import assumptions, as they affect infrastructure needs and system robustness.

The Cost of Security: Analyzing Strategies to Hedge Hydrogen Import Disruption under Stochastic Representation of Weather

The European Union’s pursuit of climate neutrality is likely to increase reliance on imported green hydrogen, introducing risks from weather-driven production variability and potential import disruptions. Existing studies often overlook these uncertainties or treat them deterministically. Chapter 3 develops a stochastic optimization framework of the European power and hydrogen system, capturing weather variability across domestic and exporting regions. Hydrogen imports are modeled via long-term contracts, with prices and supply profiles derived from a stochastic levelized cost approach. The model further evaluates mitigation strategies such as supplier diversification and reduced import dependency.

The results show that accounting for stochastic weather conditions reduces system costs significantly compared to deterministic planning. At the same time, substantially higher hydrogen storage capacities are required to manage supply variability. Cost-minimal import strategies lead to strong supplier concentration, increasing vulnerability to disruptions. Evaluating risk mitigation strategies reveals that diversification and reduced imports increase upfront system costs but can be economically justified under higher disruption risk. Together, the findings highlight the importance of explicitly incorporating uncertainty and security considerations in planning hydrogen-based energy systems.

Optimal Bidding of Uncertain Renewable Electricity in Sequential Markets – Implications of Risk Aversion and Imperfect Competition

Sequential electricity markets allow producers to adjust positions over time but also create strategic incentives under uncertainty. While forward premia are often attributed to market power, the role of risk aversion among renewable energy producers remains less understood. Chapter 4 develops a stylized two-stage model of competition between renewable and conventional producers, incorporating uncertainty in renewable generation, risk-averse behavior, and limited flexibility of conventional supply. The model distinguishes between competitive and oligopolistic renewable market structures.

The findings reveal that risk aversion increases strategic withholding by oligopolistic renewable producers, raising forward premia, especially when conventional supply is inflexible. While no welfare effects arise under perfect competition or full flexibility, the interaction of risk aversion, market power, and inflexibility leads to welfare losses. In market structures including both oligopolistic and fringe producers, fringe producers benefit from higher prices induced by oligopolistic withholding. In summary, the work shows that forward premia can be driven by the interaction of risk preferences, market power, and system flexibility, with implications for market design and welfare.

Bidding Wind and Solar: A Theory of Price Premia in Sequential Electricity Markets

Price premia between day-ahead and intraday electricity markets are well documented but not fully explained, particularly regarding their systematic diurnal patterns observed in markets such as Germany. Existing explanations based on forecast errors or market frictions provide limited insight into these temporal structures. Chapter 5 develops a stylized two-stage model in which renewable producers choose day-ahead bids under different rationales, including expected-production, risk-neutral, and risk-averse strategies that account for tail risk. The model derives closed-form solutions for bidding behavior and resulting price premia and is calibrated to the German electricity market.

The analysis points out how price premia emerge from the interaction of bidding behavior, forecast uncertainty, and supply curve convexity. In particular, heterogeneous strategies across technologies replicate observed diurnal patterns: negative premia around midday and positive premia during morning and evening hours arise when PV producers bid expected production while wind producers behave risk-averse. Overall, the findings suggest that systematic price premia reflect both risk preferences and institutional features of renewable energy marketing.

1.3. Methodological approaches

The four papers can be grouped into two methodological clusters that reflect the dual research agenda of this dissertation. Chapters 2 and 3 employ large-scale partial equilibrium models of the European power and hydrogen sectors. Chapters 4 and 5 develop analytical models of sequential electricity markets and derive closed-form solutions. Together, the chapters span a broad methodological spectrum to investigate the role of uncertainty and risk within the energy transition.

Chapter 2 introduces the partial equilibrium model HYEBRID. The model jointly optimizes investment decisions in power generation, electrolysis, hydrogen storage, and import infrastructure, together with hourly dispatch decisions for the European electricity and hydrogen sectors in the target year 2050. The model explicitly formulates take-or-pay constraints within long-term hydrogen import contracts, which impose a minimum offtake obligation on the importing country and thereby restrict import flexibility. The two-stage design, with investment decisions in the first stage and high-resolution dispatch decisions in the second stage, enables the quantification of reliability shortfalls that arise when infrastructure is dimensioned under representative rather than worst-case weather conditions. A key limitation of the analysis is the assumption of a fixed hydrogen import price irrespective of the underlying take-or-pay rate, an abstraction that warrants further research. Furthermore, the representative weather year approach in the investment stage may systematically underestimate peak infrastructure needs, a shortcoming that is addressed in Chapter 3.

Chapter 3 extends the HYEBRID model framework in two key directions. First, the deterministic treatment of weather is replaced with a two-stage stochastic optimization approach. Rather than relying on a single representative weather year, the model considers five clustered weather years, each assigned a probability weight, which allows investment decisions to reflect the full distribution of weather outcomes rather than a point estimate. While computational constraints limit the number of scenarios, this still represents a substantially richer representation of weather uncertainty than is common in the literature. Second, import prices are no longer uniform but are derived from distinct exporting regions via a stochastic calculation of the levelized cost of hydrogen supply, extending the approach of Moritz et al. (2023). Together, these extensions allow the model to endogenously account for supply-side uncertainty across both domestic generation and exporting regions when making investment decisions. Beyond weather variability, the chapter assesses dedicated strategies to hedge against import disruption risk, including geographic diversification of import sources and a reduction of the overall import volume through increased domestic production. Both strategies are implemented via additional constraints and the diversification strategy requires a reformulation of the investment problem as a mixed-integer linear program.

1. Introduction

A key limitation is that hydrogen demand is modeled as price-inelastic and exogenous, which abstracts from demand-side responses to supply disruptions. Further hedging strategies, such as electrification, are not considered and remain an avenue for future research.

Chapter 4 develops a stylized analytical model of competition between renewable energy producers and conventional producers in sequential electricity markets. The market is structured as a two-stage game: in the first stage, producers submit bids to the day-ahead market before actual renewable generation is realized; in the second stage, positions are adjusted in the intraday market as uncertainty resolves. This game-theoretic framework is used to derive optimal bidding strategies and the resulting forward premia between market stages. The central analytical contribution is the joint treatment of risk aversion among renewable producers and market power through the simultaneous consideration of competitive and oligopolistic market structures on the renewable side. Conventional producers enter the second stage with limited operational flexibility, introducing supply-side constraints that introduce welfare effects of strategic withholding. Closed-form solutions for equilibrium day-ahead bids and the resulting price premia are derived as functions of risk aversion parameters, the degree of oligopolistic concentration, and the flexibility of conventional supply.

The model is stylized and abstracts from multi-period dynamics and short-term storage technologies. Moreover, the analysis assumes normally distributed uncertainty and inelastic demand. The marginal cost curve is simplified to a linear form to derive closed-form expressions for risk-averse bidding. Heuristic expressions under a convex marginal cost curve are derived in Chapter 5.

Chapter 5 develops a complementary analytical framework to the previous chapter, using a convex marginal cost function that introduces an asymmetric price response to deviations in marketed quantities between the day-ahead and intraday market. Competitive renewable producers choose their day-ahead bids according to distinct bidding rationales: expected-production bidding, risk-neutral bidding, and risk-averse bidding that accounts for tail risk. Closed-form solutions for day-ahead bids and the resulting price premia are derived for each bidding rationale. In the second step, the theoretical model is calibrated to German electricity market data. The calibration allows the model to structurally replicate the observed diurnal premium pattern and to attribute the pattern to the interaction between technology-specific production profiles, forecast uncertainty, and supply curve convexity.

A limitation of the analysis arises from the heuristically derived risk-averse bid. As a closed-form expression is not solvable in this analytical framework, the heuristic utilizes a comparison to the risk-neutral optimal bid, to derive the characteristic of a risk-averse bid. Future research could improve this heuristic. Moreover, the model is a stylized representation of reality, assuming inelastic demand and only two trading stages, whereas reality features multiple stages

such as intraday auctions and continuous trading. However, this stylized nature enables clear identification of structural drivers.

In addition to this methodological outline, each of the following four chapters provides a comprehensive description of the methodology, underlying assumptions, limitations, and avenues for further research.

2. Assessing the Impact of Take-or-Pay Rates in Long-Term Contracts for Hydrogen Imports on a Decarbonized European Energy System

2.1. Introduction

The goal to achieve climate neutrality in the EU and other European countries by 2050 calls for fundamental changes to the energy system infrastructure across the continent. Clean hydrogen is set to become one of the key pillars of a decarbonized energy system, which is underlined by major energy system studies pointing out the future role of hydrogen (IEA, 2023, IRENA, 2023, Tarvydas, 2022). Besides using hydrogen and its derivatives in selected end-use applications or as a feedstock in industrial processes, its physical properties favor using it as a storage medium, balancing intermittent renewable energy sources (RES) over days, weeks, or months. To become an essential part of the future European energy system, infrastructure facilities such as storage and transmission grids will be required. In light of the ambitions to phase out the use of fossil gas (European Commission, 2021b), a promising and cost-saving approach is the partial reconversion of existing infrastructure. Studies have already started investigating the emergence of a European hydrogen grid from existing, reconverted natural gas pipelines (Frischmuth et al., 2022, Schlund, 2023, van Rossum et al., 2022) and exploring the technical potential of storage facilities (Caglayan et al., 2020). However, the research on cost-efficient sizing, especially for storage and potential import terminals, remains limited. Their size is of central relevance not only in terms of energy balance but also in terms of short-term power balance to guarantee security of supply in both the electricity and hydrogen sectors.

The production of hydrogen can be based on numerous primary energy carriers, but the most promising method in a decarbonized European energy system is clean electricity powering electrolyzers to split water into oxygen and hydrogen (European Commission, 2023). In light of the limited techno-economic potential of alternative emission-free generation technologies, wind and solar PV are set to be the primary electricity generation technologies. However, cost-efficient renewable energy potentials in the EU are limited. In other world regions, full-load hours for wind and solar PV, as well as land availability, can be significantly higher than in Europe. Thus, hydrogen production from renewable electricity in other world regions and subsequent transport to Europe could pose an

economically favorable case (Moritz et al., 2023). With the publication of the REPowerEU plan, the EU is aiming for global trade in derivatives of renewable hydrogen, whereby half of the hydrogen consumed in the EU should originate from imports by 2030 (European Commission, 2022). Until now, an international market and a trade framework have not emerged. Current research suggests that hydrogen is likely to be traded via long-term contracts (LTCs) (Antweiler and Schlund, 2023, IEA, 2022) to ensure the refinancing of investments for both exporter and importer. This is especially true for the initial market ramp-up, given high upfront investment costs linked to long amortization periods of the infrastructure required.

In the context of LTCs, offtake agreements serve as an instrument of risk sharing between buyer and seller and provide security for financial contracts. They can reduce the variability of cash flow and thus reduce the upfront risk of the investment associated with an LTC (Bento, 2008, Creti and Villeneuve, 2004). The minimum offtake of the contracted volume, which can be processed with physical delivery or financial compensation, is called the Take-or-Pay rate (TOP rate). Today, TOP rates find application in LTCs for trading natural gas via pipeline or liquefied natural gas (LNG). Besides these minimum offtake quantities, LTCs contain agreements on the destination of gas deliveries. In the past, LTCs were tied to specific destinations or terminals, a practice deemed by the European Commission to violate European competition law (Ason, 2022, Creti and Villeneuve, 2004). However, LTCs are now increasingly characterized by greater destination flexibility, enabling LNG cargoes to be diversified and redirected within Europe (Talus, 2023). The fact that natural gas and hydrogen transport infrastructure have similar characteristics suggests that TOP rates will remain pertinent in future hydrogen LTCs. At the same time, most studies examining hydrogen infrastructure overlook the restrictions associated with TOP rates, instead rather assuming either fully flexible or fixed hydrogen imports. For example, while ENTSO-E and ENTSG (2022) presume inflexible imports at predefined volumes, EWI (2021) assumes complete import flexibility, and other studies, such as van Rossum et al. (2022), lack transparency in their methodological assumptions. Our study aims to shed light on the bias resulting from simplifying assumptions on hydrogen import flexibility.

Implementing TOP rates in LTCs may pose challenges to the importer. A high TOP rate imposes inflexibility on the demand side, as importers are obliged to physically import hydrogen or pay financial compensation, even when imports are not required due to abundant domestic supply. The availability of domestic hydrogen supply and its trade-off with imports are significantly linked to the availability of RES and, in turn, to weather variability. Moreover, the demand side for both hydrogen and electricity in a decarbonized European energy system will be affected by weather characteristics, underscoring the need to investigate the interplay of weather variability and flexibility of hydrogen imports.

To the best of our knowledge, no research analyzes the impact of TOP rates in hydrogen LTCs on a decarbonized European energy system. Against this back-

ground, this paper aims to answer the following research questions: i) How do TOP rates in hydrogen LTCs affect the system costs of a decarbonized European energy system? ii) How do TOP rates affect the optimal configuration of the European energy system infrastructure? iii) How reliable are energy systems planned with representative weather and different TOP rates regarding weather variability?

To answer these questions, we develop the partial equilibrium model HYE-BRID, which optimizes investment and dispatch decisions for the European power and hydrogen sectors for the climate-neutral target year 2050. We follow a two-step approach. First, we determine investment decisions based on a representative weather year for six equidistant TOP rates. Subsequently, we calculate the dispatch decisions for each of these six energy systems given a set of 35 weather years in a high temporal resolution. The model comprises a holistic representation of an integrated hydrogen sector by accounting for endogenous investment in electrolysis, storage, and import facilities while considering exogenous cross-border hydrogen transport capacity from converted natural gas pipelines. In contrast to most existing models, we explicitly model capacity requirements of daily storage injection and withdrawal as well as hydrogen import terminal capacity requirements. Moreover, we account for the technical potential of reconverted natural gas storage and the theoretical potential of newly constructed hydrogen storage by salt caverns. We apply the concept of TOP rates to potential hydrogen LTCs, including destination flexibility within Europe, and analyze their effect on the configuration of the European energy system. Further, we run a stress test on the infrastructure planned under representative weather conditions by computing dispatch decisions for a set of 35 weather years. Doing so, we seek to analyze the operational inflexibility imposed by TOP rates in the context of weather variability. This research framework can as well be interpreted as analyzing the impact of unexpected short-term conditions deviating from the planning stage.

This work contributes to the existing research by firstly incorporating TOP obligations in hydrogen imports in a newly developed investment and dispatch model for power and hydrogen. We show that higher TOP rates only marginally increase total system costs but induce significant shifts in cost-minimal infrastructure requirements. This underscores the importance of taking TOP rates into consideration in today’s research and planning assessments of stakeholders and institutions responsible for energy infrastructure. We find that rising inflexibility with high TOP rates leads to an increase in hydrogen storage and withdrawal capacity, while the capacity of hydrogen terminals decreases, reducing surplus imports. We extend the scarce research on European hydrogen storage requirements by calculating a range between 63 TWh and 81 TWh and discuss key determinants for the sizing of storage. Lastly, the stress tests on the energy systems planned with representative weather point out that energy systems facing a higher TOP rate generally show a lower reliability.

The remainder of this paper is organized as follows. Section 2.2 reviews the recent literature along two coherent literature streams. Section 2.3 introduces the model framework and defines the underlying assumptions and data. Section 2.4 summarizes the results on system costs, the energy system infrastructure, and the effect of weather variability. We critically discuss the key findings concerning central assumptions and limitations of the model framework in Section 2.5 and give an outlook for future research. Lastly, Section 2.6 concludes this work.

2.2. Literature

Our research ties into existing work in European energy system optimization with a representation of the hydrogen sector. We categorize existing publications into two streams of literature. The first consists of energy system modeling, investigating the development of hydrogen infrastructure and the impact of weather variability on energy systems. The second deals with the effects of TOP rates and LTCs in natural gas and hydrogen markets.

While many modeling approaches have researched the emergence of hydrogen infrastructure on a national level (e.g., Germany (Peterssen et al., 2022, Schmitz et al., 2024, Schöb et al., 2023), France (Tlili et al., 2019), or Great Britain (Samsatli et al., 2016)), a representation on a European scale remains limited. Neumann et al. (2023) investigate the benefits of building a hydrogen network and expanding electricity transmission capacity in Europe with a linear optimization model. Their model considers a high spatial resolution with a total of 181 regions, improving the granularity of infrastructure development within countries but lacking a representation of hydrogen imports from outside Europe. Related research is done by Schlund (2023), who conducts a scenario-based approach analyzing critical dependencies between system elements for a ramp-up of hydrogen infrastructure with an integrated representation of the natural gas sector. Depending on the scenario, annual hydrogen import volumes range between 58 TWh and 561 TWh. However, the approach does not consider electricity markets.

The Ten-Year Network Development Plan (TYNDP) is a non-academic joint report by the ENTSO-E and ENTSOG and conducts detailed bottom-up modeling of the EU’s energy system up to 2050. They endogenously model investment¹ and dispatch decisions for an integrated electricity and hydrogen sector and aim to find cost-efficient infrastructure requirements for three scenario settings. The analysis accounts for hydrogen imports from non-EU countries only via retrofitted gas pipelines, i.e., excluding the possibility for imports via ship, and finds viable hydrogen imports between 358 TWh and 901 TWh to EU27 in 2050 (ENTSO-E and ENTSOG, 2022). These relatively high import volumes are caused mainly by their explicit assumption to set the import price marginally

¹Their approach does not consider the endogenous investment of hydrogen storage capacity.

lower than the price of domestically generated hydrogen. Further research has been done by Sasanpour et al. (2021), who test the effect of policy targets and constraints on system costs and infrastructure requirements in a climate-neutral European energy system with the linear optimization model REMix. Among others, they find that doubling the price for hydrogen imports compared to a reference case of 120 EUR/MWh increases system costs by 2% without specifying the quantity of imports.

The long-term scenarios 3 (Sensfuß et al., 2024), commissioned by the Federal Ministry for Economic Affairs and Climate Protection in Germany, investigate pathways to achieve climate neutrality by 2045 by identifying robust developments from various scenarios through computational modeling. The study allows for hydrogen imports from non-EU countries, underground hydrogen storage in salt caverns, and intra-European hydrogen transport in repurposed and newly built pipelines. They find viable hydrogen imports to Europe between 60 TWh and 79 TWh, while domestic hydrogen production ranges between 994 TWh and 1193 TWh.

Beyond imports, research regarding the role of hydrogen storage in a future energy system remains limited. For the case of Germany, Lux et al. (2022) determine a requirement for hydrogen storage between 42 TWh and 102 TWh, while Robinius et al. (2020) find a requirement of up to 69 TWh given an integrated modeling approach, and Kondziella et al. (2023) find a capacity between 14 TWh and 67 TWh to be optimal. Moreover, the latter analysis finds a seasonal characteristic of storage cycles. Schlund (2023) observes a similar characteristic, identifying a total capacity between 87 TWh and 197 TWh for Europe. Moser et al. (2020) find the lowest value for hydrogen storage capacity in Europe, showing a requirement of 45 TWh, albeit focusing on the effect of grid extension. However, the underlying assumptions, e.g., temporal resolution, weather characteristics, cost levels, and the research frameworks, broadly differ across the literature reviewed. With an exogenous assumption on the conversion rate for current salt cavern storage, ENTSO-E and ENTSG (2022) defines an underground storage capacity of about 102 TWh. Sensfuß et al. (2024) suggest European hydrogen storage requirements between 223 TWh and 240 TWh for 2045.

In the context of energy system modeling, existing research points out the importance of accounting for weather variability driving backup capacity and storage requirements. By processing a cost optimization model for Germany given 35 years of weather data with hourly resolution, Ruhnau and Qvist (2022) find that relying on single weather years or short-duration weather events can lead to an underestimation of storage requirements and costs. Similar findings with a regional scope of single countries result from Zeyringer et al. (2018) and Abdin et al. (2018). Caglayan et al. (2021) incorporate the effect of weather variability on a European level by deriving a robust design of a climate-neutral energy system considering the hydrogen sector. Their iterative approach of single linear model runs ensures a robust solution to 38 weather years. Nonetheless,

this approach does not guarantee optimality and relies on a low temporal resolution while neglecting the option for hydrogen imports. They conclude that considering multiple weather years instead of single ones can lead to an increase in system costs of up to 25%.

This work contributes to the existing literature body with an explicit representation of endogenous hydrogen terminal capacity for imports and hydrogen storage injection and withdrawal capacity. We acknowledge existing research pointing out a potential underestimation of capacity requirements when relying on single weather years for investment decision-making. However, the aim of our approach is not to derive highly robust systems regarding weather variability but to investigate the operational reliability of a system planned with weather that might deviate from future weather.

The second stream of literature regards the role of TOP rates as a contractual part of LTCs, which are prevalent in global energy markets, particularly natural gas markets. Historically, for natural gas delivered via pipelines, typical TOP rates range between 70% and 90% (IEA, 2020), while LTCs for LNG may reach TOP rates of nearly 100%, depending on the region (Ason, 2022). Creti and Villeneuve (2004) point out that TOP clauses are intended to introduce risk sharing between producers and buyers. Such agreements bind both parties under predefined conditions, e.g., for natural gas pipeline contracts with a term of 20 to 30 years. By committing to buy on a long-term basis, the buyer accepts a part of the risk, which arises from long lead times in investment planning and high capital intensity. Ruester (2015) analyzes 26 liquefied natural gas (LNG) projects to investigate the determinants of debt ratios in project finance. The author shows that long-term offtake agreements such as TOP clauses secure project financing and reduce cash flow variability over LNG contract periods of 15 to 25 years. Thus, the debt ratios and financial power of those projects increase. Conversely, LTCs can also present drawbacks, potentially creating lock-in effects for the contracting parties, depending on the specific terms of the agreement (Talus, 2023). Antweiler and Schlund (2023) summarize the necessary conditions for the emergence of LTCs and find that most are fulfilled for international hydrogen trade. By investigating the history of natural gas markets using an analytical framework, Dejonghe et al. (2023) suggest that the development of hydrogen trade routes may differ from natural gas. Their analysis indicates that seaborne (derivatives) shipments could take precedence over pipeline deliveries due to less concentrated global hydrogen production than today's existing natural gas reserves. The existing research shows initial investigations on potential forms of an emerging hydrogen trade, potentially via LTCs and ship-based transportation. The articles discuss similarities to existing natural gas trading via LTCs, including take-or-pay agreements, and their benefits to developing a well-functioning and reliable European market. However, no studies have numerically investigated the effects of LTCs or TOP rates on a decarbonized European energy system. This work contributes to the existing literature by explicitly incorporat-

ing six equidistant TOP rates between 0% and 100% for the maritime import of hydrogen to Europe.

2.3. Methodology

This chapter describes the model and provides a general intuition for the economic rationale of hydrogen imports with TOP rates within the model framework. Additionally, this chapter presents central assumptions and input data.

2.3.1. Model framework

To answer the research questions, we develop a new linear optimization model named HYEBRID (Hydrogen and Electricity market model with broad representation of weather variability and Import Decisions). The partial equilibrium model optimizes European electricity and hydrogen investment and dispatch decisions. It minimizes the net present value of energy system costs, comprising fixed capacity-based and variable generation costs. The model assumes complete markets and no transaction costs. Therefore, the competition of profit-maximizing symmetric firms is the dual formulation of a central planner's cost minimization. Contrasting with many existing modeling approaches, HYEBRID accounts for all key entities in a possible future hydrogen sector and its interrelations with the power sector. This includes domestic (European) generation by electrolysis, storage in underground salt caverns, non-European imports using ammonia import terminals, intra-European transmission by converted natural gas pipelines, and hydrogen consumption in the power sector and end-use sectors. Figure 2.1 presents the technologies used in the model framework and the interrelations between the power and hydrogen sectors.

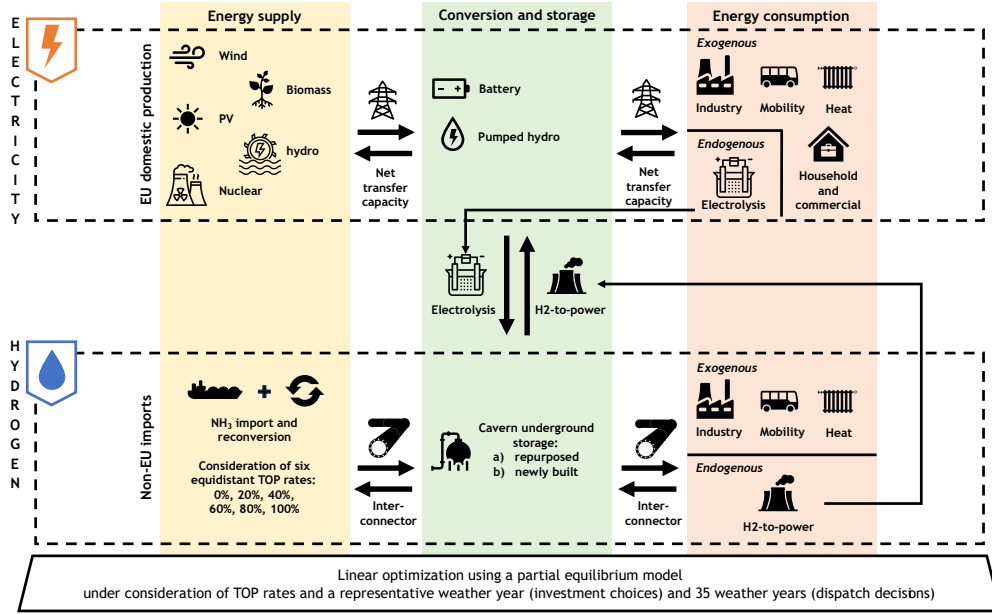


Figure 2.1.: Schematic representation of the model HYEBRID.

Another key feature of the model is the representation of weather variability. We choose a two-stage modeling approach, as illustrated in Figure 2.2. In the first step, cost-minimal investment decisions are determined based on a representative weather year. This approach mimics investors who assume average weather conditions in their decision-making. In the second step, we compute dispatch decisions for 35 weather years to capture the volatile nature of renewable availability and temperature-dependent demand influencing both the power and hydrogen sectors. Considering a set of weather years enables a stress test of systems planned without inter-annual weather variability. Regarding our research question, we can analyze the role of flexibility in hydrogen imports to balance weather vagaries during operation.

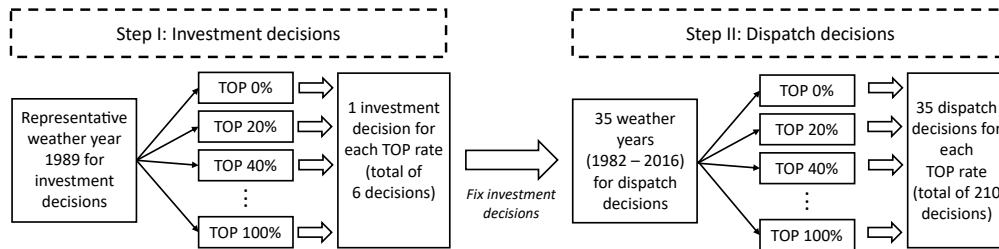


Figure 2.2.: Fundamental two-stage modeling approach.

Selection of the representative weather year

Investments in infrastructure require extensive development and construction periods and must be planned for the long term due to the associated lifespan and high capital intensity. From the central planner’s perspective, this requires making decisions today about the energy system of the future. Therefore, assumptions have to be made about future events, such as weather conditions. Ideally, energy system modeling would account for a large set of potential weather phenomena with high spatio-temporal resolution and even account for changing weather patterns owing to climate change. To keep the computational complexity within limits, this modeling approach considers a representative weather year to determine investments in the European energy system. Since no accurate definition of representative weather exists, we select what we refer to as the representative weather year, the year that exhibits the median total system costs. With a low temporal resolution, we run investment decisions for each of the 35 historic weather years considered and for a TOP rate of 0% and 100%, capturing the extremes in hydrogen import flexibility. The results on system costs show 1989 to be the median weather year for both TOP rates. Therefore, subsequent investment decisions with higher temporal resolutions are made based on the weather year 1989. Against this background, the presented approach does not aim to derive an energy system that is robust to a large set of weather phenomena. Instead, we seek to investigate how different degrees of hydrogen import flexibility (TOP rates) alter the dispatch decisions of energy systems planned with representative weather. This can be interpreted as a stress test regarding weather variability.

The model formulation poses challenges to computational complexity. Therefore, the model exhibits several limitations: the model is computed only for the climate-neutral target year 2050. Therefore, we do not account for dynamic investment decisions but consider annualized investments. Further, the model abstracts from uncertainty and assumes perfect foresight, i.e., parameters such as the availability of RES and the level of demand are known ex ante. The demand for electricity and hydrogen from end-use sectors is assumed to be inelastic, i.e., not price-responsive. On the supply side, we abstract from ramping and minimum load constraints of combined heat and power units to avoid a mixed-integer optimization. Additionally, we analyze six equidistant TOP rates (0%, 20%, 40%, 60%, 80%, 100%) to capture the key trade-offs between hydrogen import flexibility and system cost impact. While real-world TOP rates may take on intermediate values, prior test calculations with finer granularity showed no fundamentally different system behavior, making additional resolution computationally costly without adding new insights. Therefore, we focus on a broad range from full flexibility (0%) to complete inflexibility (100%) to highlight system interactions.

The following section presents the key equations of HYEBRID. All sets, parameters, variables, and indices related to the model are summarized in Table A.1 in the Appendix. The model employs total costs TC as the objective function,

which is minimized by applying linear optimization. As Equation 2.1 depicts, total costs TC are a sum over each day d and hour h in the target year, node n , and technology $tech$ of the variable costs $OPEX$, fixed operating and maintenance costs FOM , annualized² capital costs $CAPEX$, and hydrogen import costs IC .

$$\min TC = \sum_{d,h,n,tech} OPEX_{d,h,n,tech} + \sum_{n,tech} FOM_{n,tech} + CAPEX_{n,tech} + \sum_{d,n} IC_{d,n} \quad (2.1)$$

The equilibrium equation for electricity (Equation 2.2) ensures that in each hour, electricity supply $S_{d,h,n,tech}^{EL}$ from technology $tech$ to node n minus injection to electrical storage $S_{d,h,tech,n}^{EL}$ covers the exogenous electricity demand from end-use sectors $d_{d,h,n}^{EL,exo}$, the endogenous electricity demand from hydrogen production $D_{d,n}^{EL,H2}$, and the net trade balance for electricity $TRADEBAL_{d,h,n}^{EL}$ (Equation 2.3), which depicts the trade flows from other nodes under consideration of transmission losses δ^{EL} . Depending on the specification of the model, we allow for uncovered demand L^{EL} .

$$\sum_{tech} (S_{d,h,n,tech}^{EL} - S_{d,h,tech,n}^{EL}) = d_{d,h,n}^{EL,exo} + D_{d,n}^{EL,H2} - TRADEBAL_{d,h,n}^{EL} - L_{d,h,n}^{EL} \quad \forall d, h, n \quad (2.2)$$

$$TRADEBAL_{d,h,n}^{EL} = \sum_m [(1 - \delta_{m,n}^{EL}) * TRADE_{d,h,m,n}^{EL} - TRADE_{d,h,n,m}^{EL}] \quad \forall d, h, n \neq m \quad (2.3)$$

The equilibrium equation for hydrogen (Equation 2.4) is formulated such that hydrogen supply $S_{d,n,tech}^{H2}$ by electrolysis or storage withdrawal and non-European hydrogen imports dedicated for consumption $I_{d,n}^{H2,consumption}$ minus storage injection $S_{d,tech,n}^{H2}$ cover the hydrogen demand from end-use sectors $d_{d,n}^{H2,exo}$, the hydrogen demand for re-conversion into electricity $D_{d,n}^{H2,EL}$, and the net trade balance for hydrogen $TRADEBAL_{d,n}^{H2}$, which is formulated just as the net trade balance for electricity.

$$\sum_{tech} (S_{d,n,tech}^{H2} - S_{d,tech,n}^{H2}) + I_{d,n}^{H2,consumption} = d_{d,n}^{H2,exo} + D_{d,n}^{H2,EL} - TRADEBAL_{d,n}^{H2} \quad \forall d, n \quad (2.4)$$

²Annuities are computed with a discount rate of 8%.

Daily hydrogen generation within Europe is limited by electrolysis capacity $C^{H2,ELY}$ according to Equation 2.5.

$$S_{d,n,tech}^{H2} \leq C_n^{H2,ELY} \quad \forall d, n, tech \in Tech^{H2,ELY} \quad (2.5)$$

The energy balance describing the electricity input to electrolysis is formulated in Equation 2.6.

$$\sum_h D_{d,h,n}^{H2,EL} * \eta_{tech}^{H2} = S_{d,n,tech}^{H2} \quad \forall d, n, tech \in Tech^{H2,ELY} \quad (2.6)$$

In our model setting, we assume that hydrogen imports can be physically imported and consumed instantaneously ($I^{H2,consumption}$) or be stored ($I^{H2,STOR}$), or, if the underlying TOP rate forces additional imports, which are not required physically, financial compensation applies to fulfill the contractual agreement on the TOP condition ($I^{H2,financial}$). The aggregate volumes equal the total amount of non-European hydrogen imports (cf. Equation 2.7).

$$I_{d,n}^{H2} = I_{d,n}^{H2,consumption} + I_{d,n}^{H2,STOR} + I_{d,n}^{H2,financial} \quad \forall d, n \quad (2.7)$$

Hydrogen imports I^{H2} are represented by seaborne hydrogen derivatives³, which are landed via import terminals, including reconversion to hydrogen. As Equation 2.8 reveals, the import quantity of hydrogen each day is limited by the import capacity $C^{H2,IMP}$.

$$I_{d,n}^{H2} \leq C_n^{H2,IMP} \quad \forall d, n \quad (2.8)$$

Storing hydrogen is described in Equation 2.9. The storage volume ST^{H2} of the time step $d+1$ must always equal the quantity of the previous time step d under consideration of injected hydrogen into the storage $S_{t,tech,n}^{H2}$, withdrawals from storage $S_{t,n,tech}^{H2}$ in accordance with the injection and withdrawal losses $\delta^{H2,STOR}$, and imports fed into the storage $I^{H2,STOR}$.

$$ST_{d+1,n}^{H2} = ST_{d,n}^{H2} + \delta_{tech}^{H2,STOR} * (S_{d,tech,n}^{H2} - S_{d,n,tech}^{H2} + I_{d,n}^{H2,STOR}) \quad \forall d, n, tech \in Tech^{H2,STOR} \quad (2.9)$$

In our model setting, we assume all European import terminals to be under LTCs. Thus, a direct dependency exists between European terminal capacity and the underlying TOP rate in LTCs. We define the TOP rate *top* as a share of the maximum imports possible occurring under full utilization of import terminals, i.e., $C^{H2,IMP} * \#d$ with the latter being the number of days in a year. Therefore,

³This analysis assumes that ammonia serves as an imported hydrogen derivative. Further explanations can be found in Section 2.3.3.

the terminal capacity determines the minimal quantity of hydrogen imports, as described in Equation 2.10. By summation over all nodes, we ensure the destination clause is formulated regarding Europe, i.e., the TOP rate is valid for the aggregate of European countries but not for individual countries or terminals. By this definition, the following rationale applies to hydrogen imports: the higher the TOP rate, the lower the flexibility for importing hydrogen during the year. Consequently, at a TOP rate of 100%, a constant import of hydrogen results for each day of the year.

$$\sum_{d,n} I_{d,n}^{H2} \geq \sum_n C_n^{H2,IMP} * \#d * top \quad (2.10)$$

We calculate the costs for hydrogen imports IC by multiplying the quantity of imports I^{H2} with the assumed price $p^{H2,IMP}$ as formulated in Equation 2.11.

$$IC_{d,n} = I_{d,n}^{H2} * p^{H2,IMP} \quad \forall d, n \quad (2.11)$$

In case the model is not run in full temporal resolution, the variable costs $OPEX$, the costs for hydrogen imports IC , and storage injection and withdrawal quantities are scaled with the weight of representative days. Further equations, not explicitly mentioned above, include the restriction of hydrogen and electricity flows between nodes, renewable space restrictions per node, electric capacity restrictions from electrolysis, and volume restrictions for storage.

2.3.2. The economic rationale for hydrogen imports with TOP rates

This section explains the intuition behind the model outcomes for varying TOP rates in hydrogen LTCs and describes the interrelation between import capacity, import quantity, and TOP rate. From the central planner's perspective, an increase in the TOP rate can reduce the flexibility of non-European hydrogen imports, which in turn can change the optimal energy system configuration and the cost-efficient amount of non-European hydrogen imports and terminal capacities. In theory, we can differentiate between two states of solutions to the cost optimization, depending on the TOP rate. The first case refers to an equilibrium in which the cost-optimal utilization of European hydrogen import terminals U^* turns out to be equal to or higher than the assumed TOP rate. As a result, the TOP condition does not pose additional costs for hydrogen imports that might deviate from the optimum. Thus, a variation of the TOP rate does not affect the European energy system if the first case holds true. From the model's perspective, the restriction imposed by the TOP rate is non-binding. In the second case, the cost-minimal utilization rate of European import terminals is lower than stated by the TOP rate, i.e., the restriction stemming from the TOP rate is binding and forces aggregate terminals to be utilized at least with the TOP rate.

Here, the energy system configuration is adjusted to a new cost-minimal equilibrium fulfilling the constraint. The result deviates from the first case, as the TOP condition implies a reduced flexibility of non-European hydrogen imports. In the following, we refer to these cases as benchmark and individual solutions (cf. Equation 2.12 and Figure 2.3).

$$U^* \begin{cases} \geq top, & \text{benchmark solution} \\ < top, & \text{individual solution} \end{cases} \quad (2.12)$$

In the case of an individual solution, the central planner is confronted with a trade-off compared to the benchmark solution between i) additional costs imposed by additional non-European hydrogen imports or ii) additional costs imposed by additional assets within Europe to balance a reduction in non-European hydrogen imports in terms of both energy and capacity. We point out that this trade-off is highly complex, as the cost function of the European hydrogen supply is dependent on all other endogenous energy system variables and thus requires computational modeling. Moreover, the possibility of storing hydrogen adds another layer of complexity through intertemporal linkage.

2.3.3. Assumptions and data

The regional scope of the model is the EU27, the United Kingdom, Norway, and Switzerland, excluding Cyprus, Malta, Bulgaria, and Greece. The temporal scope of the model is the year 2050, which is the climate-neutral target year aimed at by the EU. Thus, a zero-emission power and hydrogen sector is a central condition for our model framework. The intra-annual resolution varies between the power and hydrogen sectors. We compute the power sector hourly, whereas hydrogen is modeled in a daily resolution to implicitly account for flexibility through the inert pipeline network. For the investment stage, we use 122 representative days, not allowing for lost load, whereas dispatch decisions are computed with full resolution and the possibility of load shedding. Since the value of lost load varies across regions and sectors and is subject to uncertainty (ACER, 2018, 2022), we assume it to be significantly higher than the highest marginal costs of any technology considered. Consequently, it is treated as the last resort to satisfy the equilibrium constraint.

The technological scope of the model is summarized in Figure 2.1. Appendix A.2 summarizes the techno-economic assumptions for the technologies considered in this analysis. For comparability, all cost-related data are converted to €₂₀₁₉. All calorific units are based on the lower heating value. For the power sector, we initialize the model with capacities for the supply, conversion, and storage of electricity for 2022. These capacities can generally be expanded using the model, making it a brownfield investment model, although nuclear and hydro capacities are assumed to maintain current levels.

Hydrogen can be produced domestically via electrolysis or imported from non-European countries through ammonia-based transport chains, including shipping, import at European terminals, and reconversion to hydrogen. Assumptions regarding import terminal costs and hydrogen import costs are based on Moritz et al. (2023). We assume a hydrogen import price of 75 EUR/MWh, corresponding to the average levelized supply costs of the 20 most cost-efficient export countries in the optimistic scenario of Moritz et al. (2023). In practice, additional transaction costs and security margins may increase hydrogen import prices beyond pure supply cost levels. Moreover, the potential emergence of a spot market for hydrogen imports and the subsequent indexation of LTCs to spot prices remain highly uncertain and are therefore not considered in this work. In addition, we assume a fixed price for hydrogen imports irrespective of the underlying TOP rate. In reality, a higher TOP rate could be associated with lower risk for the exporters' investment and lead to a lower price for hydrogen or higher exporter margins. Owing to the substantial uncertainty and the difficulty of quantifying this relationship, we abstract from such effects in the present analysis and discuss this assumption in Section 2.5.

Storing hydrogen is considered by repurposed or newly built salt caverns, currently representing the most promising and cost-effective type of long-duration underground hydrogen storage (Caglayan et al., 2020). In the model, storing hydrogen in caverns is enabled only in countries⁴ with existing and operating caverns for natural gas. Moreover, we differentiate between storage volume, injection capacity, and withdrawal capacity, as the volume-to-capacity ratio in a climate-neutral energy system may deviate from the current ratios of natural gas storage. We prescribe the filling level of storage at the end of the year to be equal to the start of the year. Electricity transmission between countries is represented by net transfer capacities (NTC), which are assumed to develop according to the TYNDP 2022 (ENTSO-E and ENTSOG, 2022). Hydrogen transmission is represented by repurposed natural gas pipelines based on ENTSOG (2023). We assume a repurpose rate of 50% and a conversion factor of 75% of the initial natural gas capacity based on Galyas et al. (2023).

The representation of annual electricity demand from end-use sectors is based on TYNDP's Global Ambition scenario for 2050 (ENTSO-E and ENTSOG, 2022). To capture the weather-dependent nature of electricity demand for both inter-annual and intra-annual variations, we use the hourly demand time series from the European Resource Adequacy Assessment (ERAA) 2022 (ENTSO-E, 2022). These time series capture the weather-dependent nature of electricity demand for 35 weather years, i.e., 1982 to 2016. We combine both sources by scaling the ERAA demand time series to match the TYNDP 2050 annual demand projections for each country. Specifically, the ERAA hourly demand profiles are multiplied by the corresponding TYNDP total annual demand for 2050 and normalized by the average annual demand across the 35 weather years. Likewise, the

⁴These countries are FR, DE, DK, NL, PL, PT, and GB, following current data from Gas Infrastructure Europe (GIE, 2021).

representation of hydrogen demand follows TYNDP’s Global Ambition scenario for 2050 (ENTSO-E and ENTSG, 2022), assuming a flat demand from the end-use sectors of industry and mobility. The degree to which hydrogen will be used in heating applications is highly uncertain. We assume that 25% of heating demand, met by natural gas today, will be met by hydrogen in 2050, introducing a degree of seasonality in hydrogen demand. To capture the intra-annual temperature dependence of future hydrogen demand for heating, we compute a linear regression of daily heating demand with temperature as the independent variable based on data from Ruhnau and Muessel (2023), which is based on Ruhnau et al. (2019). This function is applied to the daily temperature observed in the weather years 1982 to 2016. The hydrogen required for reconversion to electricity is determined endogenously. On the supply side, we feed the model with data on the hourly availability for solar PV, wind onshore, and wind offshore for all 35 weather years based on ENTSO-E (2022). Run-of-river flows, storage volumes of pumped-hydro units, and weekly hydro reservoir levels are based on the ENTSO-E (2022) as well.

2.4. Results

This section presents the effect of TOP rates on the cost-minimal configuration of the European energy system. First, we show the implications of TOP rates on system costs, investment decisions, and subsequent dispatch decisions given a representative weather year. Based on the resulting energy system configurations, we then conduct dispatch simulations for a set of 35 weather years, analyzing how the energy system configurations planned with a representative weather year and varying TOP rates respond to weather variability.

2.4.1. System costs

In our model setting, the effect of TOP rates on system costs is unidirectional. From the central planner’s perspective, an increase in TOP rates can reduce the flexibility of non-European hydrogen imports, leading to an increase in system costs. As shown in Equation 2.10, the TOP rate forces European import terminals to be utilized at least at the level of this TOP rate. Based on Equation 2.12, we can state that all benchmark solutions exhibit equal system costs. As soon as the TOP rate forces the utilization of import terminals to exceed the utilization of the benchmark solutions, the social planner is confronted with additional costs due to the obligation of the TOP rate. Thus, all individual solutions exhibit higher system costs than the benchmark solutions. The relation between the benchmark and the individual solution is illustrated in Figure 2.3. Further, we can state the following: The higher the TOP rate deviates from the benchmark terminal utilization, the higher the resulting additional system costs.

Figure 2.3 depicts the relative change in total system costs at a specific TOP rate compared to a TOP rate of 0%.

The benchmark solution is evident up to a TOP rate of at least 57%. Although we only conduct a scanning on TOP rates in steps of 20%, we can derive the precise point of change from the benchmark to individual solutions based on the average utilization rate of European hydrogen terminals. In this range, up to 57%, no TOP rate leads to an increase in system costs. Beyond this TOP rate, the results exhibit an increase in system costs, implying that the TOP rate imposes additional restrictions on the optimization.

The shape of the individual solution curve is convex, implying that marginal system costs increase with higher TOP rates. The maximum system costs can be located at a TOP rate of 100%, resulting in a markup of 0.77% compared to the benchmark results. Despite the relative increase in system costs being small, the cost increase in absolute terms can be substantial, considering the level of European energy system costs. Further, changes in system costs not only cause additional capacity requirements for a single technology but also change the equilibrium of cost-optimal technology shares along the electricity and hydrogen systems, which we analyze in the subsequent Section 2.4.2.

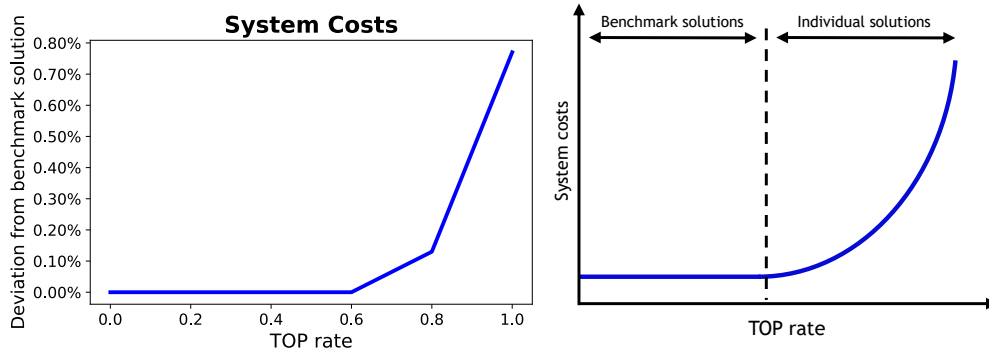


Figure 2.3.: Increase in total system costs with TOP rates for the representative weather year (left) and schematic illustration of the relationship between benchmark and individual solutions regarding total system costs (right).

The finding of convex curves for total system costs points to the importance of negotiating the lowest TOP rate possible in a potential LTC, given a fixed price for imports. However, real-world import prices may differ for varying TOP rates, as TOP rates influence the financial reliability of a project. The influence of TOP rates on LTC prices is very difficult to determine. We approach the topic by quantifying a theoretical willingness to pay a price premium on hydrogen imports at lower TOP rates from the central planner's perspective. Hence, the theoretical price premium serves as a measure to quantify the value of import flexibility in the absence of a modeled price-flexibility relationship.

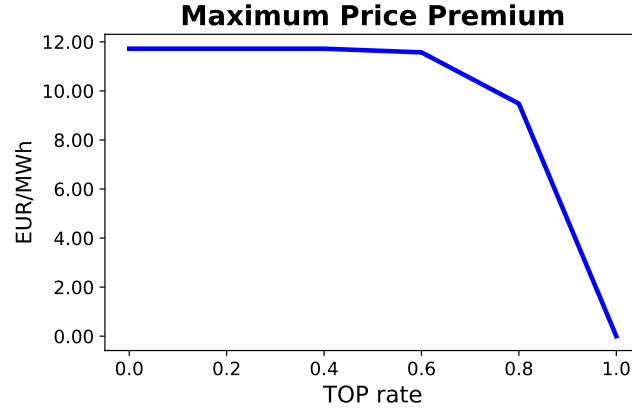


Figure 2.4.: Maximum price premium for hydrogen imports as a function of TOP rates, illustrating a theoretical cost trade-off between flexibility and contractual obligations.

This premium describes the maximum additional costs per MWh of imported hydrogen that the central planner would agree to ensure a lower TOP rate. We quantify the maximum price premium by dividing the additional system costs, an increase from a lower TOP rate to a TOP rate of 100% implies, by the corresponding quantity of imported hydrogen at lower TOP rates. Therefore, the price premium shown in Figure 2.4 indicates the maximum willingness to pay for a shift away from a TOP rate of 100% to a lower TOP rate. To reach a state of full import flexibility (benchmark solution), the willingness to pay a price premium amounts to almost 12 EUR/MWh, or 16% of the assumed hydrogen import price. We point out that assuming a price premium at lower TOP rates may alter the equilibrium, potentially adjusting capacities to the increased import price. Therefore, the premium should be interpreted as an upper bound.

2.4.2. Investment decisions under a representative weather year

To receive a holistic overview of the effect of varying TOP rates on the European energy system, we consider eight technology categories, which are optimized for each TOP rate based on the representative weather year 1989. In the following, H₂ terminal capacity is referred to as the installed capacity of aggregated European hydrogen import terminals. H₂ storage capacity measures aggregate repurposed and newly built hydrogen storage volumes. H₂ storage injection and withdrawal capacities describe the maximum daily inflows and outflows from hydrogen storage. Electrolysis capacity measures the installed electric capacity to produce hydrogen, whereas battery capacity measures the discharge power from batteries, and H₂-to-power capacity summarizes the electric capacity of all hydrogen-fired power plants. To account for the aggregate capacity of volatile

renewable energy sources, we define available wind and PV electricity as the annually available electricity from wind and solar PV before curtailment. We show the results for each technology decision as a relative change to the solution with a TOP rate of 0% in Figure 2.5.

With TOP rates exceeding 57%, investment decisions, and thus capacities, start to deviate from the benchmark solution. This deviation can be interpreted as adjusting infrastructure investments to the restrictions imposed by the TOP rate. As all investment decisions are interdependent, all capacities change simultaneously. However, the magnitude and direction of change differ across technologies. Further, most technologies exhibit a non-linear relationship to a change in the TOP rate. Except for battery capacity and H₂-to-power capacity, the technologies show a strictly increasing or decreasing slope across the TOP rates. At a TOP rate of 100%, the highest deviation compared to the benchmark solution is shown by H₂ terminal capacity (- 31%), H₂ storage capacity (+ 28%) and H₂ injection capacity (+ 25%). Conversely, the H₂-to-power capacity (+ 1.5%), available wind and PV electricity (- 1.0%), and battery capacity (+ 0.5%) exhibit the lowest relative changes at 100% TOP rate. Absolute values of investment decisions are summarized in Appendix A.3.

In a non-benchmark solution, a direct link exists between H₂ terminal capacity and imported quantity via the TOP rate, as the TOP rate determines the utilization of European import terminals. We generally observe a strictly decreasing H₂ terminal capacity, as the reduction of inflexible imports at higher TOP rates seems beneficial to the cost optimization. If the terminal capacity were to stay high at high TOP rates, this could cause excess imports that cannot be utilized by the European energy system or would pose significant additional storage requirements. The reduced terminal capacity (-533 GWh/d) is primarily offset by an increase in H₂ storage withdrawal capacity (+485 GWh/d), whose graph shows the opposite slope of the terminal capacity.

The restricted flexibility of hydrogen imports at higher TOP rates can be partially offset by additional H₂ storage volume. In this context, hydrogen storage can provide flexibility in two ways. First, with continuously high imports or high quantities of domestic hydrogen production, storage facilities absorb hydrogen in periods of excess supply. This enables a temporal shift in structuring the hydrogen import profile and can reduce the amount of otherwise curtailed electricity in periods with high RES yields. Second, hydrogen storage supports the supply side in periods with low RES yields or restricted hydrogen imports and high demand for hydrogen. As a result, H₂ storage capacity increases with increasing TOP rates.

Despite a decrease in H₂ terminal capacity, the imported quantity of hydrogen increases with higher TOP rates, as the obligation on terminal utilization outweighs the decrease in terminal capacity. As a result, there is a lower need for European hydrogen generation via electrolysis and volatile RES. Consequently, the electrolysis capacity and available wind and PV electricity slightly decrease

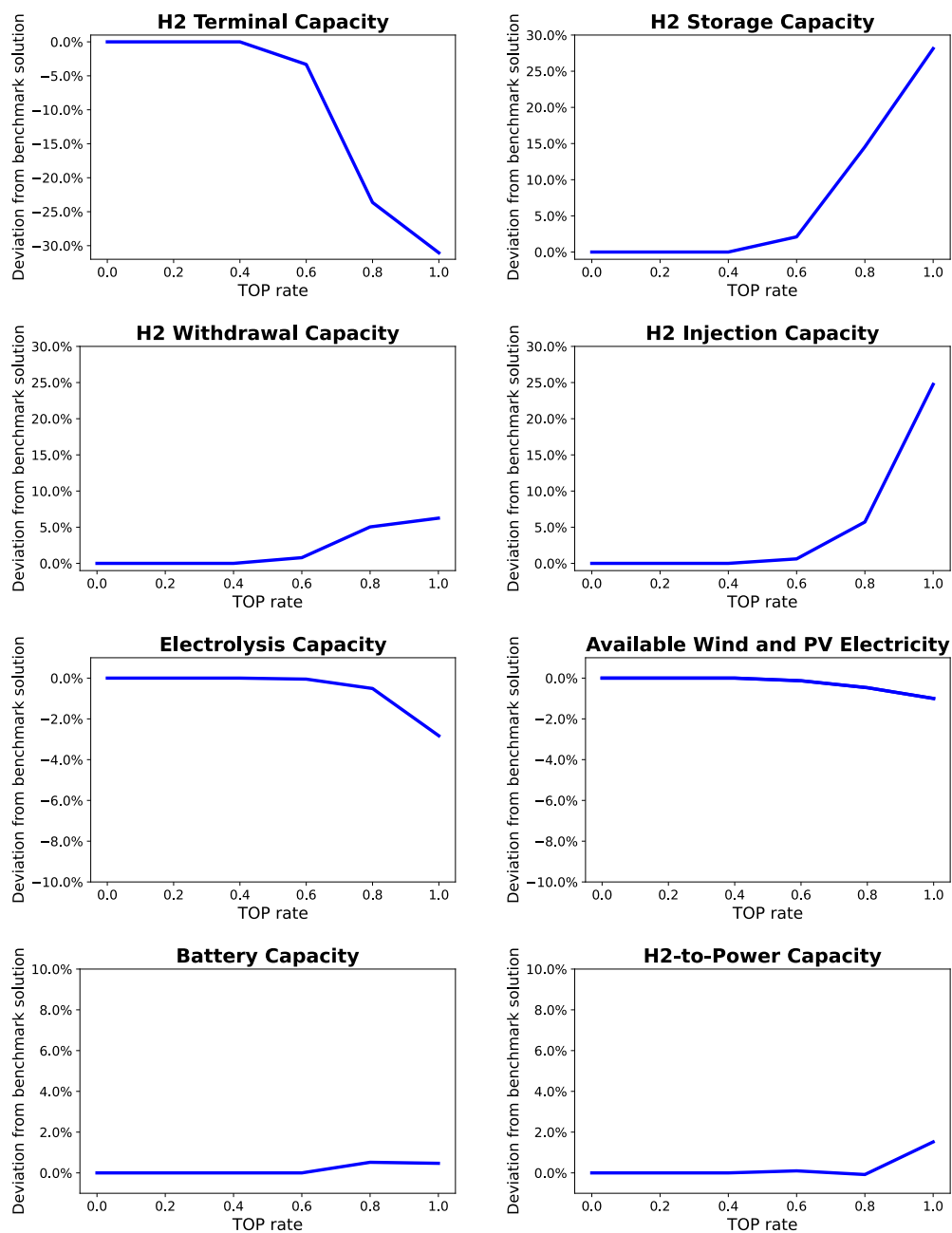


Figure 2.5.: Relative change in investment decisions as a function of TOP rates.

with rising TOP rates. Concluding, H₂ storage serves as an instrument to integrate more (inflexible) imported hydrogen at higher TOP rates.

To test the robustness of our findings, we computed investment decisions based on an alternative representative weather year. We find the year 2005 to be representative in terms of median residual load, which has been calculated with current levels of renewable capacity. The results show similar effects for varying TOP rates compared to the results under the representative weather year 1989. Whereas terminal capacity decreases for high TOP rates down to -40%, H₂ storage capacity grows by almost 60% and withdrawal capacity by 15%. Shifts in the electricity sector are ambiguous, but the magnitude of shifts is marginal compared to those in the hydrogen sector.

2.4.3. Regional insights from investment decisions

In addition to the changes in investment decisions on an aggregated European level, the following analysis reveals insights into regional shifts in investment decisions initiated by varying TOP rates. In this analysis, we compare the relative shift imposed by a TOP rate of 100% compared to a TOP rate that does not impose additional restrictions (benchmark solutions). These shifts are shown for 26 European countries in Figure 2.6.

Investment decisions in European countries respond to the restriction of inflexible hydrogen imports (TOP 100%) in a way that generally leads to reduced H₂ terminal capacities. The regions may expand storage capacities or rely on increased hydrogen flows via pipelines from neighboring countries. Therefore, countries with limited access to the European hydrogen grid respond strongly to declining import capacities. This is the case for the Iberian Peninsula, located in Southwestern Europe and consisting of Spain and Portugal. The shift to a TOP rate of 100% results in a 100% decline in H₂ terminal capacity. The region is only connected to the European hydrogen grid via limited capacity to France. Consequently, domestic hydrogen production and subsequent storage capacities significantly increase to serve the largely self-sustaining regional energy system. Similar patterns can be observed in other poorly connected regions to the European hydrogen grid. Romania uses additional storage capacities to compensate for inflexible hydrogen imports. In Finland, expanded battery capacity is an instrument for balancing short-term fluctuations as the flexibility of H₂ terminals is reduced. Central European countries, without H₂ terminal capacity but high connectivity to the hydrogen grid, expand storage and injection capacities to absorb inflexible hydrogen imports from neighboring countries. These countries are mainly the Netherlands, France, and the United Kingdom. Besides, land-locked countries react to changed investment decisions in neighboring countries. For example, a more import-oriented investment in Germany at a TOP rate of 100% with increased H₂ terminal capacity, higher H₂ imports, and less domestic H₂ production capacity coincides with decreased hydrogen production in the Czech Republic and Austria. These countries are well-connected to the German

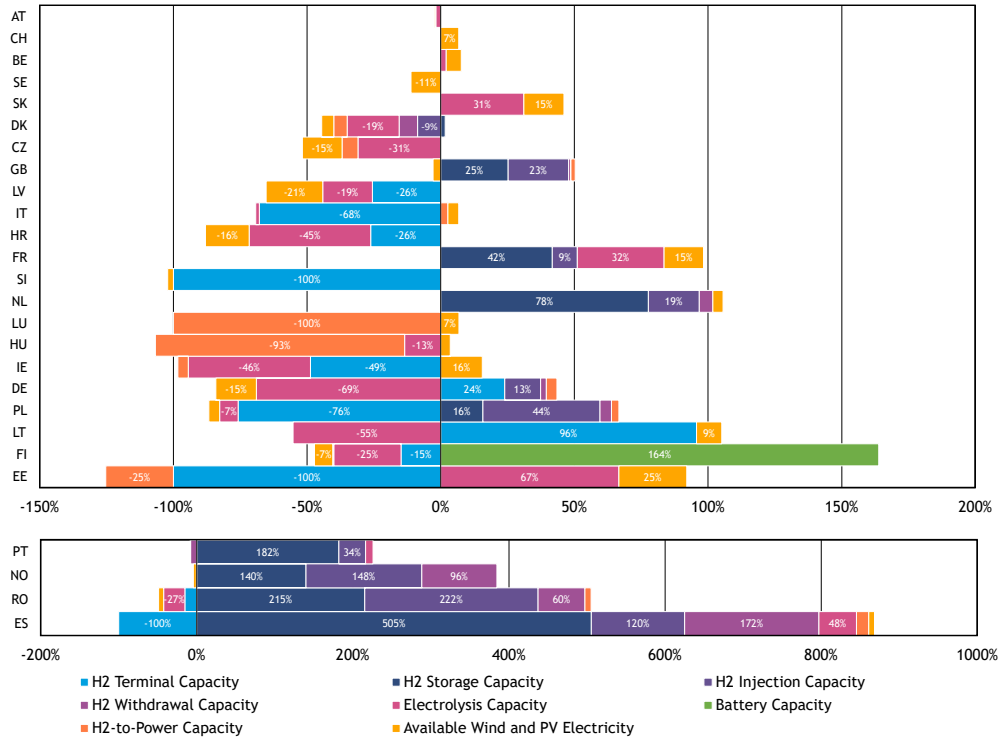


Figure 2.6.: Regional shifts in investment decisions from 0% TOP rate to 100% TOP rate.

hydrogen grid and therefore increase hydrogen imports from Germany. Similar behavior can be observed between Hungary and its neighbors.

The regional energy system adjustments highlight the importance of closely interconnected European countries and well-functioning European domestic trade. A broadly developed European hydrogen grid enables the cross-border use of the significant underground storage potential in Northwestern Europe. Simultaneously, landlocked countries without the possibility of importing hydrogen via ship are not independent of a shift in the TOP rate. These findings highlight the importance of adopting a system-wide perspective in hydrogen infrastructure planning, as the value of import infrastructure, transport networks, and storage capacities strongly depends on their interaction within the broader European energy system.

2.4.4. Dispatch decisions under representative weather year

This section analyzes the dispatch decisions for the energy systems derived in Section 2.4.2 under higher temporal resolution, i.e., each day in the case of the hydrogen sector and each hour in the case of the power sector for the representative weather year.

Lost load is the quantity of electricity demand not served due to capacity constraints. Since the combined investment and dispatch decisions have been computed with a lower temporal resolution, the lost load in the dispatch simulation with a high temporal resolution indicates the methodological error of the temporal resolution. Given any TOP rate, the lost load resulting from the dispatch decision is smaller than 0.13 TWh across Europe, implying a rather small methodological error via temporal resolution. However, we find small differences between the TOP rates: assuming no TOP obligation, we observe a lost load of 0.10 TWh across Europe, while it increases up to 0.13 TWh due to limited flexibility in cases of very high TOP rates.

The quantity of imported hydrogen from non-European countries directly results from terminal capacity and the assumption of the TOP rate in the individual solutions. In benchmark solutions, the TOP rate is not restrictive, and the imported quantity always amounts to 346 TWh. Despite a constant decrease in European H₂ terminal capacity for higher TOP rates, the imported quantity increases. The rationale is that the relative decline in capacity is not as steep as the underlying increase in the TOP rate. More generally, the optimization reflects a trade-off between the value of flexibility and energy imports. At a TOP rate of 100%, imported hydrogen volumes increase by 86 TWh (+ 25%) relative to the benchmark solutions.

The operation of hydrogen storage sites yields insights into how the limited flexibility in cases of high TOP rates is balanced. We show above that a decrease in the flexibility of hydrogen imports is partially balanced by an increase in storage capacity. However, the storage cycle, i.e., when to inject or withdraw hydrogen, is only marginally affected by a variation in the TOP rate. To illustrate an exemplary hydrogen storage cycle, Figure 2.7 depicts the aggregate daily hydrogen storage level for the representative weather year 1989, considering a TOP rate of 0% and 100%, respectively, as well as the corresponding daily demand and supply of hydrogen. Concerning the profile of non-European hydrogen imports, the graph with a 100% TOP rate (right) highlights the inflexibility of the offtake agreement. Conversely, without this obligation (left), imports are reduced whenever electrolysis via renewables is abundant.

Irrespective of the underlying TOP rate, we can derive a characteristic for the operation of hydrogen storage in a climate-neutral European energy system. Unlike today’s natural gas storage, our results do not show a strong seasonality in the operation of hydrogen storage. Considering an aggregated European H₂ storage capacity of 81 TWh in case of a 100% TOP rate, a total of 350 TWh of hydrogen is injected and withdrawn from storage facilities in Europe during the year. This corresponds to a number of 4.3 full cycles within the investigated year, compared to approximately one full cycle, which is typically observed for today’s natural gas storage facilities. Therefore, our results indicate a more dynamic operation of the storage facilities, covering both seasonal imbalances stemming from heating and short-duration supply shortages stemming from the availability of

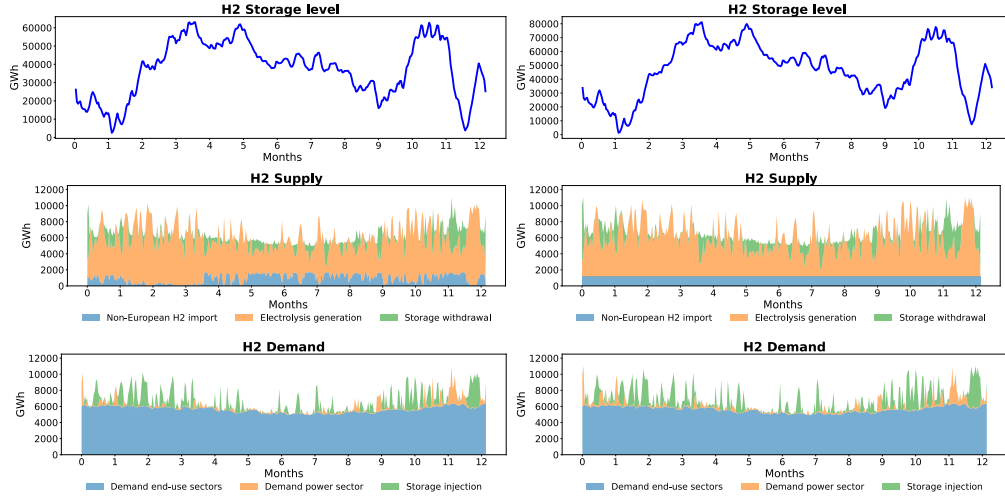


Figure 2.7.: Aggregated European hydrogen storage levels, demand, and supply profiles for the representative weather year 1989 and the TOP rates 0% (left) and 100% (right).

RES. This is underlined by high withdrawal ramps, e.g., in November. Here, the low availability of RES leads to significant hydrogen demand from the power sector, which is covered primarily by storage withdrawal. To cover this load ramp, the withdrawal capacity is sized accordingly. In the case of a 100% TOP rate, up to 10% of the total storage capacity can be withdrawn within one day. In contrast, the dynamic operation of storage facilities also results from absorbing hydrogen in periods of excess electricity supply from RES. This can be observed in February, March, and December when high injection ramps occur. The findings of storage cycles differing from those of natural gas storage cycles could be relevant for future hydrogen grid and storage operators to consider during asset configuration.

2.4.5. Dispatch decisions under 35 weather years

This section investigates the robustness of the energy systems planned under a representative weather year against weather variability. We compute the dispatch decisions for each of the energy systems planned with TOP rates between 0% and 100% for a set of 35 weather years and summarize key results in Figure 2.8. Here, each box plot represents the distribution of annual dispatch volumes across all weather years considered⁵.

⁵The box plots include the interquartile range of annual dispatch volumes across all weather years. The median is marked with a horizontal line, and the average is marked with a cross.

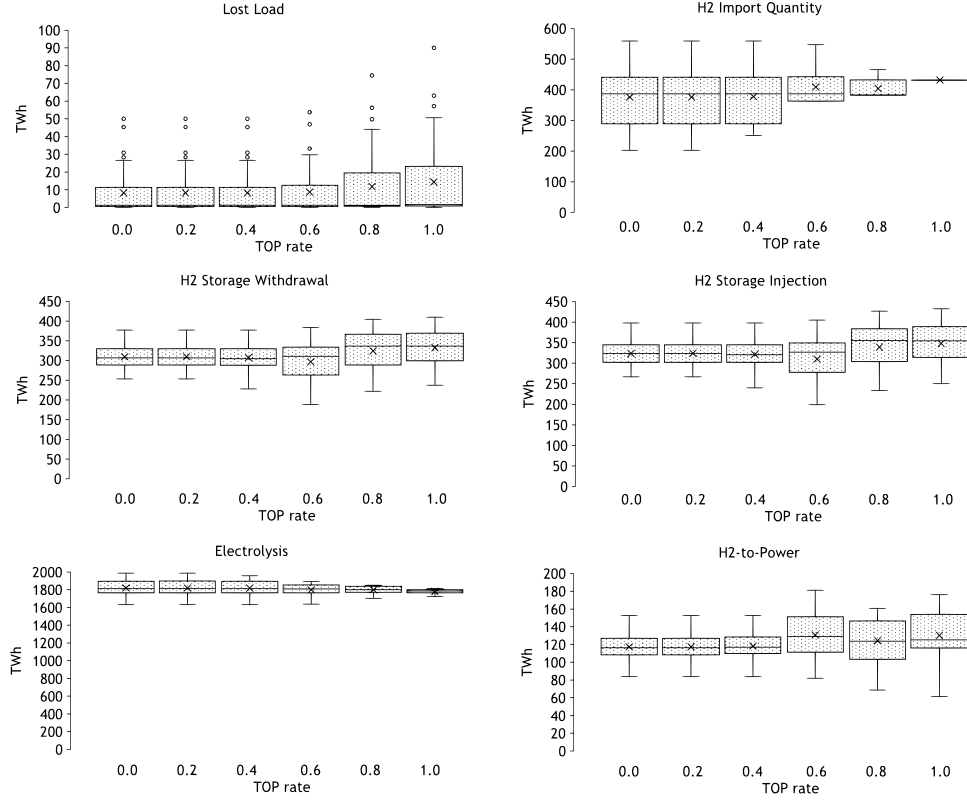


Figure 2.8.: System response to variability of 35 weather years.

The lost load observed in certain weather years occurs since the energy system was planned under a representative weather year, which does not incorporate extreme events such as cold dark lulls. The lost load in benchmark solutions amounts to 8 TWh on average across the 35 weather years and 50 TWh in the most critical weather year, 2010⁶. Notably, the reliability of energy systems decreases with increasing TOP rates, as aggregated lost load rises to a maximum of 90 TWh (2010) and an average of 14 TWh in the case of a 100% TOP rate. Despite higher storage capacity, the reduced flexibility of H₂ terminal capacity at high TOP rates prevents an adjustment of the corresponding energy system to weather variability. High costs associated with lost load cause the system with

⁶In multiple months, 2010 is characterized by below-average full-load hours for onshore and offshore wind across many European countries. In January, February, and December 2010, onshore and offshore wind utilization was up to 40% below the long-term average of all investigated weather years in Central and Northern European countries. Simultaneously, PV exhibits an availability below average compared to the long-term average during the summer months across Europe, exceptionally sharp in May (-27% on a monthly average). Further, the weather year 2010 shows a four-week cold spell starting at the end of January, with temperatures dropping ten degrees Celsius below the continent-wide average, increasing hydrogen demand. Electricity demand from end-use sectors in the weather year 2010 turns out to be almost 2% higher than the annual average of weather years under investigation.

the highest TOP rate to also imply the highest total dispatch costs. Together with the elevated investment costs (cf. Section 2.4.2), this again underlines the importance of accounting for the degree of flexibility in hydrogen imports.

Considering a TOP rate of 0%, the average H₂ import quantity is 376 TWh, while the spread resulting from all weather years considered amounts to 356 TWh. For low TOP rates, the inherent flexibility provided by H₂ terminals is used to adjust to weather vagaries. Notably, the results for a TOP rate of 40% already start to deviate from the benchmark solutions. This implies that an average utilization of European terminals below the previously determined 57% seems favorable in some weather years. With TOP rates exceeding 40%, H₂ import quantities significantly narrow up to a TOP rate of 100% without any flexibility remaining. Here, the imported quantity in every weather year amounts to 432 TWh, implying that mainly European storage facilities are posed to balance inter-annual weather variability.

As a result, the spreads of annual storage withdrawal volumes are generally higher for higher TOP rates. While the difference between minimum and maximum annual storage withdrawal is 123 TWh for a TOP rate of 0%, it grows to around 172 TWh in the case of a 100% TOP rate. In line with the slightly higher withdrawal capacity for a TOP rate of 100%, the average annual withdrawal volume (332 TWh) is slightly higher than in the benchmark solutions (310 TWh). The spreads of annual injected hydrogen volumes show characteristics similar to those of storage withdrawal.

Conversely, average annual hydrogen production via electrolysis decreases with increasing TOP rates, as its underlying capacity has decreased in the investment stage. Moreover, its utilization shows a higher variance for benchmark solutions than in the case of high TOP rates. Among other reasons, this originates from altered RES capacities for higher TOP rates, implying lower inter-annual variability in surplus electricity, which can be utilized by electrolysis.

Lastly, higher TOP rates impact the annual hydrogen quantity provided to the electricity system. On average, the hydrogen used for H₂-to-power increases slightly between the benchmark solution (117 TWh) and a 100% TOP rate (130 TWh). Among others, this results from increased hydrogen import volumes at higher TOP rates, also utilized for reconversion in the electricity system. Considering minimum and maximum H₂-to-power quantities among 35 weather years, the spread increases significantly from 69 TWh at 0% TOP rate to 130 TWh at 100% TOP rate.

The results also reveal insights into how flexibility is provided throughout the year for the energy system under varying TOP rates. We illustrate this in Figure 2.9 by showing sorted utilization curves of H₂ terminal capacity for selected TOP rates. With increasing TOP rates, the installed terminal capacity is fully utilized more frequently compared to the utilization of the benchmark solutions. Consequently, a TOP rate of 100%, characterized by a constant, non-

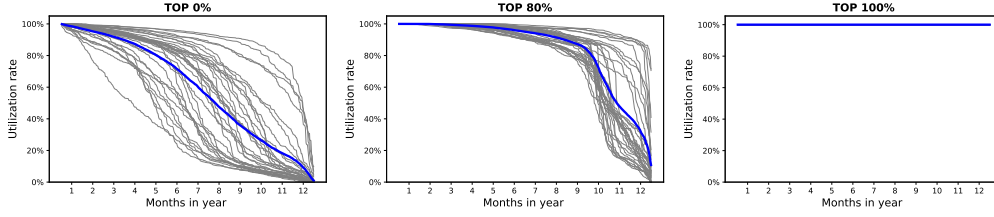


Figure 2.9.: Sorted H₂ terminal utilization for selected TOP rates on average (blue) and for all underlying weather years (grey).

flexible import of hydrogen, results in fully utilized import capacities throughout the year under all weather years.

Conversely, the highest flexibility can be exploited at low TOP rates, i.e., in the range of the cost-optimal benchmark solutions. Here, the operation of H₂ terminals adjusts to weather variability, resulting in significant inter-annual deviations in utilization and thus, import quantities. Despite this flexibility inhibiting a higher system value, it may pose challenges to the economic operation of H₂ terminals since asset owners typically strive for non-volatile cash flows.

According to our results above, the reduced flexibility of hydrogen imports imposed by higher TOP rates is mainly compensated by adjusted capacity levels of the investment decisions (cf. Section 2.4.2). Additionally, decreasing flexibility from hydrogen imports is partially substituted with increasing utilization of the European hydrogen grid, represented in this study through repurposed gas interconnector capacities (cf. Section 2.3). The average hydrogen grid utilization for the benchmark solutions is 45%. With decreasing flexibility from H₂ terminal capacity, intra-European hydrogen transport via pipelines increases, on average, by 2.5% at a TOP rate of 100%. Although this is not a particularly large increase on average, grid utilization deviates by up to +15% or -14% at a TOP rate of 100%, depending on the weather year. Despite the exogenous representation of transmission capacity in our model, the flexibility of hydrogen imports has an impact on the utilization of the European hydrogen grid. Therefore, further research with endogenous determination of transmission capacities may be required for the economic planning of a future European hydrogen grid.

2.5. Discussion

The following section summarizes and discusses the key findings of this work. Further, we reflect upon central limitations of the modeling and suggest opportunities for future research.

2.5.1. Key findings and implications

We investigate the effect of TOP rates as part of hydrogen LTCs on the design of a future decarbonized European energy system. The analysis is conducted with the integrated hydrogen and electricity market model HYEBRID. Using a representative weather year for investment decisions, we employ six equidistant TOP rates between 0% and 100% to analyze the impact of hydrogen import flexibility on the European asset configuration. Subsequently, we conduct a 'stress test', simulating dispatch decisions for 35 weather years for each of the six energy systems. This enables investigating the operational aspects of TOP rates under weather variability. To our knowledge, this is the first publication with an explicit representation of TOP rates in hydrogen LTCs.

Our results show that changing the underlying TOP rate significantly impacts the optimal configuration of the European energy system. With higher TOP rates, total system costs increase, as high TOP rates impose inflexibility on the import of hydrogen. This is balanced by an alternative configuration of other technologies, primarily hydrogen storage. We observe a convex system cost curve to an increase in TOP rates, indicating the importance of avoiding very high TOP rates for importers given a fixed import price for hydrogen. At a TOP rate of 100%, system costs increase by 0.77%, representing a substantial absolute contribution to system costs. TOP rates up to 57% do not impose restrictions, and therefore no additional system costs occur.

By calculating a theoretical maximum willingness to pay a price premium for hydrogen import flexibility, we provide an indication for the system value of the flexibility implied by lower TOP rates. We find a price premium of 12 EUR/MWh for LTCs without a minimum offtake obligation to be indifferent from LTCs without a price premium and total inflexibility in imports. Based on our analysis, future research could improve calculating the value of hydrogen import flexibility, which could provide guidance to European stakeholders when negotiating LTCs with exporters.

A further important finding is that varying TOP rates induce significant shifts in cost-minimal infrastructure requirements of the energy system. A notable example is more hydrogen storage and withdrawal capacity and less terminal capacity at high TOP rates. These changes highlight the critical need to address the flexibility of hydrogen imports when planning the future energy system. Moreover, this finding suggests existing publications could be biased by neglecting this issue.

This work also contributes to the existing body of literature by calculating European hydrogen storage requirements under consideration of imports. Our results exhibit a hydrogen storage capacity between 63 TWh and 81 TWh depending on the TOP rate. Comparing our results to the literature, which exhibits a range of required hydrogen storage capacity between 45 TWh and 240 TWh, our results can be assigned to the lower range of this spectrum, although some

publications showing high storage capacities do not allow for hydrogen imports. Unlike other publications, we model hydrogen storage injection and withdrawal capacity independent of storage volume, showing that their capacity requirements are linked to the hydrogen demand from the power sector and supply from domestic hydrogen production. This representation enables a cost-efficient trade-off between hydrogen supply from storage, import, and electrolysis. Another key distinction from existing studies is the assumed costs of storage. While Sensfuß et al. (2024) adopt a value of 550 EUR/MWh for newly built storage, this work assumes 1454 EUR/MWh. Lastly, the underlying weather characteristics play a central role in the investment decision. Our analysis is based on a representative weather year, whereas Sensfuß et al. (2024) assume the weather year of 2010, which we characterize as an extreme year with a cold dark lull in the dispatch analysis. Moreover, we calculate hydrogen import volumes between 203 TWh and 559 TWh, which can be assigned to the middle range of existing research.

Irrespective of the underlying TOP rates, our findings reveal that the operational characteristics of future hydrogen storage may differ from today's natural gas storage. Instead of a definite seasonal profile, hydrogen storage is also used for short- to midterm balancing with multiple full cycles a year, particularly to bridge hydrogen demand peaks from the power sector and to absorb excess hydrogen from domestic production in periods of excess electricity supply from renewables. The characteristic of high withdrawal and injection ramps, which we observe for all 35 weather years, can yield valuable insights into the requirements of future hydrogen storage operations. This finding differs from existing publications such as Kondziella et al. (2023), Schlund (2023) and Sensfuß et al. (2024), which use a different model framework and mostly find a seasonal profile for hydrogen storage use. In contrast to our approach, Kondziella et al. (2023) assume exogenous RES, implicitly imposing a seasonality in electricity generation, and Schlund (2023) lacks a representation of an integrated hydrogen and electricity market. Sensfuß et al. (2024) only find non-seasonal storage requirements during earlier stages of the hydrogen market ramp-up, while seasonal profiles result under increased storage costs as the energy system approaches climate neutrality. The most similar to our finding is Junge et al. (2022), who find a partially non-seasonal operation of hydrogen storage.

The response of the six energy systems planned under a representative weather year to weather variability exhibits significant inter-annual spreads. As extreme events are not considered in the planning stage, the results reveal significant quantities of lost load in the electricity sector. We observe a rise in the maximum lost load from about 50 TWh in the case of low TOP rates up to 90 TWh if a TOP rate of 100% applies. Although our approach does not consider weather variability in the planning stage, our analysis highlights that reserve requirements are generally higher when flexibility from hydrogen imports is absent and future weather differs from the planning stage.

A regional analysis reveals insights into adjustments at a national level. Countries with limited access to the European hydrogen grid show a rather self-sustaining regional system at high TOP rates, while well-connected countries gain benefits from the cross-border use of infrastructure such as neighboring storage facilities. In addition, landlocked countries react indirectly to varying TOP rates by adapting their energy systems to the shifts in neighboring countries. The findings point to the relevance of establishing a European hydrogen grid, similar to suggestions by Schlund (2023), to facilitate intra-European hydrogen trade, utilize regional infrastructure potential across borders, and thus increase security of supply and limit additional costs for infrastructure investments.

2.5.2. Limitations and future research

This work should be interpreted in light of important assumptions and limitations of the model framework. General assumptions include perfect foresight, complete markets, and inelastic demand of end-use sectors. The future degree of price responsiveness for both electricity and hydrogen demand could affect the degree to which flexibility must be provided on the supply side to ensure a reliable energy system.

Another important assumption is the cost level for infrastructure investment and the price level for hydrogen imports. Due to the model formulation, cost assumptions are not linked to the capacities resulting from the model, i.e., there is no representation for effects such as technological learning like in Seck et al. (2022). A change in the cost assumption could alter the configuration of the energy system. As a test, we increased the price of hydrogen imports, resulting in lower import quantities. Nevertheless, the overall effect of varying flexibility of hydrogen imports via TOP rates does not change fundamentally.

The fixed price assumption for hydrogen imports, irrespective of the underlying TOP rate, as stated in Section 2.3, may not hold in reality due to the lower risk for the exporter's investment at higher TOP rates. The degree to which the import price might change for different TOP rates is subject to the risk perception of the exporter and is difficult to quantify. Indeed, a TOP rate-dependent import price would alter the system cost curve, making it a relevant topic for future research. With the analysis on the maximum willingness to pay for import flexibility, we take a first step in this direction. However, the qualitative findings of this study remain unchanged: higher TOP rates still reduce flexibility, leading to lower system reliability, increased reliance on storage, and an effect on overall system costs. Apart from this, we do not account for a potentially emerging spot market for seaborne hydrogen. Further, distinguishing exporting regions and considering fluctuations in hydrogen supply due to weather variability in the exporting regions leaves room for further research, which is addressed in Chapter 3.

In addition, our approach does not consider technologies such as thermal power plants with carbon capture and storage (CCS) or direct air capture (DAC). The political ambiguity surrounding CCS and the underlying cost assumptions for DAC induce uncertainty. However, a representation of these could alter the demand for hydrogen and renewable generation capacity, but the effect of TOP rates on the energy system is not set to change fundamentally. In addition, we abstract from non-European imports via pipeline and focus on seaborne imports instead. Despite cost levels largely differing between hydrogen terminals and pipelines, the concept of TOP rates is transferable to pipelines. Again, the overall effect of import flexibility would not change.

Lastly, an important limitation is the representation of weather and weather variability. We exclusively consider historical weather patterns. However, future weather can differ from historical characteristics due to climate change and impact infrastructure requirements (Peter, 2019). The approach in this work assumes a single weather year in the investment stage without allowing for lost load. Subsequently, we analyze the implications of weather variability in the dispatch stage, allowing for electric lost load. A more adequate planning approach should account for weather variability already in the investment stage, which results in more robust energy system configurations. Despite this limitation, the two-step approach highlights the following: if the assumption on future weather is not precise, i.e., real weather differs from assumed weather, the energy system with a higher TOP rate turns out to be less reliable. Nonetheless, future research could investigate the effect of TOP rates using advanced methods such as multi-year models (cf. Ruhnau and Qvist (2022)), stochastic models, or heuristic methods similar to Grochowicz et al. (2023). Researchers could also investigate the implications of risk-averse investment decisions, since our results indicate a link between the quantity of lost load and the underlying TOP rate.

2.6. Conclusion

Hydrogen is set to become a central commodity in a future decarbonized European energy system. Yet, a European hydrogen market, fed by domestic production and non-European imports, is still in its very early stages. To accelerate the market ramp-up, a cost-efficient implementation of hydrogen infrastructure is required, which is closely linked to the development of the power sector. Moreover, research on seaborne hydrogen impacting the European energy system is minimal, and the effect of minimum offtake agreements in LTCs on the design and operation of such infrastructure requirements still needs to be investigated.

Thus, this work seeks to shed light on the implications of TOP rates in hydrogen import LTCs on the European energy system. To answer the research questions, we develop the new integrated electricity and hydrogen market model HYEBRID. The partial equilibrium model optimizes European electricity and hydrogen investment and dispatch decisions while accounting for hydrogen im-

ports, domestic production, underground storage, and pipeline transport. We compute the model for six equidistant TOP rates and optimize the investment decisions of the European energy system based on a representative weather year. To analyze the system responses to weather variability, we simulate cost-minimal dispatch decisions for a set of 35 weather years.

The results reveal that high TOP rates significantly impact the energy system configuration and increase total system costs. To avoid excess imports and counteract a lack of flexibility, hydrogen import terminal capacity at 100% TOP rate is 31% lower compared to a case without TOP obligation, while hydrogen storage capacity is 28% higher, respectively. In this context, hydrogen storage provides flexibility by absorbing hydrogen in periods of surplus hydrogen stemming from inflexible imports and supplying hydrogen in periods of low RES production or insufficient hydrogen imports. Despite a decrease in terminal capacity, more hydrogen imports and less domestic production follow from the increased utilization of terminals with higher TOP rates. The energy system configuration, planned under representative weather, exhibits significant variations in dispatch quantities when being exposed to the characteristics of 35 weather years. While a system with no or low TOP rate can mostly adjust to weather variability, the reliability of the energy system decreases with higher TOP rates, resulting in higher dispatch costs⁷.

Apart from the numerical results, our analysis provides multiple real-world implications to stakeholders. The convex system cost curve underlines the importance of flexibility in hydrogen imports and advises importers to pay attention to the TOP rate in negotiations with exporters. Although we do not differentiate import prices for varying TOP rates, we indicate the willingness to pay a premium for flexibility, which may guide stakeholders in negotiations. Nonetheless, if future seaborne suppliers insist on high TOP rates, we show that the diversity in the European technology landscape, especially hydrogen storage facilities, can offset inflexibility of imports to some degree. Given the technological shifts induced by varying TOP rates, our findings highlight the importance of accounting for the degree of import flexibility in energy system studies and suggest that most existing publications may be biased by neglecting this. Lastly, in light of the revived discussions in some European countries about capacity markets and resource adequacy in general, our findings on the altered system reliability depending on the TOP rate are something to consider when designing future mechanisms fostering security of supply.

The presented modeling approach is the first to explicitly represent TOP obligations in hydrogen imports. However, limitations such as the deterministic nature of weather variability, a fixed price for hydrogen imports at all TOP rates, exogenous hydrogen transmission capacity, or inflexible demand leave room for further research.

⁷The exact dispatch costs strongly depend on the underlying assumption for the value of lost load and are not explicitly evaluated.

3. The Cost of Security: Analyzing Strategies to Hedge Hydrogen Import Disruption under Stochastic Representation of Weather

3.1. Introduction

The European Union’s pursuit of climate neutrality necessitates a fundamental shift in energy sourcing and an expanded role for green energy within its system (European Commission, 2022). This transition increasingly involves the import of diverse renewable energy carriers, with ongoing discussions addressing the optimal mix and scale of such imports (Neumann et al., 2025). Within this evolving energy landscape, imported green hydrogen is positioned as a pivotal component of Europe’s decarbonization strategy, aiming for climate neutrality by 2050. Ambitious targets include 10 million tons of renewable (green) hydrogen imports by 2030, as outlined in the REPowerEU Plan (European Commission, 2022). Nevertheless, reliance on imported energy commodities inherently introduces risks related to import disruptions and price volatility, as history has repeatedly demonstrated. The gas crisis of 2022 serves as an urgent reminder of the profound economic and social repercussions of overreliance on a limited number of external suppliers (Emiliozzi et al., 2023).

The development of a nascent international hydrogen market may lead to a concentration of supply similar to early natural gas markets (Dejonghe et al., 2023). Future supply chains could be shaped by long-term contracts (Antweiler and Schlund, 2023), infrastructure development (Kountouris et al., 2024, Schlund, 2023), and geopolitics (Van de Graaf et al., 2020), all of which are subject to considerable uncertainties. Amid growing geopolitical risks, there are calls for a more independent European energy policy (Herranz-Surrallés, 2024), advocating for enhanced domestic production capabilities (EU Parliament & Council, 2024) and a higher degree of self-sufficiency (Jerzyniak, 2024). However, security concerns and risk exposure within emerging hydrogen markets, particularly concerning potential disruptions and market concentration, remain largely underinvestigated.

Although a future international green hydrogen market could offer a pivotal pathway for Europe’s decarbonization, its fundamental reliance on water electrolysis powered by renewable energy sources inherently links global production facilities to weather variability. The Levelized Cost of Hydrogen (LCOH) is a

common metric for estimating the supply costs of green hydrogen and its derivatives from diverse regions worldwide, as derived, for example, by Moritz et al. (2023). These studies often identify cost advantages for importing hydrogen to Europe. Nevertheless, the calculations are typically based on single weather years, which can lead to inaccurate revenue and cost projections for exporting facilities. Furthermore, weather variability emerges as a crucial factor for the design and operation of domestic hydrogen production via electrolysis. Despite its importance, current European long-term infrastructure planning, as detailed in the TYNDP reports by ENTSO-E and ENTSOG (2022, 2025), often relies on single weather years. Moreover, deterministic approaches with limited consideration of weather variability are commonly employed to assess future European hydrogen infrastructure needs (Frischmuth et al., 2024, Neumann et al., 2023). A profound understanding of weather variability is vital, as investment decisions for a future climate-neutral energy system involve long planning horizons, and such considerations become increasingly relevant amid discussions on enhancing the resilience of European energy systems. While stochastic optimization approaches have been applied within the electricity sector to manage uncertainties (Fürsch et al., 2013, Möbius et al., 2023, Scott et al., 2021), their application to the hydrogen sector remains notably limited. This highlights a critical gap in comprehensive, uncertainty-aware modeling frameworks for an integrated European electricity and hydrogen system that explicitly addresses the multifaceted impact of weather variability.

Against this background, this work addresses the following research questions: (i) How does the stochastic representation of weather variability impact LCOH estimations? (ii) What is the cost advantage of a stochastic optimization of European electricity and hydrogen infrastructure over a deterministic optimization, and what are the implications for infrastructure investments? (iii) What are the additional costs of hedging against the risk of a potential disruption in hydrogen imports?

To answer these research questions, we extend the work of Moritz et al. (2023) with a stochastic calculation of LCOH and compare the results with deterministically determined LCOH. The LCOH then inform the coupled electricity and hydrogen market model HYEBRID, first introduced in Keutz and Kopp (2025a). We extend the HYEBRID model with a stochastic representation of weather and demonstrate its benefit over a deterministic representation of weather using the Value of Stochastic Solution (VSS). This analysis is followed by an evaluation of the resulting energy system configuration and hydrogen import structure. Given the potential for high market concentration in hydrogen imports, we assess mitigation strategies to hedge the risk of a disruption in imports: *diversification*, *reduction of imports*, and a *combined strategy*. Finally, the *cost of security* through mitigation strategies is contextualized by translating the cost premium of full autarky into a perceived disruption probability of exporters, providing a benchmark for policymakers.

By providing a robust, uncertainty-aware modeling framework, this paper offers significant methodological contributions to the energy economics literature along with crucial insights for industry stakeholders, policymakers, and European regulatory authorities. First, it enhances understanding of how weather-dependent hydrogen production in exporting regions and European weather variability could influence long-term contract pricing. Second, it demonstrates how a stochastic treatment of weather uncertainty enables robust investment for the European electricity and hydrogen sectors. We find significant infrastructure shifts, such as increased hydrogen storage capacity, to manage both domestic and export-side weather variability. Third, it quantifies the *cost of security* for proactive mitigation strategies, introducing an economic benchmark that relates the cost of mitigation to the level of perceived exporter disruption risk required to justify it. Finally, our findings guide policymakers and industry stakeholders in designing robust hydrogen import strategies, informing both infrastructure investment and future contractual frameworks.

The remainder of this paper is structured as follows. Section 3.2 reviews the relevant literature. Section 3.3 details the LCOH calculation and the extended HYEBRID model, outlining the stochastic methodology for incorporating weather variability and assessing disruption risks, alongside key assumptions. Section 3.4 presents the findings, beginning with LTC prices and the quantification of the VSS, followed by an analysis of mitigation strategies to hedge the risk of import disruption. Section 3.5 offers a thorough discussion of our findings, reflecting on assumptions and limitations. Finally, Section 3.6 concludes the paper.

3.2. Literature

This work addresses two key streams of literature. The first stream focuses on the optimization of electricity and hydrogen sectors, including critical modeling inputs such as hydrogen import prices. The second stream investigates import risks and resilience in emerging hydrogen markets. This area encompasses historical analyses of energy import disruptions, particularly within the natural gas market.

Several studies investigate the combined optimization of European electricity and hydrogen infrastructure, though each study emphasizes different aspects. High spatial resolution is a key aspect of the work by Neumann et al. (2023), which uses a linear optimization model that spatially resolves European countries into 181 regions to improve the visibility of within-country infrastructure investments. Further studies focus on the intertwined development of hydrogen networks and electricity transmission expansion across Europe (Frischmuth et al., 2024, Neumann et al., 2025). Neumann et al. (2025) specifically analyze varying import scenarios by coupling global and European energy system models, underscoring the potential for system cost reductions through coordinated im-

port strategies. Keutz and Kopp (2025a) investigate the impact of Take-or-Pay (TOP) obligations on infrastructure investment and system dispatch under different weather conditions, revealing the sensitivity of cost-optimal infrastructure and reliability to TOP rates. Frischmuth et al. (2024) quantify hydrogen infrastructure development using pan-European energy system (SCOPE SD) and gas market (IMAGINE) models, highlighting the influence of storage costs and market uptake on storage demands and the necessity for substantial infrastructure expansion beyond repurposed methane pipelines. Complementing these model-based analyses, Schlund (2023) adopts a scenario-based approach to examine the interdependencies of energy system elements for hydrogen integration into existing gas infrastructure. Long-term infrastructure projections, such as the TYNDPs 2022 and 2024 (ENTSO-E and ENTSOG, 2022, 2025) or the Long-term Scenarios 3 (Sensfuß et al., 2024), also model energy system investment and dispatch to project cost-efficient infrastructure needs and viable hydrogen import volumes. However, a common limitation in these analyses is the frequent use of deterministic optimization.

Stochastic approaches have been applied to electricity system modeling to address uncertainties. For example, Möbius et al. (2023) analyze the impact of risk aversion on investment strategies using a stochastic transmission and generation expansion model. Scott et al. (2021) examine the effects of different uncertainty sources on generation expansion planning while Fürsch et al. (2013) use a linear multi-stage stochastic investment and dispatch model to analyze the effects of uncertain renewable energy deployment. Riepin et al. (2021) quantify the value of encoding the uncertainty of input parameters, finding that the expected costs of ignoring uncertainty can constitute up to 20% of cumulative costs from investments in power generation capacity.

The application of stochastic approaches to the hydrogen sector remains limited, often focusing on national or regional levels and specific supply chains. Examples include Almansoori and Shah (2012), who model a stochastic hydrogen supply chain network for Great Britain under demand uncertainty; Türkali Özbek and Güler (2025), who develop a multi-objective stochastic model for hydrogen supply chain planning in Turkey; Kim et al. (2008), who design hydrogen supply chains under uncertain demand in Korea; and Ochoa Bique et al. (2021), who employ a scenario tree for a multi-stage stochastic programming model to address hydrogen demand uncertainty in Germany. In light of the limited application to the European scale, this paper expands the capabilities of the HYEBRID model by integrating a stochastic approach into a European electricity and hydrogen investment and dispatch model.

The second stream of literature investigates prices, risks, and resilience aspects surrounding hydrogen imports. LCOH often serve as a reference point for future hydrogen prices. A significant body of literature defines and calculates LCOH for various hydrogen supply chains, with recent studies expanding on global potentials and cost drivers. For instance, Moritz et al. (2023) conduct a techno-economic analysis to estimate global production and supply costs for

green hydrogen and various hydrogen-based energy commodities in 113 countries, building upon the work of Brändle et al. (2021). Further comprehensive analyses, such as the Fraunhofer IEE PtX-Atlas (Pfennig et al., 2021) and the work of Franzmann et al. (2023), also present global LCOH estimations. They provide detailed cost-potential curves, often considering the full process chain of hydrogen exports. Radner et al. (2024) analyze off-grid hydrogen production and supply costs to Europe, incorporating country-specific investment risks and transport. Additionally, studies by Mendler et al. (2024) and Kigle et al. (2024) explore methodologies to optimize capacity ratios and analyze the impact of country-specific investment risks on LCOH. However, LCOH calculations usually rely on a single or limited selection of historical weather years, overlooking the significant impact of inter-annual weather variability on the operational performance and cost-effectiveness of hydrogen production. This can lead to biased LCOH.

Lessons from natural gas market disruptions offer valuable insights into potential geopolitical risks for future hydrogen markets. The European energy crisis of 2022, triggered by Russia’s weaponization of natural gas supplies, serves as a relevant example. The curtailment led to unprecedented price surges across European markets, necessitated a significant reduction in gas consumption, and fundamentally reshaped global LNG trade as Europe sought alternative supplies (Emiliozzi et al., 2023). In response, the EU swiftly transformed its energy policy; for instance, the REPowerEU plan focused on diversifying gas supplies away from Russia and accelerating the transition to renewables (Calanter and Zisu, 2022, Lambert et al., 2022). Research has also investigated operational aspects, with studies on diversification strategies to foster resilience (Hauser, 2021) and analyses of collaborative versus selfish behavior during energy scarcity (Mannhardt et al., 2023). These works identify adaptation strategies, including diversifying imports, shifting to non-gas generation, and reducing demand.

The insights from the 2022 gas crisis regarding supply security, price volatility, and the imperative of diversification and collaborative action offer valuable lessons for the nascent international hydrogen market. However, research targeting risks related to international hydrogen trade remains notably limited.

Existing studies on hydrogen trade risks identify factors such as high investment costs for production and delivery technology, insufficient electrolyzer capacity, and policy or regulatory challenges in Europe (Azadnia et al., 2023). Notably, some analyses of supplier failure primarily concern material suppliers rather than geopolitical risks affecting hydrogen imports. Dejonghe et al. (2023) examine whether future hydrogen imports enhance EU energy security or perpetuate vulnerabilities, drawing lessons from historical natural gas trade in North-west Europe. They suggest that policy-driven market development could lead to a less concentrated market, potentially reducing supply disruption risks. Targeting policymakers, Ansari and Pepe (2023) identify criteria to select trade partners and craft trade frameworks. Moreover, strategies, such as Germany’s 2024 hydrogen import strategy (BMWK, 2024), emphasize resilient imports through

diversification, broad export origins, and parallel import infrastructure. Furthermore, Nuñez-Jimenez and De Blasio (2022) analyze three strategic scenarios for the European Union’s renewable hydrogen market (hydrogen independence, regional imports, and long-distance imports), finding that long-distance imports can offer supply diversification and enhance security without substantially increasing costs.

3.3. Methodology

This section outlines the methodological framework. We describe the stochastic extension made to the HYEBRID model, including the disaggregation of hydrogen exporters. Furthermore, we describe the stochastic approach to determine hydrogen import prices based on LCOH and the selection of weather years. Finally, we present the scenarios employed to investigate strategic approaches to hydrogen import contracting, followed by a summary of the key assumptions and data sources that parameterize the model.

The methodological framework consists of a two-step approach, as visualized in Figure 3.1. This approach is designed to represent weather variability through stochastic optimization in both exporting countries (step I) and European countries (step II). In step I, we stochastically calculate the LCOH for multiple exporters, optimizing their production assets under inter-annual weather variability to determine robust LTC prices (cf. Section 3.3.2). These fixed LTC prices are then used as inputs for the HYEBRID model in step II. Here, we conduct a stochastic optimization of the European electricity and hydrogen system to determine the cost-optimal system design and operation under various strategies that mitigate the effect of import disruptions (detailed in Sections 3.3.1 and 3.3.5).

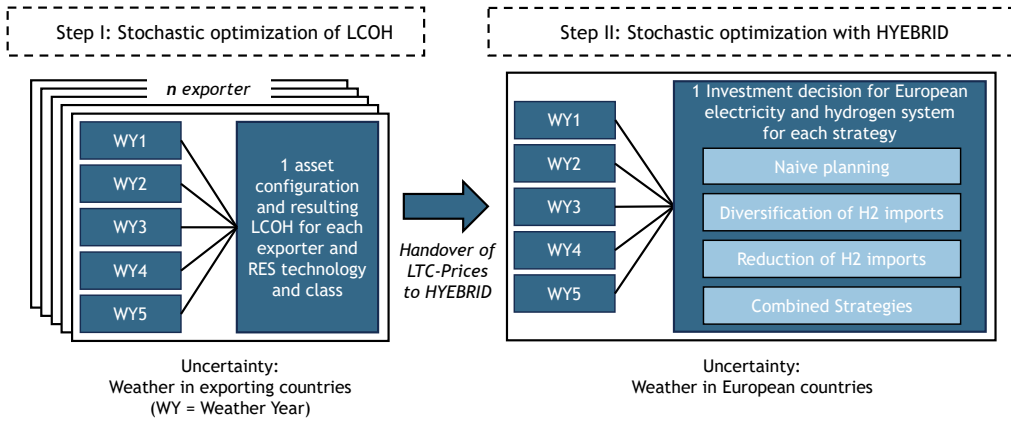


Figure 3.1.: Overview of the two-step stochastic modeling approach.

3.3.1. Stochastic model of the European electricity and hydrogen system

The methodological framework is based on the coupled electricity and hydrogen market model HYEBRID, first introduced in Keutz and Kopp (2025a). We extend the model in two ways. First, we disaggregate hydrogen exports to Europe from a single virtual exporter into multiple exporters, each characterized by individual cost structures and quantities. Second, we introduce inter-annual weather variability directly into the investment stage of the model through a stochastic approach. Figure 3.2 illustrates the overall model structure, including the upstream determination of LTC prices (detailed in Section 3.3.2) and the subsequent optimization of the European energy system that incorporates these prices.

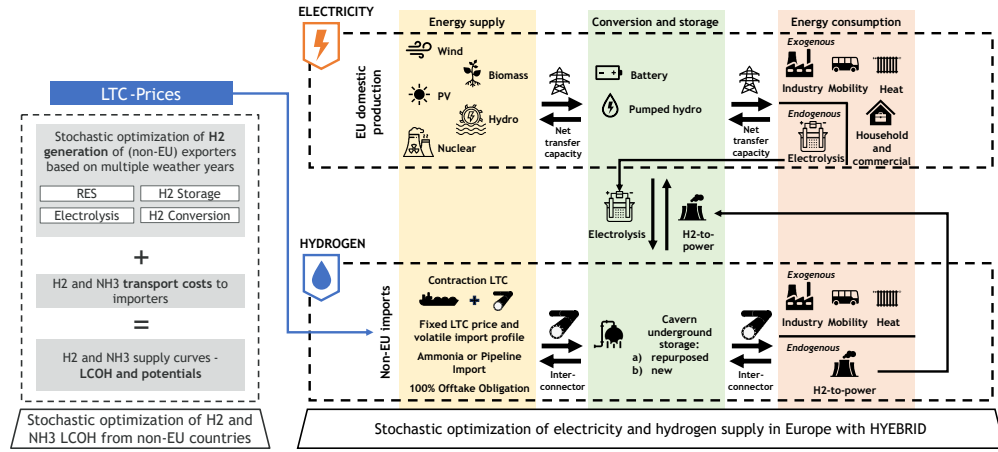


Figure 3.2.: Schematic model overview: stochastic determination of LTC prices and the European energy system.

Existing research has shown that relying on single weather years in modeling investment decisions can result in lower reliability of the energy system (Keutz and Kopp, 2025a, Ruhnau and Qvist, 2022). To overcome this, we incorporate multiple weather years with a stochastic approach, capturing the inherent uncertainty induced by weather variability. The approach used in this work is a linear two-stage stochastic program, similar to Möbius et al. (2023) and based on the general formulation as described in Birge and Louveaux (2011). The rationale behind this formulation is that first-stage (investment) decisions must be made before the uncertainty in risk-related parameters is resolved. The first-stage problem minimizes investment costs and the expected costs of the second stage. In our case, the second-stage uncertainty stems from the impact of weather on both supply and demand. This uncertainty is represented through a set of discrete weather scenarios, each associated with a specific probability. In the second stage, the uncertainty is considered resolved, and the optimal dispatch of assets is determined for each scenario, ensuring feasibility across all realizations

of weather. Both first- and second-stage decisions are solved jointly within a single optimization framework. It is important to note that the model represents a long-run equilibrium, in which the probability-weighted weather scenarios are assumed to accurately reflect the long-term variability of actual weather conditions. Consequently, the stochastic programming approach captures the expected distribution of outcomes across multiple representative years, rather than simulating real-time uncertainty. In this sense, the formulation resembles a probability-weighted multi-year linear program.

This section presents key changes to the deterministic model formulation of HYEBRID, first outlined in Keutz and Kopp (2025a). The total cost function (Equation 3.1) minimizes fixed costs for operation and maintenance FOM and annualized fixed costs AFC for all technologies $tech$ at each node n . These costs can be associated with the first-stage problem. The second-stage costs comprise variable costs $OPEX$ and costs for hydrogen imports from non-European countries IC , which are calculated for each scenario s . The model framework assumes risk neutrality, and therefore, we minimize the expected total costs. The expected value of second-stage costs per scenario is calculated by multiplying these costs by the probability of each scenario p_s . The sum of all scenario probabilities is one.

$$\begin{aligned} \min TC = & \sum_{n,tech} (FOM_{n,tech} + AFC_{n,tech}) + \\ & \sum_{d,h,n,tech,s} OPEX_{d,h,n,tech,s} \cdot p_s + \sum_{d,n,s} IC_{d,n,s}^{H2} \cdot p_s \end{aligned} \quad (3.1)$$

All equations that include second-stage variables are formulated for every scenario individually. Equation 3.2 exemplifies the adjustment with the equilibrium constraint of electricity. $S_{d,h,n,tech,s}^{EL}$ is the electricity supplied by a technology $tech$ to a node n at day d and hour h in the scenario s , $d^{EL,exo}$ is the exogenous electricity demand, $D^{EL,H2}$ is the endogenous electricity demand by electrolysis, $TRADEBAL^{EL}$ is the electricity trade balance, and L^{EL} represents uncovered electricity demand.

$$\begin{aligned} \sum_{tech} (S_{d,h,n,tech,s}^{EL} - S_{d,h,tech,n,s}^{EL}) = & d_{d,h,n,s}^{EL,exo} + D_{d,n,s}^{EL,H2} - \\ & TRADEBAL_{d,h,n,s}^{EL} - L_{d,h,n,s}^{EL} \quad \forall d, h, n, s \end{aligned} \quad (3.2)$$

Second-stage variables are generally constrained by first-stage variables, which creates a link between the two stages. This applies to all capacity variables, e.g., renewable capacity, storage volume, or transmission capacity. We exemplify this

relationship with the domestic generation of hydrogen, which is constrained by electrolysis capacity in Equation 3.3.

$$S_{d,n,tech,s}^{H2} \leq C_n^{H2,ELY} \quad \forall d, n, s, tech \in Tech^{H2,ELY} \quad (3.3)$$

Unlike the initial formulation of HYEBRID, this work does not account for explicit investments in hydrogen terminal capacity. Instead, import infrastructure costs are included in the LCOH and differentiated between imports via ship and pipeline (cf. Section 3.3.2). Moreover, we assume a take-or-pay rate of 100%; that is, the total annual volume of the contracted LTC has to be imported or financially compensated. Non-European hydrogen export options are indexed by e . For notational brevity, e subsumes the exporting country, the renewable energy technology and resource class used for hydrogen production, and the transport option (ship or pipeline), so that each e is associated with a specific LCOH, export potential, and delivery profile. The import costs IC at node n are calculated as the sum over all export options of the LCOH of export option e delivered to node n , $lcoh_{n,e}$, which include the cost of the respective transport option, multiplied by the corresponding imported quantity $I_{d,n,s,e}^{H2}$ (Equation 3.4).

$$IC_{d,n,s}^{H2} = \sum_e lcoh_{n,e} \cdot I_{d,n,s,e}^{H2} \quad \forall d, n, s \quad (3.4)$$

Although the import quantity is a second-stage variable, its volume is determined by a first-stage variable. In the first stage, importers decide on an LTC with a predefined *profile* for hydrogen deliveries. The decision variable $LTC S_{n,e}$ determines the share of the total export potential $expot_e$ of export option e contracted by node n , and thus, the quantity and temporal structure of imports from each export option, $I_{d,n,s,e}^{H2}$ (Equation 3.5).

$$I_{d,n,s,e}^{H2} = LTC S_{n,e} \cdot profile_{d,s,e}^{H2} \cdot expot_e \quad \forall d, n, s, e \quad (3.5)$$

In summary, the model formulation simulates the optimal allocation of resources, encompassing long-term investment decisions and the contracting of hydrogen imports, co-optimized under uncertain weather conditions.

3.3.2. Stochastic model of hydrogen import prices

To optimize the European energy system configuration, we rely on assumptions for the prices of hydrogen LTCs, using the LCOH as a reference. A comprehensive approach to calculate the LCOH of various potential exporters worldwide was first developed by Brändle et al. (2021), which has since been used as a benchmark for import costs in numerous other publications, including the TYNDP 2024 (ENTSO-E and ENTSG, 2025). Our assumptions for the calculation of LCOH are specifically based on Moritz et al. (2023) who extend the

methodology initially presented in Brändle et al. (2021). Their approach optimizes asset combinations (e.g., PV and electrolysis) and divides the assets' total costs by the anticipated hydrogen output over technical lifetimes, yielding the levelized cost of hydrogen generation. This generation cost is then combined with the levelized cost of various transport methods (pipeline, ship) and routes from each exporter to each potential importer, determined based on distances. Together, these components result in the LCOH for each combination of exporter, importer, renewable energy class and resource, and transport method. Note that, in contrast to Section 3.3.1, n here denotes the production site in the exporting country, and the notation follows Moritz et al. (2023).

Moritz et al. (2023) calculate expected output based on a single weather year. This approach is insufficient for our analysis, as the contracting of LTCs within HYEBRID is determined under significant weather uncertainty. Weather characteristics not only influence demand and supply within Europe but also crucially impact the availability and output of non-European hydrogen supply, directly affecting the LCOH. Against this background, we adjust the deterministic linear optimization used in Moritz et al. (2023) by implementing a stochastic linear optimization of assets that incorporates multiple weather years.

Similar to the approach detailed in Section 3.3.1, the formulation of all second-stage (dispatch) variables in the calculation of LCOH is extended to account for distinct scenarios. Again, these scenarios contain information on the realization of individual weather years. The total cost functions, as originally defined in Moritz et al. (2023) (Equations A.3 and A.4 therein) remain unchanged, as only the capacity-related first-stage variables are included in the objective function. The first-stage capacity decision restricts the second-stage variables. Specifically, Equation 3.6 ensures that hydrogen production in every weather year s , hour h , resource class r , and at node n for the combination of res technology and electrolysis res, el is constrained by the renewable technology capacity C , the time-dependent capacity factor cf , and the electrolysis efficiency η^{el} . The methodology for calculating these capacity factors is described in Appendix B.1. Correspondingly, Equation 3.7 restricts the hourly hydrogen output by the electrolysis capacity. Lastly, Equation 3.8 ensures that the hydrogen demand d is met. We parameterize the demand such that a mean output of one kilogram of hydrogen per hour must be produced across all weather years weighted with probability p_s .

$$Q_{n,r,h,s}^{res,el} \leq C_{n,r}^{res} \cdot cf_{n,r,h,s}^{res} \cdot \eta^{el} \quad \forall n, r, h, s \quad (3.6)$$

$$Q_{n,r,h,s}^{res,el} \leq C_{n,r}^{el} \cdot \eta^{el} \quad \forall n, r, h, s \quad (3.7)$$

$$\sum_s \sum_h Q_{n,r,h,s}^{res,el} \cdot p_s = d_{n,r}^{res,el} \quad \forall n, r \quad (3.8)$$

This model framework enables the identification of the optimal asset composition res,el at node n . The LCOH are derived by multiplying the annualized total cost of the optimized asset composition by the lower heating value lhv (33.33 kWh/kg) and dividing by the expected annual hydrogen output of the assets, i.e., the probability-weighted output across all weather years (Equation 3.9).

$$lcoh_{n,r}^{res,el} = lhv \cdot \frac{TC_{n,r}^{res,el}}{\sum_h \sum_s Q_{n,r,h,s}^{res,el} \cdot p_s} \quad (3.9)$$

In this way, the LCOH describe the expected costs of hydrogen supply, specifically considering the inter-annual weather variability over the lifetime of the assets. Adding the levelized transport costs from the exporting country to the respective European node, as in Moritz et al. (2023), yields the LCOH $lcoh_{n,e}$ for each export option e used in Equation 3.4, where n again denotes the European import node. These LCOH are used to parameterize LTC prices in the subsequent optimization of the European energy system. As a result, the LTC price is fixed and independent of the weather realization. Despite an intermittent quantity, hydrogen exporters face no risk of failing to recover their investment if actual weather conditions are correctly reflected in the stochastic optimization. We assume that long-run weather conditions are represented within the stochastic investment decision, which guarantees refinancing. This constitutes an approximation, since the variability within the clustered set of representative weather years is lower than the actual variability observed across a broader historical range. In addition, future weather patterns will be affected by climate change, which is not well captured by past data.

We note that the LTC price could alternatively be formulated to depend on scenario s and adjust to inter-annual output variability to guarantee a constant revenue stream for the exporter in every weather year. However, this formulation would be equivalent to assuming a constant LTC price when optimizing the import decision in the HYEBRID model, since under risk-neutral cost optimization the expected total import cost of an LTC remains unchanged compared to a fixed LTC price.

Figure 3.3 compares the LCOH resulting from multiple single-year optimizations with the LCOH from a single stochastic optimization that incorporates all of those weather years. The variability in the LCOH for single weather years reflects the inter-annual output variability. The mean LCOH of the single optimizations is a hypothetical case and should not be used for subsequent calculations, as each single-year optimization inherently yields a distinct, specific asset structure optimized only for that particular year's weather. In contrast, the stochastic optimization method generates a single, robust asset structure designed to perform well across all considered weather years.

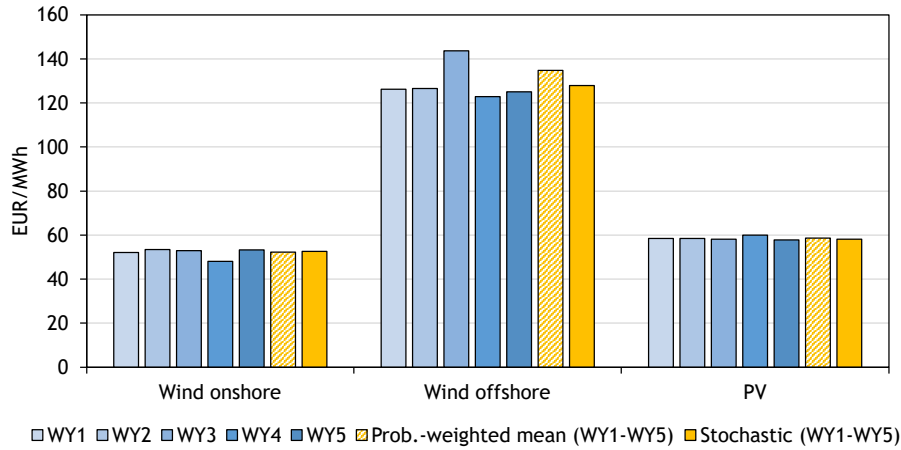


Figure 3.3.: Exemplified LCOH of Morocco (MA) for single years and stochastic optimization in the target year 2050.

To further illustrate the impact of this methodological choice, Figure 3.4 compares the stochastically calculated LCOH with the probability-weighted mean of LCOH values from single-year optimizations. The analysis is shown for 15 potential exporting countries, using exclusively onshore wind potentials for hydrogen production. The stochastic LCOH can be either higher or lower than the probability-weighted mean, depending on the region's specific weather patterns. This demonstrates that a simple deterministic average can be misleading, and the stochastic approach provides a more realistic and reliable cost basis for long-term contracts. For a comprehensive comparison, the results for offshore wind and PV are provided in Figures B.1 and B.2 in Appendix B.2.

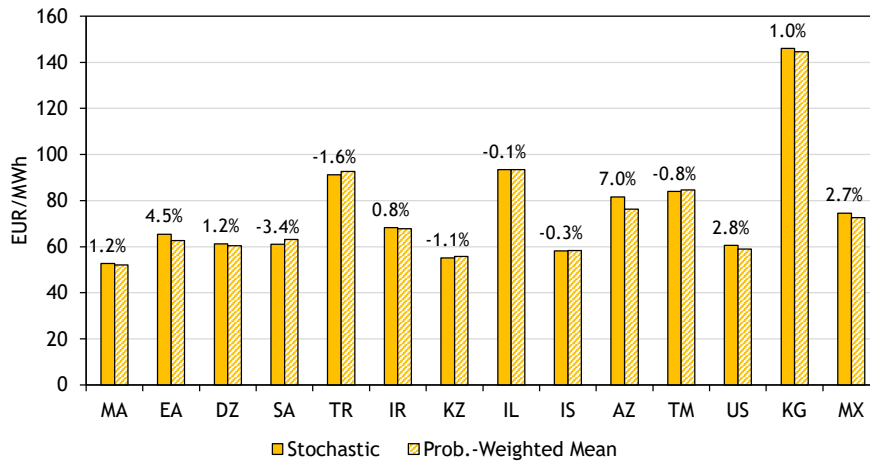


Figure 3.4.: Comparison of stochastic LCOH and probability-weighted mean LCOH for onshore wind across various exporting countries. Percentages indicate the differences between both methodological approaches.

3.3.3. Determination of representative weather years

The computational complexity inherent in the stochastic optimization of the European energy system limits the number of scenarios that can be included. To address this, we reduce a total set of 27 available weather years to a more manageable set of five years using a clustering approach.

Numerous publications apply or develop a clustering of large time-series data to make computation of energy system models feasible. For example, Pfenninger (2017) and Kotzur et al. (2018) show the need to capture extreme events within the clustering process. However, as Hilbers et al. (2019) point out, it is difficult to define before a model run which periods can be considered extreme (a circular situation). Against this background, we cluster our initial set of 27 weather years based on the system costs they imply. Our objective is to select a reduced set of weather years that effectively captures the overall distribution of system costs, including those years that lead to extreme costs.

We run the HYEBRID model for each of these single weather years. This yields a distribution of total system costs, which varies depending on the specific weather characteristics of each year. Figure 3.5 illustrates the relative deviation of these system costs for each weather year compared to the mean system cost across all 27 years. This analysis demonstrates the sensitivity of the energy system's performance to the unique weather characteristics of each year.

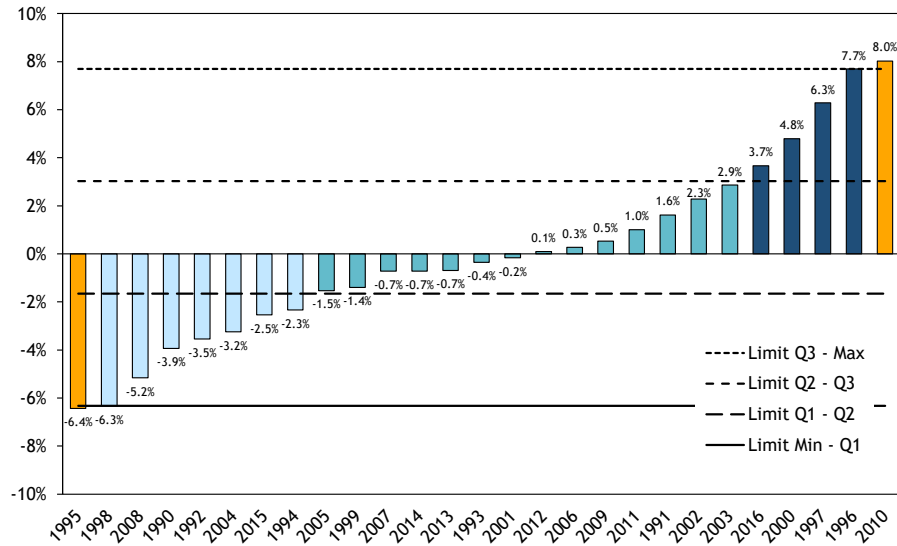


Figure 3.5.: Relative deviation in total system costs of single weather years from the average of 27 weather years computed with the model HYEBRID.

To select the five representative weather years, we employ a hybrid approach combining interval partitioning and representative selection from the distribu-

tion of total system costs. The grouping methodology establishes five distinct groups based on cost deviations. The most critical weather year (2010) results in a deviation from the mean system cost of 8%, while the least critical weather year (1995) results in a deviation of -6.4%. These two extreme weather years are highlighted in orange in Figure 3.5. The remaining 25 weather years exhibit system cost deviations within this range, which illustrates the spectrum of weather impact on system costs.

The years with the absolute minimum (1995) and maximum (2010) system cost deviations each form a singleton group. The boundaries of the three remaining groups are determined by dividing the range of relative system cost deviation between the second-least critical weather year (1998, -6.3%) and the second-most critical weather year (1996, 7.7%) into three equidistant intervals (approximately 4.7% each). This ensures a relatively even distribution of weather years across the intermediate groups.

The resulting classification of weather years into groups is visually represented by the different colored groups in Figure 3.5, with the horizontal dashed lines indicating the equidistant limits between each group. From each of these five groups, the representative weather year is selected as the year with the system cost deviation closest to the mean deviation of all weather years within that specific group. This process yields the following representative weather years: Cluster 1: 1995, Cluster 2: 1992, Cluster 3: 2012, Cluster 4: 1997, and Cluster 5: 2010. The representative years, along with their associated probabilities ($\frac{1}{27}$ for 1995 and 2010, $\frac{7}{27}$ for 1992, $\frac{14}{27}$ for 2012, and $\frac{4}{27}$ for 1997), form the basis of the scenario set used in the model and in the calculation of LCOH.

The clustering methodology does not account for whether the correlation of renewable energy source (RES) yields between the EU and exporting regions is adequately represented in the clustered weather years. Addressing this aspect would require multi-criteria clustering approaches capable of capturing both the variability in RES yields and an accurate representation of their interregional correlation. Nevertheless, Appendix B.3 presents an ex-post assessment of the correlations and illustrates how effectively the clustering reproduces the relationships observed in the full dataset.

3.3.4. Assumptions and data

The regional scope of the model encompasses the EU27, the United Kingdom, Norway, and Switzerland, excluding Cyprus, Malta, Bulgaria, and Greece. The temporal scope is the year 2050, aligned with the EU's climate-neutrality target. This necessitates a zero-emission power and hydrogen sector within the model framework. The model considers 32 representative days with hourly resolution for each representative weather year. The representative days are identified using k-medoids clustering based on today's residual load (cf. Kotzur et al. (2018)). We allow for electric lost load in the model. The Value of Lost Load (VOLL)

varies by region and sector and is highly uncertain (ACER, 2022). Therefore, we set the VOLL to the maximum clearing price of the single day-ahead coupling (ACER, 2023).

The model’s technological scope is summarized in Figure 3.2. A detailed overview of the techno-economic assumptions for the technologies considered in this analysis is provided in Appendix B.4. All cost data are converted to €₂₀₁₉, and calorific units are based on the lower heating value. For the power sector, the model initializes with 2022 capacities for electricity supply, conversion, and storage, allowing for expansion except for nuclear and hydro capacities, which are held constant. Hydrogen can be produced domestically by electrolysis or imported from non-European countries. Assumptions for the costs and temporal structure of hydrogen imports are based on Section 3.3.2. Hydrogen storage is modeled using repurposed or newly built salt caverns, currently representing the most promising and cost-effective type of long-duration underground hydrogen storage (Caglayan et al., 2020). Moreover, the model differentiates between storage volume, injection capacity, and withdrawal capacity, as the volume-to-capacity ratio in a climate-neutral energy system may deviate from the current ratios for natural gas storage. To ensure consistency over the modeling period, we prescribe the filling level of hydrogen storage at the end of the year to be equal to that at the start of the year. Hydrogen transmission is modeled using hydrogen interconnectors created by repurposed natural gas pipelines, based on ENTSOG (2023). A repurposing rate of 50% and a conversion factor of 75% of the initial natural gas capacity, derived from Galyas et al. (2023), is assumed.

Annual electricity demand is based on TYNDP’s Global Ambition scenario for 2050 (ENTSO-E and ENTSOG, 2025). To capture the weather-dependent nature of electricity demand, we use the hourly demand time series from the European Resource Adequacy Assessment (ERAA) 2023 (ENTSO-E, 2023) and combine the two sources following the approach presented in Keutz and Kopp (2025a). Similarly, hydrogen demand follows TYNDP’s Global Ambition scenario for 2050, assuming a flat demand from the end-use sectors of industry and mobility and a temperature-dependent demand from the residential sector (cf. Keutz and Kopp (2025a)). Hydrogen demand for electricity reconversion is determined endogenously. The hourly availability of solar PV, onshore wind, and offshore wind is derived from ENTSOG (2023). Run-of-river flows, storage volumes of pumped-hydro units, and weekly hydro reservoir levels are based on ENTSOG (2023) as well.

3.3.5. Scenario framework

Intuitively, a cost optimization favors selecting the most affordable LTCs for hydrogen imports and leverages the potential of the least expensive options until equilibrium with domestic generation is achieved. However, the lessons learned from the gas crisis in 2022 underscore the significant risks of overreliance on a limited number of exporters, including high prices and broader economic reper-

cussions, such as inflation resulting from a sudden import disruption. The following scenario framework is therefore designed to investigate proactive measures to address disruption risks.

The scenario *naive planning* serves as our baseline, where the optimal import structure is determined solely by cost minimization, excluding any risk mitigation strategies. While such an optimization may lead to highly concentrated import markets, it provides an essential benchmark against which the other mitigation strategies are evaluated.

The scenario *diversification* investigates trade decisions and their impact on the European energy system under enforced diversification of hydrogen imports. The Herfindahl-Hirschman Index (HHI) is a widely used metric to measure market concentration and competition. As an example, De Rosa et al. (2022) use the HHI to quantify the historical diversification of energy supply in the European Union, whereas Kim et al. (2025) use an adjusted HHI to analyze the energy security of coal, oil, and natural gas, decomposing risk related to market concentration and geopolitics. We integrate the HHI as a constraint, thereby enforcing a minimum degree of diversification, represented by an HHI threshold. We test four specifications of this HHI threshold ($\text{HHI} \leq 4,000, 3,000, 2,000,$ and $1,000$), enabling us to quantify the additional costs associated with varying degrees of diversification. Mathematically, the HHI is defined as the sum of the squared market shares s of each exporter i (cf. Equation 3.10). For instance, a monopolistic market would have an HHI of 10,000, while a market with five exporters, each holding an equal share, would result in an HHI of 2,000, with s expressed in percentage terms.

$$\text{HHI} = \sum_i s_i^2 \quad (3.10)$$

While the HHI is a standard measure of market concentration, we employ it as a proxy to manage the criticality of an exporter disruption. As our modeling framework is based on LTCs, neglecting a hypothetical emergence of a spot market, a sudden supply disruption cannot be replaced. Therefore, each exporter is pivotal. Consequently, the HHI in our framework measures the concentration of a non-replaceable disruption risk. For this reason, we apply the HHI to the import market only, i.e., the part of the hydrogen supply subject to exogenous risk. Enforcing a low HHI threshold is thus a mechanism to reduce the potential magnitude of damage from any single disruption.

The quadratic nature of the HHI term necessitates reformulating the HYE-BRID model as a quadratically constrained problem, as the market share s is a variable in our model. To maintain computational feasibility, we linearize this constraint, transforming the model into a mixed-integer linear program. However, even with linearization, s would remain non-linear, as both exports from a single exporter and total exports are variables. Therefore, we fix the total quantity of all exports to the quantity determined in the scenario *naive planning*

when implementing this constraint and explore the implications of lower total exports in the *combined strategies* scenario.

In the scenario ***reduction***, we optimize trade decisions and the European energy system configuration, assuming a lower total quantity of imports compared to the scenario *naive planning*. This scenario includes four specifications, with total import volumes set to 75%, 50%, 25%, and 0% of the level determined in the *naive planning* scenario. The rationale behind this scenario is to reduce Europe’s exposure to unexpected shortfalls in imports, consequently fostering a more independent European hydrogen supply.

Finally, the scenario ***combined strategies*** evaluates the simultaneous implementation of both import *diversification* and *reduction* measures. This comprehensive scenario framework allows us to systematically assess the effects of each mitigation strategy, individually and in combination, on total system costs, exporter selection, and import structures.

3.4. Results

This section presents the results of the analysis, organized as follows. First, we present the LTC prices derived from the stochastic LCOH calculation for exporting countries. This is followed by a discussion of the value of the stochastic solution for the European energy system. We then detail the results of the scenario *naive planning*, which does not apply a strategy to hedge against the risk of import disruption. Subsequently, we explore the results of the mitigation strategies: *diversification*, *reduction*, and *combined strategies*.

3.4.1. Hydrogen import prices

This section presents the LTC prices derived from the stochastic optimization of LCOH. These LTC prices are key input data for the cost optimization within the HYEBRID model. Figure 3.6 illustrates LTC prices from various exporting regions to Germany, considering different RES technologies (wind onshore, wind offshore, and solar PV). A comprehensive overview detailing LTC prices for a wider range of importing countries is provided in Appendix B.5.

The results show significant differences in LTC prices across RES technologies and exporting countries. LTCs based on onshore wind (81.3–205.8 EUR/MWh) and PV (88.9–141.8 EUR/MWh) generally exhibit lower prices, while offshore wind (119.2–395.4 EUR/MWh) tends to be more expensive due to higher specific investment costs. Lower LTC prices are typically observed for regions with higher full-load hours (FLH) and RES yields, as well as shorter transport distances to Europe (e.g., Morocco or Eurasia).

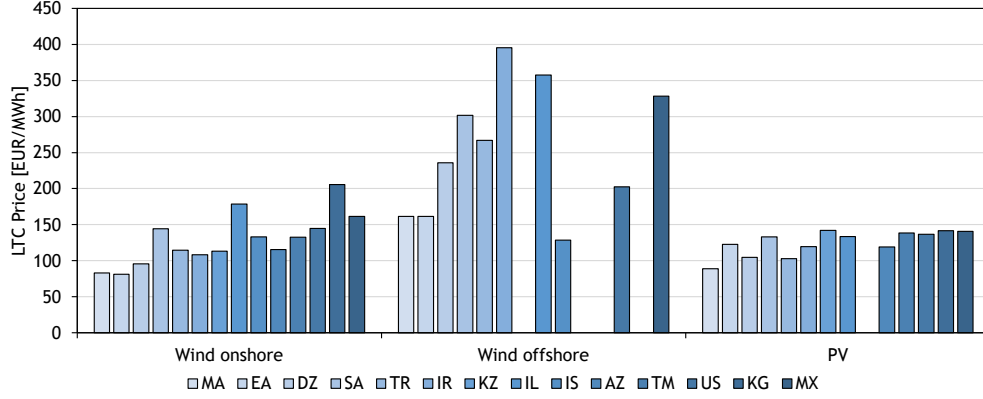


Figure 3.6.: LTC prices including transport to Germany from various exporters.

3.4.2. Value of the stochastic solution (VSS)

To ensure a reliable and cost-efficient energy system, it is crucial to account for uncertainty in the investment planning stage. A deterministic approach, relying on a single weather year for investment decisions, can lead to a system design that is not robust enough to handle a wide spectrum of weather conditions. This results in lower system reliability when weather characteristics during operation differ from those assumed in the planning stage, potentially causing supply shortfalls (Keutz and Kopp, 2025a). A stochastic modeling approach, in contrast, optimizes investments across a range of possible weather scenarios, leading to a more resilient system configuration.

The benefit of this approach is quantified by the VSS. This metric measures the cost difference between a stochastic model and a deterministic model that uses the expected values of the uncertain parameters (Conejo et al., 2010). For a cost minimization problem, it can be calculated as

$$VSS = TSC^{Det} - TSC^{Stoch}. \quad (3.11)$$

TSC^{Stoch} represents the total system costs from the stochastic model. TSC^{Det} represents the total system costs obtained after first solving a deterministic problem, using an average weather year to identify investment decisions, and then evaluating the system's performance across all five weather scenarios. For this comparison, all relative costs are expressed as a percentage of the total deterministic system costs TSC^{Det} , which serve as the baseline.

As shown in Figure 3.7, the deterministic approach leads to an underinvestment in assets. This results in lower investment and dispatch costs (61.2%) than in the stochastic solution. However, the system designed with the deterministic approach is unable to cope with varying weather conditions, resulting in significant costs for uncovered demand (38.8%) for a VOLL of 5,000 EUR/MWh. In

contrast, the stochastic model leads to higher upfront investment and dispatch costs (64.6%) to build a resilient system that almost entirely avoids reliability penalties, incurring only 0.1% in costs for uncovered demand. The total economic benefit of adopting the robust stochastic approach is 35.3% of the deterministic system costs. While the investment and dispatch costs would adjust slightly to a different VOLL, the costs for uncovered demand would change proportionally, significantly altering the total costs of the deterministic approach.

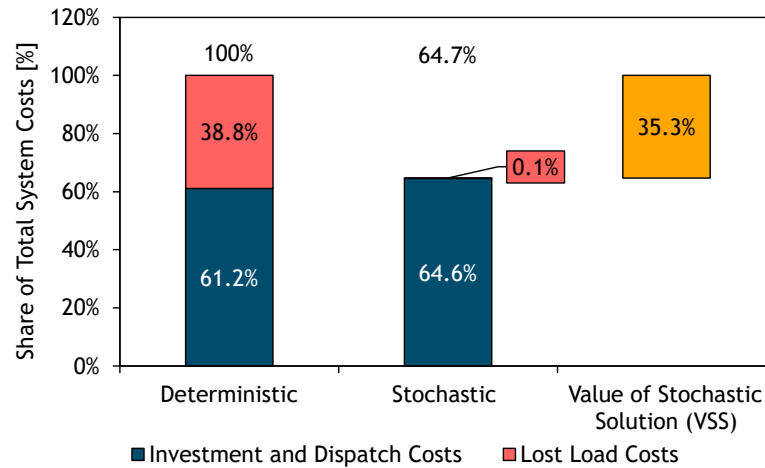


Figure 3.7.: Comparison of total system costs from the stochastic and deterministic modeling approaches, assuming a VOLL of 5,000 EUR/MWh.

The primary implication of the stochastic approach is a strategic shift towards greater investment in system flexibility, particularly a substantial increase in hydrogen storage capacity (349 TWh vs. 215 TWh) and hydrogen import quantity (916 TWh vs. 685 TWh) to manage weather-induced variability from both domestic production and imports.

3.4.3. Naive planning

This section presents the results of the scenario *naive planning*, establishing a reference point against which to evaluate the impact of import risk mitigation strategies. The optimization of import decisions in HYEBRID is based on the LTC prices shown in Section 3.4.1 as well as the weather-dependent delivery profile for each LTC. In addition to import decisions, the model simultaneously optimizes investment and dispatch decisions in Europe for the target year 2050. As outlined in Section 3.3.3, the model incorporates five weather years (1992, 1995, 1997, 2010, and 2012), consistent with those used in the calculation of LTC prices.

Figure 3.8 illustrates the resulting investment and dispatch⁸ decisions for the European electricity and hydrogen sector. The results exhibit a significant deployment of RES, with available wind and PV electricity reaching 6,254 TWh. RES are complemented by battery and H2-to-power capacity, guaranteeing a secure operation of the power system. More than two-thirds of the European hydrogen demand is served by domestic production (1,971 TWh), provided by a total of 665 GW of electrolysis capacity in Europe. To balance intermittent hydrogen production, imports, and demand, 349 TWh of hydrogen storage capacity is employed. The corresponding injection capacity for hydrogen storage is 4,607 GWh/d, while the withdrawal capacity is 9,141 GWh/d, reflecting the need for rapid withdrawal to meet demand spikes from the electricity sector.

The total hydrogen import quantity amounts to 916 TWh, covering roughly one-third of the European hydrogen demand in 2050. These imports are sourced from three major exporters—Morocco, Eurasia, and Algeria—all supplying hydrogen exclusively via pipeline. This import structure yields a Herfindahl-Hirschman Index (HHI) of 4,800, indicating a concentrated market. This HHI indicates a significant security risk, as the system is exposed to a disruption of pivotal exporters.

The optimization in HYEBRID considers both the price and temporal structure of deliveries associated with an LTC. Our results indicate that exporters are selected based on the lowest prices; therefore, variations in the delivery profile between exporters do not significantly influence import decisions in the scenario *naive planning*. This contrasts with the subsequent scenarios, where weather variability becomes a more decisive factor for import decisions.

⁸All dispatch results shown are weighted averages from five weather years, with each year's probability of occurrence accounted for, as detailed in Section 3.3.

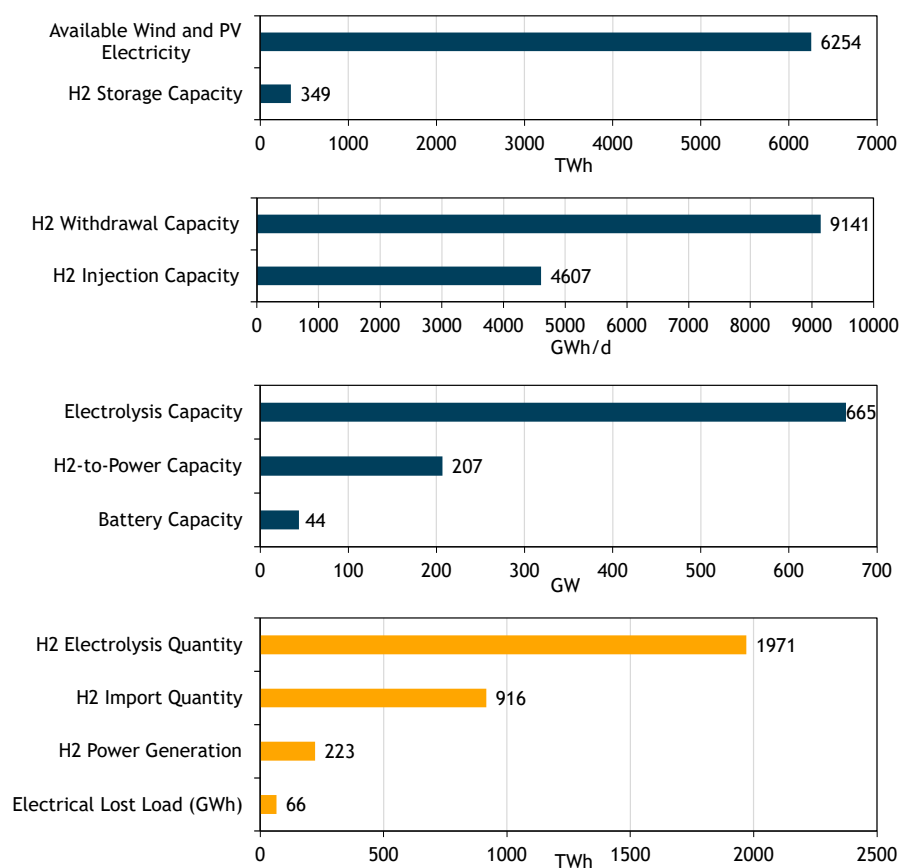


Figure 3.8.: Overview of investment (blue) and dispatch (yellow) results for the scenario *naive planning*.

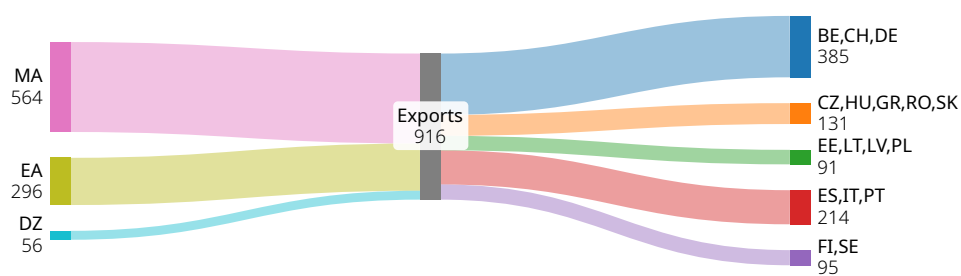


Figure 3.9.: Average annual hydrogen trade flows in the scenario *naive planning*.

3.4.4. Diversification of hydrogen imports

In the scenario *diversification*, the model is forced to select a broader range of import sources by considering increasingly strict HHI targets. To isolate the

effect of diversification through HHI targets, the total import quantity is kept constant at 916 TWh, matching the level from the scenario *naive planning*.

Figure 3.10 illustrates the effects of stricter HHI targets on total system costs and import structures. The number of exporters increases from three in the scenario *naive planning* to fourteen in the HHI 1,000 specification. As a result, the import share of individual exporters decreases significantly: Morocco, the largest exporter in the scenario *naive planning*, drops from 20% to 6% market share. However, diversification comes at a cost. The stricter the HHI target, the higher the total system costs. In the scenario *naive planning*, exporters with high full-load hours (FLH), large RES potentials, and proximity to Europe are preferred. As the HHI target tightens, exporters with lower FLH and RES potentials and often greater distances to Europe are contracted as suppliers, requiring more expensive transport options, such as seaborne imports. Consequently, average LTC prices increase, resulting in additional system costs. The shape of the system cost curve is convex as a function of the HHI, indicating that marginal system costs increase as diversification is strengthened. The maximum system costs are found in the specification HHI 1,000, with a cost mark-up of 5.7% compared to the scenario *naive planning*. Despite these higher costs, the overall asset configuration of electricity and hydrogen infrastructure is only marginally affected. The cost increase is primarily driven by more expensive hydrogen import procurement.

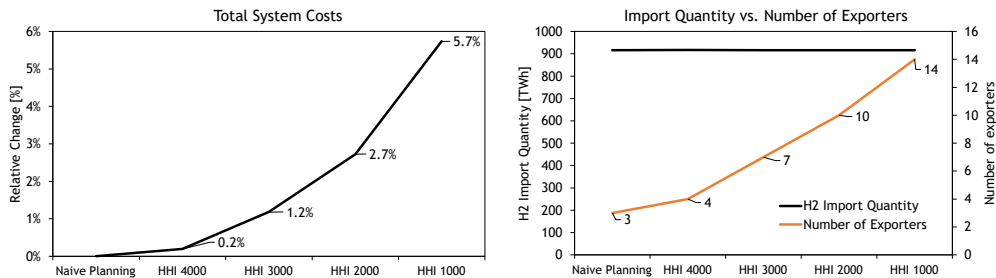


Figure 3.10.: Impact of diversification of hydrogen imports by HHI targets on total system costs and number of exporters.

To understand the dynamics of increased procurement costs, Figure 3.11 illustrates a detailed overview of the LTC prices and corresponding export volumes for each exporter, presented in ascending order of price. The LTC prices shown represent a European-wide volume-weighted average import price for hydrogen, reflecting individual deliveries and transport expenses to various European countries. The basis for these weighted import prices is detailed in Section 3.4.1 (cf. Figure 3.6 and Table B.2 in the Appendix). The figure highlights the relationship between import prices and export volumes at different stages of diversification. As the HHI target becomes stricter, more exporters are selected by the model, leading to greater diversification of the import structures. In the HHI 2,000 and HHI 1,000 specifications, several exporters with relatively high prices are selected with similar export volumes, resulting in similar individual contribu-

tions to the overall HHI. Simultaneously, individual export volumes decrease as import volumes are distributed more evenly across a larger number of exporters.

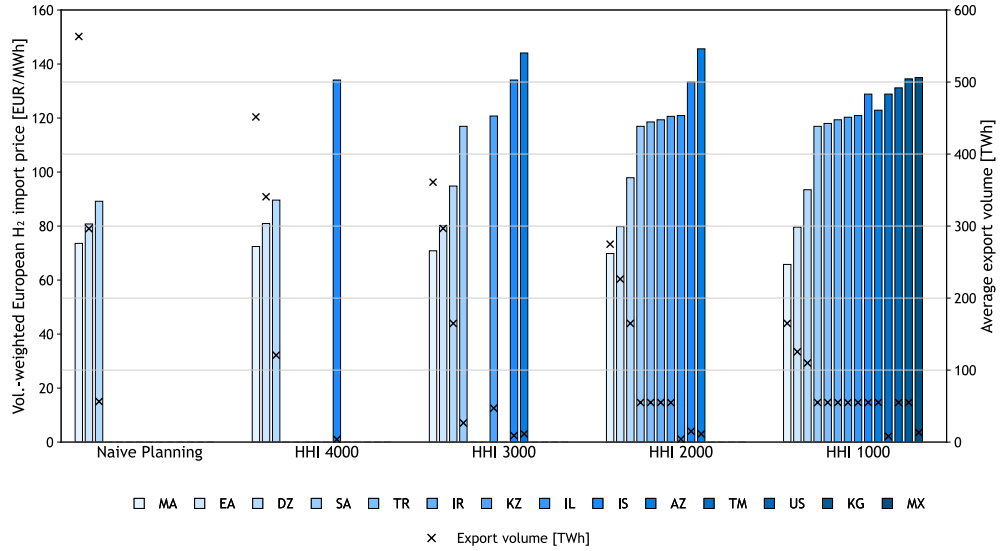


Figure 3.11.: Volume-weighted European hydrogen import prices by exporter and HHI target (left axis), and average export volumes (right axis).

Notably, the results reveal that LCOH is not the sole decisive factor for import decisions; rather, the system-friendliness of a delivery profile plays a crucial role. For example, in the scenario HHI 4,000, imports are sourced from Morocco (MA), Eurasia (EA), and Algeria (DZ), similar to the scenario *naive planning*. Due to the HHI target, additional exporters must be included. From a price perspective, the next most cost-efficient exporter would be Saudi Arabia (SA), followed by Turkey (TR), and Iran (IR) (cf. Figure 3.11). Yet, instead of prioritizing these low-cost exporters, imports from Iceland (IS) are contracted at a higher cost. The rationale for this decision appears to be the weather-dependent delivery profile of Iceland, which presumably better aligns with the required import profile. Similar import decisions and observations can be found in the HHI 3,000 case. This demonstrates that non-cost factors, such as weather variability and the resulting import profile, play a role in the import decision. However, providing conclusive evidence for the model's exact reasoning is challenging due to its inherent complexity.

3.4.5. Reduction of hydrogen imports

The scenario *reduction* explores the effects of reducing hydrogen imports through import share targets. These targets are implemented as exogenous caps on total European hydrogen imports, based on the import quantity of the scenario *naive planning*. This approach forces the optimization to reduce hydrogen imports

from 916 TWh to zero in four equidistant steps, resulting in fixed hydrogen import volumes of 687 TWh, 458 TWh, 229 TWh, and 0 TWh, respectively.

Figure 3.12 depicts the effects of reduced hydrogen imports on total system costs and import structures. The results indicate that reduced hydrogen imports are substituted by increased domestic hydrogen production within Europe. Consequently, electrolysis production increases proportionally to the reduction in imports. However, this increase is slightly less than the corresponding reduction in imports, as the hydrogen demand from hydrogen-fired power plants is also reduced due to the concurrent build-up of domestic RES capacities. In the extreme case of no imports (scenario Import 0%), a self-sufficient electricity and hydrogen system within Europe is established. Here, domestic hydrogen production amounts to 2,847 TWh, a 44% increase compared to the scenario *naive planning*.

The model consistently selects the same three exporters as in the scenario *naive planning*: Morocco, Eurasia, and Algeria. Morocco's import share increases substantially from 32% in the scenario *naive planning* to nearly 90% in the scenario Import 50%. This leads to an HHI of 7,900, significantly higher than in the scenario *naive planning*, indicating a very high concentration of the import market.

This shift towards higher levels of self-sufficiency, culminating in a solely self-sufficient European energy system, results in additional system costs. The stricter the import share targets become, the more the total system costs increase (cf. Figure 3.12), resulting in a convex system cost curve. The maximum increase in total system costs is observed in the specification Import 0%, with a cost markup of 2.9% compared to the scenario *naive planning*.

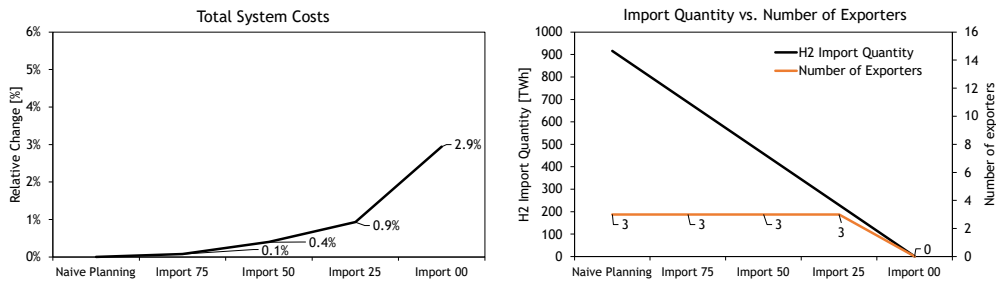


Figure 3.12.: Impact of reduction of hydrogen imports by import share targets on total system costs and number of exporters.

It is important to note that this 2.9% cost markup represents a conservative estimate, as it is highly dependent on the assumed weighted average cost of capital (WACC) for domestic versus non-European production. The WACC spread assumed in these results is 6% ($WACC_{non-EU} - WACC_{EU}$), reflecting higher perceived investment risks for non-European projects. This spread increases the price of imports relative to domestic production and narrows the cost gap compared to full autarky. Figure 3.13 illustrates this sensitivity. As

the WACC spread decreases, imports become comparatively cheaper, and the additional system costs for full self-sufficiency rise significantly. For instance, assuming equal WACC (0% WACC spread) results in an increase of the cost premium for the scenario *Import 00* of 13.6%.

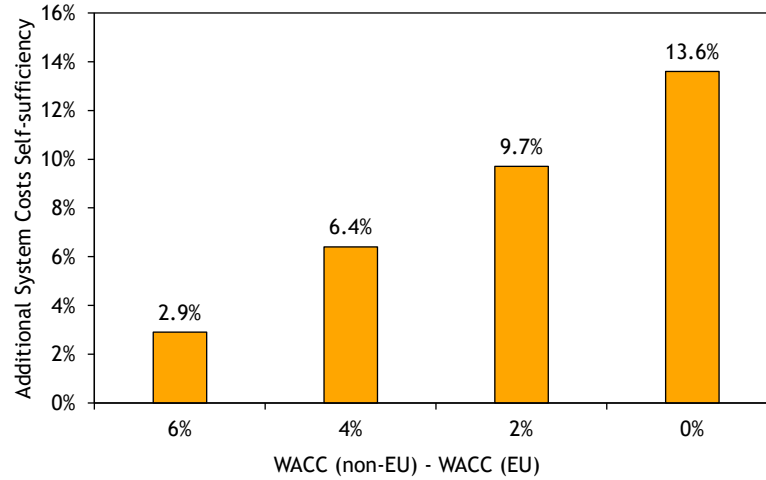


Figure 3.13.: Sensitivity of additional system costs for autarky as a function of the WACC spread between exporters and Europe.

In contrast to the scenario *diversification* using HHI targets, where higher system costs are driven by more expensive hydrogen imports, the cost increases in the scenario *reduction* arise from substantial investments in domestic hydrogen production. In the case of full autarky, the capacity increase compared to the scenario *naive planning* amounts to 39% for electrolysis capacity, 22% for available wind and PV electricity, and 6% for hydrogen storage capacity.

3.4.6. Combined strategies

This section investigates the combined effects of diversifying and reducing hydrogen imports to provide a more comprehensive assessment of import risk mitigation. While the preceding sections analyze each strategy in isolation, their simultaneous implementation reveals interdependent effects on the optimal import strategy and energy system configuration. To manage the analytical complexity of the twelve possible combinations (four HHI targets and three import share targets), we present a focused analysis highlighting key trends and the most salient findings.

- **HHI 4,000 75%:** This specification combines a moderate diversification target (HHI 4,000) with a relatively high import share (75%). It represents a scenario where policymakers prioritize low-cost imports while gradually introducing diversification to mitigate disruption risks.

- **HHI 1,000 75%:** This specification examines the effect of stringent diversification (HHI 1,000) while maintaining a high import share (75%). It highlights the impact of strong diversification when import reduction is less pronounced.
- **HHI 4,000 25%:** This specification explores the impact of a significant reduction of imports compared to the scenario *naive planning* (25% import share) while allowing for moderate diversification (HHI 4,000). It shows the system's response when reliance on imports is reduced, but some diversification is still pursued.
- **HHI 1,000 25%:** This specification represents the most restrictive case, combining stringent diversification (HHI 1,000) with a substantial reduction of imports (25% import share). It illustrates the potential system-wide costs of pursuing ambitious energy security goals.

Figure 3.14 presents the impact of the *combined strategies* on total system costs and the number of exporters.

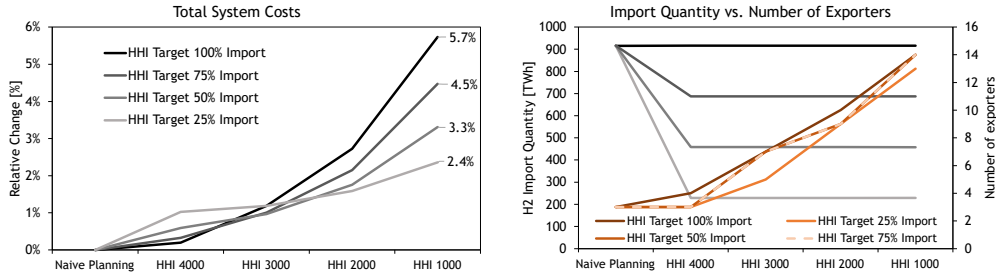


Figure 3.14.: Impact of *combined diversification* and *reduction* of hydrogen imports on total system costs and number of exporters.

System costs: Stricter HHI targets and lower import shares generally lead to increased system costs. This trend is reflected in the specifications of the scenario *combined strategies*, with HHI 1,000 25% exhibiting the highest cost increase and HHI 4,000 75% the lowest. However, the cost increase is not simply additive. For instance, combining a 25% import share with HHI 4,000 results in a smaller cost increase than the sum of the individual cost increases for the HHI 4,000 and Import 25% specifications (cf. Figures 3.10 and 3.12). This suggests a partially mitigating effect, where reduced import volumes lessen the cost burden of diversification. Conversely, combining stringent diversification (HHI 1,000) with a high import share (75%) results in a near-additive cost increase, indicating that the cost of strong diversification is more pronounced when import volumes remain high.

Number of exporters: The number of exporters is primarily driven by the HHI target. Specifications with HHI 1,000 consistently show a larger number of exporters compared to HHI 4,000, regardless of the import share target. The import share target influences the absolute import volumes from these exporters.

With a 25% import share, the overall import volume is lower, leading to smaller individual export volumes.

These findings highlight the complex interplay between *diversification* and *reduction*. While both strategies individually increase system costs, their combined effect exhibits non-linear interactions. Reducing import volumes can partially offset the cost of diversification, but stringent diversification remains costly, especially when import volumes are high.

3.4.7. Relating the cost of autarky to a perceived import disruption risk

Autarky results in a cost mark-up of 2.9% compared to the scenario *naïve planning*. This premium of 2.9% is equivalent to approximately 12 billion EUR annually. This section contextualizes this cost of security by determining the perceived disruption probability for a single exporter at which the additional costs for autarky become indifferent to the *naïve planning*.

We translate the 12 billion EUR additional system costs into a disruption probability for each of the three main exporters identified in the scenario *naïve planning*: Morocco, Eurasia, and Algeria. This probability is calculated as the indifference point where the expected annual cost of a potential disruption from a single exporter (probability, disruption volume, and VOLL) equals the cost markup of autarky of the scenario specification *Import 00*. Figure 3.15 presents the results.

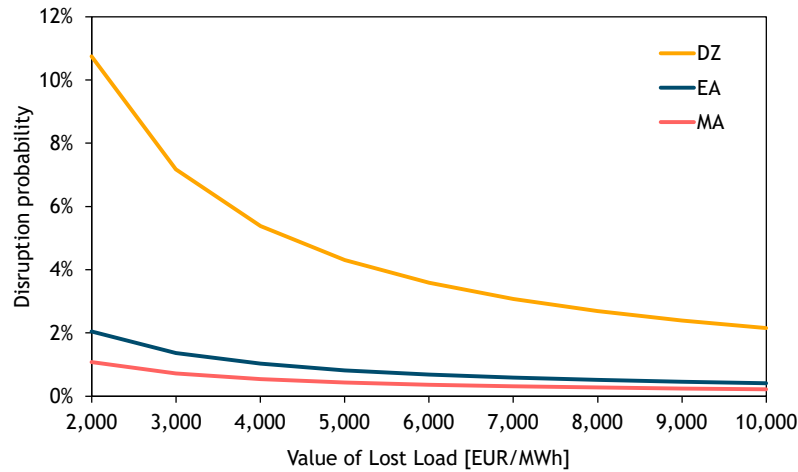


Figure 3.15.: Disruption probability by exporter required to justify the cost of full autarky as a function of the Value of Lost Load.

The analysis reveals two key insights. First, the calculated disruption probability has an inverse relationship with the VOLL; the higher the assumed economic damage of a disruption, the lower the disruption probability needs to be to justify

the cost of autarky. Second, the perceived disruption probability differs significantly based on the import volume of the specific exporter, meaning the costs of autarky can be justified under different risk perceptions. For example, the autarky cost can be reasonable given a low perceived annual disruption probability for the largest supplier, Morocco (1.1% at a VOLL of 2,000 EUR/MWh), whereas it requires a significantly higher perceived probability for the smallest supplier, Algeria (10.8% at a VOLL of 2,000 EUR/MWh).

This analysis provides a benchmark for decision-making. By comparing specific geopolitical risk assessments for each hydrogen exporter against the calculated disruption probabilities, an economically informed decision can be made on whether the cost premium for full self-sufficiency is a justifiable investment. However, the analysis assumes that disrupted import volumes cannot be compensated through alternative suppliers or demand-side flexibility over the course of a year and considers only isolated disruptions of single exporters. Despite these simplifying assumptions, the results provide a useful indication of the economic trade-off between supply security and system costs.

3.5. Discussion

This section summarizes the key findings of the analysis and highlights real-world policy implications. In addition, it reflects on the methodology, assumptions, and limitations of this work.

3.5.1. Stochastic calculation of LCOH

This work is the first to stochastically derive LCOH for a set of potential exporting countries worldwide, building upon the methodological framework introduced in Moritz et al. (2023). The stochastic formulation enables the explicit consideration of inter-annual weather variability and, thus, incorporates hydrogen production variability into the decision rationale of exporters. As a result, the asset configuration and LCOH derived are valid over a range of weather years rather than a single deterministic realization. A key insight from our analysis is that accounting for a sufficiently large set of weather data affects the efficiency of the asset configuration in exporting countries and the basis for determining the offtake price for potential LTCs.

3.5.2. Stochastic optimization of European hydrogen import decisions

We optimize European import decisions using LTCs with the stochastically determined LCOH as a reference point for LTC prices. A key contribution is that the model HYEBRID, which optimizes European investment decisions, is

stochastically expanded to represent the same uncertainty-aware framework as the determination of LCOH.

We quantify the value of the stochastic extension via the VSS. The VSS reflects a reduction in system costs of 35%, and represents the avoided costs of supply shortfalls that arise if planning were based on a deterministic, average-weather-year approach. This finding highlights the critical need for long-term planning frameworks to account for weather variability already in the investment stage. This need is often overlooked in current planning, such as the TYNDP reports (ENTSO-E and ENTSOG, 2022, 2025) or the Long-term Scenarios (Sensfuß et al., 2024), which rely on a deterministic optimization. However, it should be noted that the precise magnitude of the VSS is highly sensitive to the assumed VOLL, which scales the penalty for supply shortfalls, and to the underlying weather year of the deterministic solution.

The stochastic representation of weather in the optimization of European assets points to higher infrastructure requirements. Specifically, the analysis reveals significant balancing challenges that necessitate a substantial expansion of hydrogen storage capacity within Europe. In the scenario *naive planning*, we find that 349 TWh of storage is cost-efficient, substantially higher than in most other studies (Neumann et al. (2023): max. 43 TWh, Moser et al. (2020): 45 TWh, Keutz and Kopp (2025a): max. 81 TWh, Frischmuth et al. (2024): max. 221 TWh, Sensfuß et al. (2024): max. 240 TWh, and Schnaars et al. (2024): max. 275 TWh).

The scenario *naive planning* further reveals a mean annual import quantity of 916 TWh, a figure that is sensitive to the underlying cost assumptions from Moritz et al. (2023). This translates to approximately one-third of the total European hydrogen demand. The imports are sourced from the three exporters with the lowest LTC prices: Morocco, Eurasia, and Algeria. An ex-post analysis of the import structure yields an HHI of 4,800, indicating a high level of market concentration. Such a concentrated market could pose a severe risk to Europe’s security of supply and affordability in the event of sudden exporter disruptions.

3.5.3. Mitigation strategies

To address the vulnerability to an exporter disruption, we investigate two exemplary strategies that mitigate the impact of a sudden disruption: *diversification* and *reduction* of imports. Diversification, enforced by imposing a maximum HHI in the optimization, leads to a more diverse exporter portfolio. For an HHI of 1,000, the number of exporters increases to 14, resulting in an annual system cost increase of 5.7% compared to the scenario *naive planning*. This cost increase is primarily attributed to the need to contract more expensive LTCs. The second mitigation strategy, *reduction* of imports, restricts the total amount of imports, thereby decreasing Europe’s dependence on external supply. In the extreme case of European autarky (no imports), the additional annual system costs amount to

2.9%. Substituting imports with domestic production necessitates significantly more renewable capacity and electrolysis. The additional system costs of full independence in hydrogen supply are in line with the results of Kountouris et al. (2024), who find additional system costs of 3% with a similar but deterministic approach. We note that this quantification is conservative given that we assume significantly higher WACC in exporting countries than in Europe, as pointed out in Section 3.4.5.

Finally, combining the *diversification* and *reduction* strategies provides a more granular understanding of mitigation options. Our analysis suggests that maintaining the baseline import level (one-third of European demand) while diversifying is generally more costly than reducing overall imports. The finding is highly dependent on the relationship between LTC prices of different exporters; if the supply curve of exporters were steeper, this relationship would become even more pronounced. Therefore, for Europe to manage disruption risk effectively and at moderate additional costs, a precise assessment of these cost relationships is crucial.

Collectively, our findings offer strategic insights for European energy security policy and long-term infrastructure planning. As analyzed in Section 3.4.7, relating the cost of autarky to perceived import disruption risk provides a benchmark for policymakers: the additional costs of autarky can be justified even with a low perceived disruption probability for the largest exporter (e.g., 1.1% for Morocco at 2,000 EUR/MWh VOLL), but require a significantly higher perceived disruption risk for smaller exporters to be beneficial (e.g., 10.8% for Algeria). Current cross-national long-term infrastructure planning, such as the TYNDP (ENTSO-E and ENTSG, 2025), often treats imports from non-European countries as exogenously given, with variations across scenarios that exhibit several shortcomings. Specifically, these approaches fail to account for the temporal variability of imports, which must be managed within Europe. Additionally, they overlook the potential consequences of import disruptions and do not consider the co-optimization of European infrastructure assets alongside decisions on import quantities. As a result, current methodologies are likely to fall short in terms of both security and cost-efficiency. This work therefore advocates for a comprehensive assessment of hydrogen import costs and potentials that explicitly considers inter- and intra-annual production variability, disruption risks, and the interaction between import strategies and European energy infrastructure planning. Integrating these dimensions into long-term optimization frameworks can improve both the robustness and cost-effectiveness of future energy systems.

3.5.4. Limitations

The results of this work should be interpreted in light of several limitations and underlying assumptions. At a general level, it must be noted that we employ a linear stochastic optimization model that minimizes total system costs, which, by virtue of the duality theorem, is equivalent to the risk-neutral profit maximiza-

tion of investors. This equivalence requires the existence of complete markets, a condition that may not hold in practice. Moreover, quantitative results, such as the magnitude of hydrogen imports or the required storage capacity, depend on the scenario framework adopted, especially the demand level. Therefore, the results should be interpreted as scenario-consistent rather than absolute projections.

In addition, simplifications are made regarding the temporal and weather representation in the HYEBRID model. We cluster a set of 27 historical weather years into five representative years, which approximate but do not fully capture the true inter-annual variability or the temporal correlations between European and exporting regions (cf. Appendix B.3). Furthermore, we assume that the weather conditions represented in the investment decision correspond to those in the long-run equilibrium, which is an abstraction, as actual weather patterns are subject to climate change and long-term shifts. Nevertheless, even under these simplifying assumptions, the model highlights significant effects of inter-annual weather variability, for example, regarding the LCOH and the VSS. The framework also reveals structural relationships, such as the fact that some costly LTCs are preferred due to more favorable weather profiles.

Further assumptions relate to market and system boundaries. Our approach determines LTC prices solely based on stochastic LCOH, whereas in the real world, prices may include security premia and be influenced by asset cost uncertainties and other factors. We also acknowledge that not accounting for heterogeneity of renewable yields within individual European countries could lead to an underestimation of additional system costs through autarky, given the limited land available for renewable energies in Europe. Furthermore, our analysis assumes no risk of severe disruption originating within Europe.

3.6. Conclusion

This paper presents a comprehensive stochastic modeling approach to analyze the cost-optimal design and operation of a decarbonized European energy system, with a particular focus on the integration of hydrogen imports. By extending the HYEBRID model to incorporate inter-annual weather variability and various import risk mitigation strategies, this research provides crucial insights into the complexities of achieving energy security in a climate-neutral future.

Methodologically, this work introduces a stochastic framework for determining the LCOH for non-European exporters, ensuring robust asset configurations and LTC pricing across diverse weather patterns. The LCOH estimates then inform the stochastic HYEBRID model, which simulates the European hydrogen and electricity system's investment and dispatch decisions under weather uncertainty. The stochastic representation of weather yields a significant advantage, quantified by a 35% reduction in total system costs compared to deterministic

planning using an average weather year. A pivotal finding from this modeling is the imperative for a substantial increase in European hydrogen storage capacity, considerably exceeding previous estimates.

Addressing a critical research gap, this study explicitly quantifies the economic implications of hydrogen exporter disruptions and various mitigation strategies that reduce the impact of disruptions. The analysis suggests that the cost-optimal scenario *naive planning*, with its highly concentrated import market (HHI 4,800), poses significant supply risks. *Diversification* via stricter HHI targets reduces concentration but incurs higher LTC procurement costs. Conversely, reducing import volumes by increasing domestic production also raises system costs, shifting the burden to domestic infrastructure. The non-linear interplay between mitigation strategies suggests a balanced approach that can partially offset diversification costs.

This study yields key policy implications for Europe’s energy security. Long-term planning should robustly analyze hydrogen import costs and potentials and incorporate production variability. Policymakers should integrate supply disruption risks into exporter selection and the development strategies to enhance security and cost-effectiveness. The relationship between the additional costs of autarky and the perceived disruption probabilities of exporters provides a first quantitative benchmark for this trade-off, demonstrating that the cost premium for full autarky can be justified. These insights are vital for informing infrastructure investment and shaping future contractual frameworks to promote long-term supply security.

Despite its significant contributions, this research should be interpreted in light of several limitations. Key modeling assumptions include the existence of complete markets for the stochastic optimization, a simplified weather representation using clustering, and the determination of LTC prices based solely on stochastic LCOH, omitting real-world factors like security premia. The limitations point to valuable directions for future research. Future work could enhance the robustness of our analysis by integrating disruption risk directly into the investment stage of the stochastic optimization and by conducting broader sensitivity analyses on the LCOH calculations. Additionally, investigating alternative LTC designs and the impact of dispatch-stage weather variability that deviates from investment-stage assumptions would provide further valuable insights.

4. Optimal Bidding of Uncertain Renewable Electricity in Sequential Markets – Implications of Risk Aversion and Imperfect Competition

4.1. Introduction

Electricity markets balance supply and demand through sequential markets. These involve a day-ahead market for forward scheduling, followed by intraday and balancing markets. Positions taken in the day-ahead market can be adjusted in the intraday market, which allows continuous trading close to delivery (EPEX SPOT SE, 2025a). The intraday market plays an increasingly important role in absorbing fluctuations of variable renewable energy sources (RES), as the share of RES increases. In principle, sequential trading allows market participants to incorporate updated information over time, improving efficiency under uncertainty (Ito and Reguant, 2016). However, it also creates strategic opportunities. For example, a renewable energy (RE) producer expecting a certain output may bid conservatively in the day-ahead market, then increase quantities in the intraday market if forecasts improve to abate high balancing costs. Economic theory predicts that, in frictionless settings, prices across stages should converge in expectation. Yet, empirical studies show systematic price differences between the day-ahead and intraday market, so-called forward premia, which can emerge from the use of market power (Borenstein et al., 2008, Ito and Reguant, 2016, Saravia, 2003). Besides market power, another explanation for the emergence of forward premia could be the risk perception of RE producers influencing bidding behavior on the day-ahead market (Botterud et al., 2010).

While existing research has studied forward premia and strategic bidding, these analyses often rely on simplified assumptions about risk preferences and market structure (Allaz, 1992, Ito and Reguant, 2016). We address this gap by analyzing how risk aversion, the degree of flexibility among conventional producers, and heterogeneity among RE producers jointly influence the bidding behavior of RE producers in sequential electricity markets. We develop a stylized analytical model of competition between RE and conventional producers in two sequential stages. The first stage represents the day-ahead market, where producers submit bids before actual renewable output is known. The second stage corresponds to the intraday market, where uncertainty is resolved and producers can adjust their positions based on realized generation.

The findings reveal that risk-averse RE producers in an oligopolistic setting withhold more than risk-neutral producers in the first stage, which increases forward premia. The premium rises with the degree of risk aversion, especially when demand is sufficiently high relative to expected RE production and when conventional supply is inflexible. Limited flexibility among conventional producers amplifies the welfare losses associated with risk-averse behavior. Finally, we demonstrate that fringe producers can benefit from the market power exerted by risk-averse oligopolists, reshaping the distribution of rents.

This work contributes to the literature on strategic bidding in sequential electricity markets by focusing on the interaction between risk aversion, uncertainty in RE generation, and market power. A first line of research studies forward contracting and strategic behavior in sequential markets. The foundational work by Allaz and Vila (1993) shows that firms can use forward contracts to commit output strategically, thereby mitigating market power and promoting more competitive outcomes in subsequent spot markets. Building on this, Ito and Reguant (2016) develop a two-stage model showing that market power and limited arbitrage can jointly generate systematic forward premia. Using microdata from the Iberian market, they find that dominant firms withhold in the day-ahead market, while fringe producers exploit price differences. They show that enabling full arbitrage reduces consumer prices but may not improve welfare if market power persists in the intraday market. A similar contribution by Knaut and Obermüller (2016) shows that withholding by RE producers declines with increasing competition and disappears under perfect competition. The model further illustrates that the steepness of the intraday supply curve reduces withholding, and that welfare losses arise primarily when the steepness is high relative to the steepness in the day-ahead market, and when the renewable sector is concentrated. Obermüller (2017) shows that weather-related uncertainty drives withholding, and thus, forward premia in the German market. However, the aforementioned studies do not consider risk aversion. Crampes and Renault (2021) address this by showing that risk aversion and supply inflexibility jointly shape forward premia, with forward contracting and operational flexibility acting as substitutes in managing demand risk. Limited flexibility, in turn, constrains efficient risk sharing and amplifies welfare losses.

Beyond theoretical models, some empirical studies confirm that forward premia in electricity markets are often driven by strategic behavior and market power. Borenstein et al. (2008) show that observed premia in California cannot be fully attributed to estimation errors or transaction costs. Instead, their findings point to market power as a likely explanation. Similar results have been reported for other electricity markets: Longstaff and Wang (2004) find persistent forward premia in the Pennsylvania-New Jersey-Maryland (PJM) market, Hadsell (2008) documents systematic price differentials between day-ahead and real-time prices in New England, and Bowden et al. (2009) report similar patterns for the Midwestern United States wholesale electricity market.

While the above literature focuses on strategic interactions in sequential markets and the role of market power, a complementary strand emphasizes risk-related explanations for forward premia in electricity markets. Bessembinder and Lemmon (2002) develop a general equilibrium model showing that forward premia in electricity markets emerge from the net hedging pressure of risk-averse market participants under demand uncertainty. Retailers, seeking to insure against high spot prices, tend to take long forward positions, whereas producers, aiming to protect against low spot prices, take short positions. The resulting net hedging pressure determines both the sign and magnitude of the premium, with its absolute value increasing in demand volatility and the convexity of production costs. Under perfect competition or risk neutrality, the premium vanishes. Schwenen and Neuhoff (2024) find that stronger negative covariance between renewable output and spot prices reduces hedging needs of conventional generators and increases forward premia. Bunn and Chen (2013) investigate drivers of forward premia in the British market and show that they are driven more by behavioral factors such as reaction to past premia rather than fundamental factors.

Our analysis is based on the research approach and the findings of Ito and Reguant (2016) and Knaut and Obermüller (2016). We contribute to the literature in three key ways. First, we extend the theoretical model by explicitly incorporating risk aversion into the bidding rationale of RE producers. Second, we analyze how risk-averse RE producers adjust their bids in response to differences in the flexibility of conventional producers. Third, we introduce heterogeneity among RE producers, allowing for both fringe and risk-averse oligopolistic RE producers. In particular, we quantify impacts on bids, price premia, rent distributions, and overall welfare.

4.2. Analytical model

This section introduces the stylized two-stage model of sequential electricity markets in which RE producers with uncertain output and conventional producers trade electricity. The first stage is associated with trading in the day-ahead market, while the second stage corresponds to the intraday market. The framework builds directly on the approach of Ito and Reguant (2016) and Knaut and Obermüller (2016), extending it by incorporating risk-averse bidding behavior and altering the composition of RE producers.

4.2.1. Model setup

We consider a market in which N RE producers submit bids in the first stage and adjust their positions in a subsequent second stage where the uncertainty is resolved. The demand side is modeled as deterministic and perfectly inelastic with total demand d . Conventional producers act as perfectly competitive and

have positive marginal costs. We abstract from purely financial market participants: no arbitrageurs trade between the two stages. Consequently, expected price differences across stages are not eliminated by arbitrage and may arise endogenously. Together, the conventional producers form a linear marginal cost curve:

$$MC(q) = a \cdot q + b \quad (4.1)$$

where a represents the slope of the cost curve and b represents the intercept. Depending on the case, we differentiate between the slope of the first stage a_1 and the second stage a_2 . We assume that RE producers have zero marginal costs.

Each RE producer i allocates its production between the two stages. In the first stage, RE producers face production uncertainty, modeled as a normally distributed random variable:

$$Q_i \sim \mathcal{N}(\mu_{Q_i}, \sigma_{Q_i}^2), \quad (4.2)$$

where Q_i is the output of the RE producer i , with an expected value μ_{Q_i} and standard deviation σ_{Q_i} . We abstract from withholding in the second market stage; that is, the total production must be sold after the second stage. The bid of an RE producer i in the first stage is given by q_{i1} and the aggregate bid of all symmetric RE producers by $q_1 = \sum_i q_{i1}$.

The market-clearing prices of both stages are derived from the intersection of the respective marginal cost curves and residual demand. In the first stage, conventional producers plan to produce $d - q_1$, and in the second stage, they adjust to meet the residual demand $d - Q$. We assume that the second-stage cost curve pivots around the clearing point of the first stage with slope a_2 . The term $(a_1 - a_2) \cdot (d - q_{i1} - (N - 1) \cdot q_{j1})$ in Equation 4.3b shifts the second-stage cost curve to the clearing point of the first stage.

The total profit of an RE producer i consists of revenues earned in the first and second stage. These are defined as follows:

$$\pi_{i1} = (a_1 \cdot (d - q_{i1} - (N - 1) \cdot q_{j1}) + b) \cdot q_{i1}, \quad (4.3a)$$

$$\pi_{i2} = (a_2 \cdot (d - N \cdot Q_i) + b + (a_1 - a_2) \cdot (d - q_{i1} - (N - 1) \cdot q_{j1})) \cdot (Q_i - q_{i1}), \quad (4.3b)$$

$$\pi_i = \pi_{i1} + \pi_{i2} \quad (4.3c)$$

with prices:

$$p_1(q_1) = a_1 \cdot (d - q_1) + b \quad (4.4a)$$

$$p_2(q_1) = a_2 \cdot (d - Q) + b + (a_1 - a_2) \cdot (d - q_1) \quad (4.4b)$$

RE producers bid a quantity in the first stage, which maximizes their utility U_i . In a risk-neutral setting, the utility equals the total expected profits. Our central contribution is to extend this established framework by analyzing how

risk-averse preferences affect bidding strategies. Risk-averse preferences of RE producers are modeled using a mean-variance utility function (cf. Markowitz (1991)). In this setting, profit variance enters negatively in the utility function and is weighted with the degree of risk aversion λ .

$$U_i = \mathbb{E}[\pi_i] - \frac{\lambda}{2} \cdot \text{Var}(\pi_i). \quad (4.5)$$

This approach is commonly used when assuming symmetric profit distributions. However, as q_{i1} enters quadratically into π_1 and π_2 , the expected profit distribution is not necessarily symmetric. In classical portfolio theory, a standard metric for risk aversion with asymmetric profit distribution is the conditional value at risk (CVaR), which takes tail risk into account (Rockafellar et al., 2000). However, we cannot solve the CVaR approach analytically, as the inverse cumulative density function of the profit is required. An approximation with the profit's skewness and kurtosis is also difficult to solve analytically, as terms above the fifth degree would result. Our numerical results indicate that the CVaR correlates strongly with variance. Therefore, we argue that using variance as a risk metric is a valid approximation to the CVaR approach (cf. Appendix C.1).

4.2.2. Model specification

Our approach aims to investigate optimal bidding strategies of RE producers under risk aversion and imperfect competition. To extract the effects, we compare the results to optimal bids under risk neutrality and vary the degree of competition between RE producers. In addition, we consider the effect of two other market conditions. One is the degree of flexibility of conventional producers to adjust their schedules on short notice. The other is the degree of homogeneity across RE producers. The two market conditions are specified below, and Table 4.1 summarizes which assumptions are made in each case under investigation. A combination of the two market specifications is omitted due to limited additional effects (cf. Section 4.4).

Table 4.1.: Overview of modeled cases.

Assumption	Case 1 (4.3.1)	Case 2 (4.3.2)	Case 3 (4.3.3)
Conventional producer flexibility	Flexible ($a_1 = a_2$)	Inflexible ($a_2 > a_1$)	Flexible ($a_1 = a_2$)
Composition of RE producers	Homogeneous	Homogeneous	Heterogeneous

Conventional producer flexibility

In real-world electricity markets, the number of conventional power plants usually decreases as trading approaches delivery. Technical constraints on certain types of power plants prevent them from adjusting their production schedule on short

notice. Another contributing factor is transaction costs. To account for the varying degree of participation in stage two, we define case 2 in which the slope of the second-stage cost curve exceeds the slope of the first-stage cost curve, i.e., $a_2 > a_1$. This setup enables us to investigate how the lack of flexibility in the second stage impacts the bidding behavior of RE producers under both risk neutrality and risk aversion.

Composition of RE producers

In the basic model setup, we assume equally large RE producers (case 1 and case 2). We relax this simplification by splitting the total amount of renewable electricity Q into two ownership categories (case 3). We interpret one part of Q as being owned by oligopolistic RE producers, who can exert market power. The number of oligopolistic RE producers is M . The quantity of renewable electricity from all oligopolistic producers is Q_M , and the quantity of an individual oligopolistic producer is Q_k . The remainder of renewable electricity is assumed to be owned by RE producers of atomistic size and thus represents a competitive fringe, unable to exert market power. We define this quantity as Q_F . The parameter s defines the share that splits Q into a quantity under oligopolistic and fringe producers:

$$Q_M = s \cdot Q \quad (4.6a)$$

$$Q_F = (1 - s) \cdot Q \quad (4.6b)$$

By assuming that a share of total renewable electricity bids the expected production μ_Q , we mimic a real-world setting in the German spot market. In the German market, a significant share of renewable electricity is marketed by transmission system operators (TSOs). The renewable energy regulation (§2 EEG) requires TSOs to offer the expected forecasted renewable electricity in the day-ahead market, so that deviations in quantities from the intraday market are minimized (BMJV, 2025). In our stylized analytical model, this bidding behavior corresponds to risk-neutral bidding of a competitive fringe. Against this background, Equation (4.7) defines the profit function of an oligopolistic RE producer k .

$$\begin{aligned} \pi_k = & [a_1 \cdot (d - q_{k1} - (M-1) \cdot q_{l1} - (1-s) \cdot \mu_Q) + b] \cdot q_{k1} \\ & + [a_2 \cdot (d - Q) + b] \\ & + (a_1 - a_2) \cdot (d - q_{k1} - (M-1) \cdot q_{l1} - (1-s) \cdot \mu_Q) \cdot (Q_k - q_{k1}) \end{aligned} \quad (4.7)$$

An analysis of the market concentration for the direct marketing of solar PV and wind capacities in Germany indicates the potential to exert market power. The top three wind marketers held 26% of the total installed wind capacity in 2024, while the top ten wind marketers held 63%. The market concentration for solar

PV is significantly lower, with 15% marketed by the top three, and 25% marketed by the top ten solar PV marketers, respectively (Energie & Management, 2025).

4.2.3. Numerical assumptions

To visualize subsequent results, we feed the analytical model with numerical assumptions on each parameter. We choose a set of assumptions that reflects a common condition in many markets with moderate expected renewable output relative to demand.

Table 4.2.: Numerical assumptions of parameters.

Parameter	a_1	b	μ_Q	σ_Q	d
Value	0.4	20	40	6	100

Beyond techno-economic parameters, we assume a degree of risk aversion among RE producers, which we derive using the certainty-equivalent method. This method defines a guaranteed profit π_{gi} , an RE producer i would be indifferent between accepting or rejecting it compared to an uncertain profit π_i (cf. Equation 4.8).

$$\pi_{gi} = E[\pi_i] - \frac{1}{2} \cdot \lambda \cdot \sigma_{\pi_i}^2 \quad (4.8)$$

The calculation of the degree of risk aversion is described in Appendix C.2.

4.3. Results

This section presents the model results of the three cases defined in subsection 4.2.2. Crucially, for all cases, we establish the risk-neutral solutions ($\lambda = 0$) by replicating the established literature as a baseline and compare these to our main results under risk aversion ($\lambda > 0$). We begin with the first case and analyze homogeneous risk-averse RE producers facing equal supply cost curves in the two market stages. We then introduce different slopes of the supply cost curves in the first and second stages to study the effects of inflexible conventional production as delivery approaches. In a third case, we add RE producer heterogeneity by distinguishing between oligopolistic and fringe RE producers. For all three model setups, we calculate the optimal bidding strategy for RE producers and resulting market prices. Finally, we evaluate the implications of bidding strategies in terms of consumer and producer surplus as well as welfare.

4.3.1. Case 1: Risk-averse renewable oligopoly: flexible conventional production and homogeneous composition of RE producers

In the first model specification, we assume identical cost functions of conventional producers in the two market stages ($a_1 = a_2 = a$) and a homogeneous composition of RE producers. Proposition 1 shows the optimal bidding strategy for an RE producer in the first stage.

Proposition 1. *Under the above assumptions, the profit-maximizing quantity for a risk-averse renewable oligopolist in the first stage is q_{i1}^* .*

$$q_{i1}^* = \frac{\mu_Q N + \lambda[\sigma_Q^2(2\mu_Q a - ad - b)]}{N(N + \lambda\sigma_Q^2 a + 1)} \quad (4.9)$$

Proof. The profit function of the RE producer i is described in Eq. (4.3). Given $a_1 = a_2$, we can simplify the profit function for the RE producer i to:

$$\pi_i = [a \cdot (d - q_{i1} - (N - 1) \cdot q_{j1}) + b] \cdot q_{i1} + [a \cdot (d - N \cdot Q_i) + b] \cdot (Q_i - q_{i1}) \quad (4.10)$$

The profit-maximizing quantity results from the derivative of the utility function (Eq. (4.5)) with respect to q_{i1} :

$$\frac{dU_i}{dq_{i1}} = \frac{d\mathbb{E}(\pi_i)}{dq_{i1}} - \frac{\lambda}{2} \frac{d\text{Var}(\pi_i)}{dq_{i1}} \quad (4.11)$$

with

$$\frac{d\mathbb{E}(\pi_i)}{dq_{i1}} = a \cdot (N\mu_{Q_i} - 2q_{i1} - (N - 1)q_{j1}) \quad (4.12)$$

and

$$\frac{d\text{Var}(\pi_i)}{dq_{i1}} = 2N\sigma_{Q_i}^2 a (-2\mu_{Q_i} Na + Naq_{i1} + ad + b) \quad (4.13)$$

Setting the derivative of U_i to zero and solving for q_{i1}^* results in the profit-maximizing first-stage bid of the RE producer i :

$$q_{i1}^* = \frac{2\mu_{Q_i} N^2 \sigma_{Q_i}^2 a \lambda + \mu_{Q_i} N - N \sigma_{Q_i}^2 a d \lambda - N \sigma_{Q_i}^2 b \lambda - (N - 1) q_{j1}}{N^2 \sigma_{Q_i}^2 a \lambda + 2}. \quad (4.14)$$

Applying the symmetry assumption ($q_{i1} = q_{j1}$, $\mu_Q = \mu_{Qi} * N$, and $\sigma_Q = \sigma_{Qi} * N$), we obtain Eq. (4.9):

$$q_{i1}^* = \frac{\mu_Q N + \lambda[\sigma_Q^2(2\mu_Q a - ad - b)]}{N(N + \lambda\sigma_Q^2 a + 1)}$$

Since $\lambda > 0$ and $a > 0$, the second derivative of U_i is negative (Eq. (4.15)).

$$\frac{d^2 U_i}{dq_{i1}^2} = -2a - \frac{\lambda}{2} 2N^2 a^2 \sigma_{Qi}^2 \quad (4.15)$$

Therefore, q_i^* is the profit-maximizing quantity. $\square$

For the aggregated first-stage bid of all RE producers q_1^* , the term N in the denominator of Eq. (4.9) cancels out. In the case of perfect competition ($N \rightarrow \infty$), it can be shown that $N \cdot q_{i1}^*$ converges to the expected value μ_Q (Eq. (4.16)). This implies that risk aversion has no effect on bidding behavior under perfect competition if the supply curve is linear and risk aversion is modeled using a mean-variance utility function.

$$\lim_{N \rightarrow \infty} N \cdot q_{i1}^* = \lim_{N \rightarrow \infty} \frac{\mu_Q N^2}{N^2} = \mu_Q \quad (4.16)$$

Corollary 1. *Under risk aversion and flexible conventional production ($a_1 = a_2 = a$), the first-stage equilibrium price is*

$$p_1^* = a(d - q_1^*) + b, \quad \text{where } q_1^* = \frac{\mu_Q N + \lambda\sigma_Q^2(2a\mu_Q - ad - b)}{N + \lambda\sigma_Q^2 a + 1}. \quad (4.17)$$

The expected forward premium, defined as $FP := \mathbb{E}[p_1^ - p_2(Q)]$, is positive and strictly increasing in the risk aversion parameter λ whenever*

$$d > \mu_Q \frac{N+2}{N+1} - \frac{b}{a}. \quad (4.18)$$

Since p_1^ is linearly related to q_1^* and the second-stage price does not depend on q_1^* , condition (4.18) also implies that q_1^* is strictly decreasing in λ .*

Proof. By plugging in the optimal first-stage quantity of Eq. (4.9) into Eq. (4.4a), we obtain the first-stage equilibrium price. The subtraction of the expected second-stage price from the first-stage equilibrium price results in the expected forward premium (Eq. (4.19)).

$$\begin{aligned}
 FP &= p_1^* - \mathbb{E}[p_2] \\
 &= a \left[d - \frac{\mu_Q N + \lambda \sigma_Q^2 (2\mu_Q a - ad - b)}{N + \lambda \sigma_Q^2 a + 1} \right] + b - \mathbb{E}[a(d - Q) + b] \\
 &= a \left[\mu_Q - \frac{\mu_Q N + \lambda \sigma_Q^2 (2\mu_Q a - ad - b)}{N + \lambda \sigma_Q^2 a + 1} \right]
 \end{aligned} \tag{4.19}$$

To model the impact of risk aversion on the forward premium, we take the derivative of the forward premium FP with respect to λ :

$$\begin{aligned}
 \frac{\partial FP}{\partial \lambda} &= -a \cdot \frac{d}{d\lambda} \left(\frac{\mu_Q N + \lambda \sigma_Q^2 (2\mu_Q a - ad - b)}{N + \lambda \sigma_Q^2 a + 1} \right) \\
 &= -a \cdot \frac{\sigma_Q^2 \left[(2\mu_Q a - ad - b)(N + \lambda \sigma_Q^2 a + 1) - a\mu_Q N - a\lambda \sigma_Q^2 (2\mu_Q a - ad - b) \right]}{(N + \lambda \sigma_Q^2 a + 1)^2} \\
 &= -a \cdot \frac{\sigma_Q^2 [(2\mu_Q a - ad - b)N + (2\mu_Q a - ad - b) - a\mu_Q N]}{(N + \lambda \sigma_Q^2 a + 1)^2}
 \end{aligned} \tag{4.20}$$

As the denominator is positive, the sign of the derivative is determined by the numerator. The forward premium rises with the degree of risk aversion if:

$$\frac{\partial FP}{\partial \lambda} > 0 \iff -a \cdot \sigma_Q^2 [(2\mu_Q a - ad - b)(N + 1) - a\mu_Q N] > 0 \tag{4.21}$$

Together with $a > 0$ and $\sigma_Q^2 > 0$:

$$(2\mu_Q a - ad - b)(N + 1) - a\mu_Q N < 0 \tag{4.22}$$

Reformulate:

$$(2\mu_Q a - ad - b)(N + 1) < a\mu_Q N \tag{4.23a}$$

$$2\mu_Q a(N + 1) - ad(N + 1) - b(N + 1) < a\mu_Q N \tag{4.23b}$$

$$-ad(N + 1) < a\mu_Q N - 2\mu_Q a(N + 1) + b(N + 1) \tag{4.23c}$$

$$d > \mu_Q \frac{N + 2}{N + 1} - \frac{b}{a} \tag{4.23d}$$

□

If the demand d is sufficiently large compared to expected renewable output μ_Q , the forward premium rises with the degree of risk aversion. The rationale is that risk-averse producers withhold even more in the first stage to reduce profit variance. This leads to an increase in p_1^* , while the expected second-stage price remains independent of the first-stage bid.

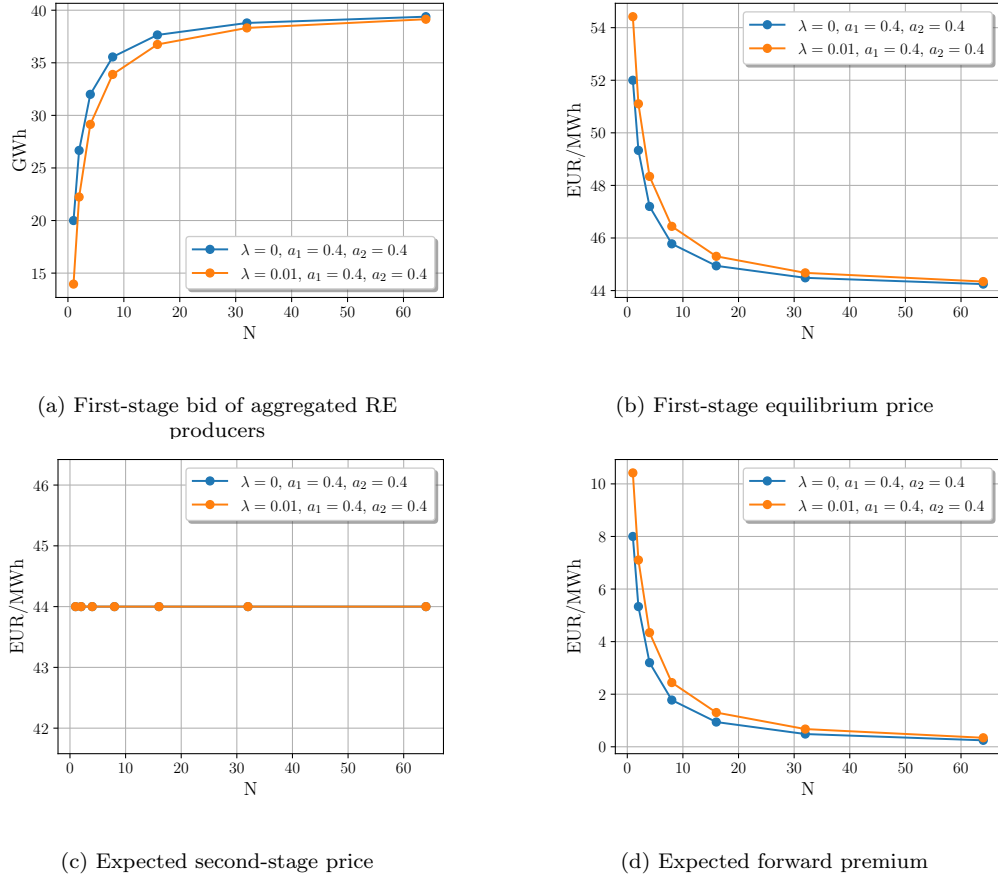


Figure 4.1.: Results under identical supply curve slopes in stage one and two for risk-averse and risk-neutral producers: bids, prices, and forward premium

Note: N is the number of symmetric RE producers. λ is the coefficient of risk aversion. Results are based on a numerical example with the following parameter values: $a_1 = a_2 = a = 0.4$, $b = 20$, $d = 100$, $\mu_Q = 40$ and $\sigma_Q = 6$. The blue line represents the risk-neutral case, whereas the orange line corresponds to risk-averse RE producers.

Figure 4.1 illustrates the effects of risk aversion ($\lambda > 0$) in comparison to risk neutrality ($\lambda = 0$) in a setting with N symmetric RE producers and identical cost curves in both market stages ($a_1 = a_2 = a$). Figure 4.1 (a) reveals that risk-averse producers (orange line) withhold more quantity in the first stage compared to the risk-neutral case (blue line). This behavior arises because withholding reduces the variance of profits, which risk-averse producers seek to avoid. As a result,

the aggregate forward supply decreases. This extends earlier findings from the literature (Ito and Reguant, 2016, Knaut and Obermüller, 2016). As the number of RE producers N increases and competition intensifies, the effect diminishes.

Figure 4.1 (b) demonstrates the effect of the bidding behavior on prices: the reduced first-stage bid leads to higher first-stage market-clearing prices, *ceteris paribus*. As risk-averse producers bid lower quantities to limit profit variability, aggregate supply decreases, pushing first-stage prices upward. Thus, risk aversion systematically raises first-stage prices in the presence of market power.

In contrast, Figure 4.1 (c) shows that the expected second-stage price remains unchanged under risk aversion (the blue and orange lines overlap). This holds under two conditions: the second-stage cost curve is identical to the first-stage cost curve, and RE producers must sell their entire generation in the second-stage market.

Figure 4.1 (d) displays the expected forward premium. The premium increases with the degree of risk aversion, as strategic withholding in the first stage shifts first-stage prices upward. In this sense, risk-averse behavior by symmetric RE producers in an oligopoly induces a higher premium than under risk neutrality.⁹ However, similar to the case assuming risk-neutral RE producers, the premium converges to zero under perfect competition.

4.3.2. Case 2: Risk-averse renewable oligopoly: inflexible conventional production and homogeneous composition of RE producers

In this case, we introduce a decrease in flexibility of the conventional production in the second stage. We model this by increasing the slope of the second-stage cost curve relative to that of the first-stage cost curve ($a_2 > a_1$). This reflects more realistic market conditions, where second-stage participation is often limited. The following proposition characterizes the optimal first-stage bid under risk aversion for a single RE producer i :

Proposition 2. *The profit-maximizing quantity for a risk-averse RE oligopolist in the first stage is presented in Eq. (4.24):*

$$q_{i1}^* = \frac{A + \lambda B}{C + \lambda D} \quad (4.24)$$

⁹As already shown, this result holds if the demand is sufficiently large compared to expected renewable output (cf. Corollary 1).

where the components are defined as follows:

$$\begin{aligned}
A &= \mu_Q N (Na_2 + a_2 - a_1) \\
B &= \sigma_Q^2 \left(2\mu_Q Na_2^2 - 2\mu_Q a_1 a_2 + 2\mu_Q a_2^2 - Na_1 da_2 - Nba_2 + a_1^2 d + a_1 b - a_1 da_2 - ba_2 \right) \\
C &= N(N^2 a_2 + Na_2) \\
D &= N \left(\sigma_Q^2 \left(-Na_1 a_2 + 2Na_2^2 + a_1^2 - 3a_1 a_2 + 2a_2^2 \right) \right)
\end{aligned}$$

Proof. See Appendix C.3.1. $\square$

In the limit of perfect competition ($N \rightarrow \infty$), $N \cdot q_{i1}^*$ converges to the expected value μ_Q , similar to (4.16). Hence, even in the presence of inflexible conventional producers, risk aversion has no effect on bidding behavior under perfect competition given the assumptions stated in 4.2.

Corollary 2. *Under the above assumptions, the optimal first-stage bid of a monopolist decreases in the degree of risk aversion if $\mu_Q < \frac{2a_2(a_1 d + b)}{a_1(4a_2 - a_1)}$. The expected forward premium increases with the degree of risk aversion, if the condition holds.¹⁰*

Proof. From Eq. 4.23, we learn that the condition under which risk aversion lowers the first-stage bid relaxes with higher N. The same holds for the following proof. To simplify the calculation, we look at the most conservative condition, assuming $N = 1$.

$$\frac{dq_{i1}^*}{d\lambda} = \frac{BC - AD}{(2a_2 + \lambda D)^2} \quad (4.25)$$

with:

$$B = \sigma_Q^2 [\mu_Q(4a_2^2 - 2a_1 a_2) + (-2a_1 da_2 - 2ba_2 + a_1^2 d + a_1 b)] \quad (4.26a)$$

$$C = 2a_2 \quad (4.26b)$$

$$A = \mu_Q(2a_2 - a_1) \quad (4.26c)$$

$$D = \sigma_Q^2(2a_2 - a_1)^2 \quad (4.26d)$$

See Appendix C.3.2 for reformulation of $\frac{dq_{i1}^*}{d\lambda}$.

$\frac{dq_{i1}^*}{d\lambda} < 0$ if:

$$\mu_Q < \frac{2a_2(a_1 d + b)}{a_1(4a_2 - a_1)}, \quad (4.27)$$

The condition in Eq. 4.27 holds under common market conditions. We further test two edge cases, i) $a_2 = a_1$ and ii) $a_2 \gg a_1$:

For i), the expression becomes the same as in Eq. 4.23:

¹⁰It can be shown that this condition becomes weaker for higher N.

$$\mu_Q < \frac{2(a_1d + b)}{3a_1} \quad (4.28)$$

For ii), the expression becomes:

$$\mu_Q < \frac{da_1 + b}{2a_1} \quad (4.29)$$

Given that q_1 decreases in λ , prices and the expected forward premium become:

$$p_1(q_1^*) = a_1(d - q_1^*) + b \quad (4.30a)$$

$$\mathbb{E}(p_2(q_1^*, q_2)) = a_2(d - \mu_Q) + b + (d - q_1^*)(a_1 - a_2) \quad (4.30b)$$

$$\mathbb{E}(FP) = a_2(\mu_Q - q_1^*) \quad (4.30c)$$

Since the expected forward premium is a linear function of q_1^* , and $a_2 > 0$, the expected forward premium increases in the degree of risk aversion, if the condition in Eq. 4.27 holds.

□

Similar to subsection 4.3.1, risk aversion reduces the first-stage bid if demand is sufficiently large compared to expected renewable output.

Corollary 3. *Under risk aversion and imperfect competition, the optimal first-stage bid increases with lower flexibility of conventional production in the second stage, represented by an increase in a_2 , if the condition in Equation (4.33) holds. A higher first-stage bid decreases the first-stage price. However, the second-stage price decreases more than the first-stage price, since $a_2 > a_1$. Thus, we can conclude that the expected forward premium increases with reduced flexibility under the aforementioned condition.*

Proof.

$$q_{i1}^* = \frac{\mu_Q(2a_2 - a_1) + \lambda \left[\sigma_Q^2 (4\mu_Q a_2^2 - 2\mu_Q a_1 a_2 - a_1 d a_2 - b a_2 + a_1^2 d + a_1 b) \right]}{2a_2 + \lambda \left[\sigma_Q^2 (-a_1 a_2 + 2a_2^2 + a_1^2 - 3a_1 a_2 + 2a_2^2) \right]} \quad (4.31)$$

From the following definitions:

$$A = \mu_Q(2a_2 - a_1) + \lambda\sigma_Q^2(4\mu_Q a_2^2 - 2\mu_Q a_1 a_2 - a_1 d a_2 - b a_2 + a_1^2 d + a_1 b) \quad (4.32a)$$

$$B = 2a_2 + \lambda\sigma_Q^2(4a_2^2 - 4a_1 a_2 + a_1^2) \quad (4.32b)$$

$$A' = 2\mu_Q + \lambda\sigma_Q^2(8\mu_Q a_2 - 2\mu_Q a_1 - a_1 d - b) \quad (4.32c)$$

$$B' = 2 + \lambda\sigma_Q^2(8a_2 - 4a_1) \quad (4.32d)$$

follows:

$$\frac{dq_{i1}^*}{da_2} > 0 \iff \frac{A'B - AB'}{B^2} > 0 \iff A'B - AB' > 0. \quad (4.33)$$

The condition at which the corollary holds is highly complex. However, we show numerically that it holds even under extreme parameterization in the degree of risk aversion and for various levels of expected RE production (cf. Figure 4.2).

□

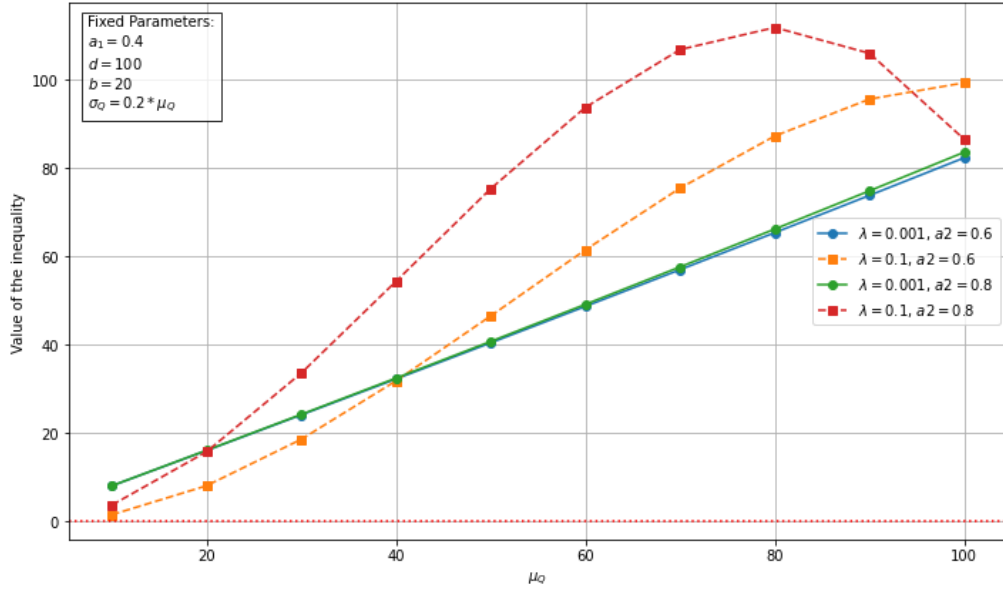
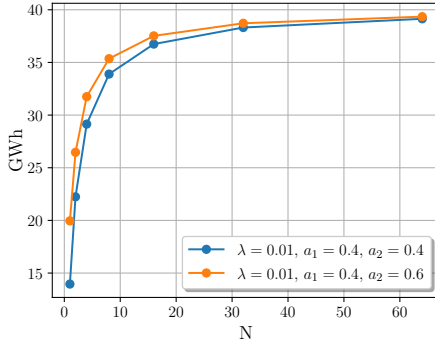
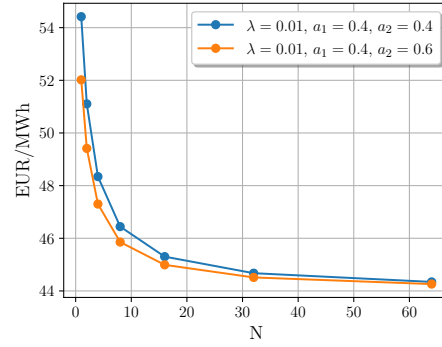


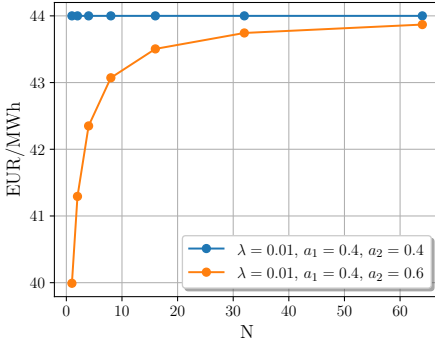
Figure 4.2.: Numerical assessment of inequality 4.33.



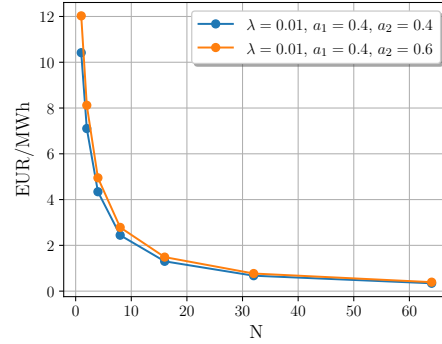
(a) First-stage bid of aggregated RE producers



(b) First-stage equilibrium price



(c) Expected second-stage price



(d) Expected forward premium

Figure 4.3.: Results under risk aversion and inflexible supply curve: bids, prices, and forward premium.

Note: N is the number of symmetric RE producers. λ is the coefficient of risk aversion. Results are based on a numerical example with the following parameter values: $a_1 = 0.4$, $a_2 = [0.4; 0.6]$, $b = 20$, $d = 100$, $\mu_Q = 40$ and $\sigma_Q = 6$.

Figure 4.3 illustrates the effects of risk aversion ($\lambda > 0$), where the second-stage supply curve is steeper than the first-stage supply curve ($a_2 > a_1$). This setting reflects limited flexibility in the second-stage market, i.e., the intraday market. Figure 4.3 (a) shows that when the second-stage supply is less flexible than in the first stage, producers anticipate higher repurchase costs and withhold less in the forward market compared to the case of flexible conventional producers. Thus the first-stage bids of aggregated RE producers are higher with inflexible conventional producers (orange line above the blue line).

Figure 4.3 (b) demonstrates that the reduced withholding under asymmetric slopes dampens first-stage prices compared to the case of flexible conventional producers. Figure 4.3 (c) highlights the price effect in the second stage. When supply slopes differ, the first-stage price influences the intercept of the second-stage supply curve. Withheld quantities are fully sold in the less flexible second

stage, where they face a steeper slope, resulting in lower second-stage prices. Under perfect competition ($N \rightarrow \infty$), differing slopes have no effect, and prices converge to the competitive outcome. Figure 4.3 (d) shows that under risk aversion, a higher (a_2/a_1) ratio leads to stronger price effects and thus larger premia (orange line above blue line).¹¹

4.3.3. Case 3: Risk-averse renewable oligopoly: flexible conventional production and heterogeneous composition of RE producers

In Cases 1 and 2, all RE producers are treated symmetrically. To approximate real-world German spot-market practice, where TSOs are required to offer the expected output of RE in the day-ahead market, we now assume that a certain share of the total RE generation is marketed based on its expected value. Fringe producers (or TSOs acting on their behalf) bid their expected generation in the first stage. The remaining share is supplied by a group of symmetric, oligopolistic RE producers.

This hybrid setup better reflects actual market conditions, where M denotes the number of oligopolistic RE producers. The parameter s defines the share of total RE output subject to strategic behavior. Similar to Case 1, we assume flexible conventional producers, which implies $a_1 = a_2 = a$.

As the fringe bid is fixed to the expected value $(1-s) \cdot \mu_Q$, the first-stage price is determined as:

$$p_1 = a_1 \cdot (d - q_{k1} - (M-1) \cdot q_{l1} - (1-s) \cdot \mu_Q) + b \quad (4.34)$$

which is structurally equivalent to the price under a symmetric oligopoly from Case 1, after (i) shifting the effective demand intercept by $d \mapsto d - (1-s) \cdot \mu_Q$ and (ii) replacing the number of strategic firms N with M .

Since the fringe bid only shifts the intercept of residual demand, all first-order conditions, and thus all comparative-static results on risk aversion, flexibility, prices, and forward premia, carry over directly from Case 1 under the substitutions $d \mapsto d - (1-s) \cdot \mu_Q$ and $N \mapsto M$. Accordingly, in this hybrid setting with a competitive fringe bidding the expected value $(1-s) \cdot \mu_Q$ in the first stage, the profit-maximizing bid of each oligopolistic RE producer is given by Proposition 1 after the substitutions $d \mapsto d - (1-s) \cdot \mu_Q$ and $N \mapsto M$. Thus, the analytical results from the symmetric case remain applicable, providing a consistent foundation for interpretation.

As in Case 1, we derive numerical results for this setting. The qualitative patterns remain unchanged: risk-averse RE producers reduce their first-stage bids, raising first-stage prices and leading to a positive forward premium. This premium decreases with increasing competition and vanishes in the limit of perfect

¹¹This result holds under Eq. (4.33) (see Corollary 3).

competition. However, a significant distributional effect arises in this framework with respect to the rents of RE producers, discussed in detail in subsection 4.3.5.

4.3.4. Rents and welfare implications of Cases 1 and 2

So far, we have examined how risk aversion and market structure shape the bidding behavior of RE producers, market prices in the first and second stage, and the resulting forward premium. We now turn to the implications of these findings for welfare outcomes and the distribution of rents among market participants, specifically conventional producers, RE producers, and consumers.

Figure 4.4 provides a comprehensive overview of the results. It displays producer surplus (separately for RE and conventional producers), consumer surplus, and total welfare across four scenarios: risk neutrality vs. risk aversion, each under flexible and inflexible conventional producers. At this stage, we focus on the case of symmetric RE producers.

Producer surplus

The total producer surplus consists of the surplus earned by RE producers as well as conventional producers. RE producers sell part of their uncertain output Q in the first stage and the remainder in the second stage. They face no marginal costs and operate under uncertainty. Their expected producer surplus is given by:

$$\mathbb{E}[\Pi_R(q_1)] = p_1 q_1 + \mathbb{E}[p_2(Q - q_1)] \quad (4.35)$$

The expected conventional producer surplus is given by:

$$\mathbb{E}[\Pi_C(q_1)] = p_1(d - q_1) - C_1(q_1) + \mathbb{E}[p_2(q_1 - Q)] - \mathbb{E}[C_2(q_1)] \quad (4.36)$$

Eq. (4.36) defines the expected conventional producer surplus, accounting for both market stages. We obtain the costs in the first stage by integrating over the marginal cost function:

$$C_1(q_1) = \frac{1}{2}a_1(d - q_1)^2 + b(d - q_1) \quad (4.37)$$

The expected cost function for the second stage is:

$$\begin{aligned} \mathbb{E}[C_2(q_1)] = \mathbb{E} \left[\frac{1}{2}a_2(d^2 - 2d\mu + \mu^2 + \sigma^2 - (d - q_1)^2) \right. \\ \left. + (a_1 - a_2)(d - q_1)(q_1 - Q) + b(q_1 - Q) \right] \end{aligned} \quad (4.38)$$

By inserting Eqs. (4.38) and (4.37) in Eq. (4.36) we obtain the conventional producer surplus. By further plugging in the optimal quantity, we can quantify the producer surplus of RE and conventional producers.

Figure 4.4 (a) illustrates the effects of risk aversion and flexibility of conventional producers on the surplus of RE producers. For small values of N , risk aversion leads to lower rents. In our parameterization, the first-stage bid of a risk-averse monopolist is significantly lower than that of a risk-neutral monopolist. This behavior reduces profit variance, but also significantly reduces first-stage revenues. However, as N increases, first-stage bids of RE producers under risk aversion also increase, and their surplus increases to the point at which they cumulatively bid the optimal quantity under a risk-neutral monopoly. From this point onward, the surplus of risk-averse oligopolists is higher than the surplus of risk-neutral ones, as the need to reduce profit variance through lower first-stage bids generates higher overall revenues. Inflexible conventional producers (i.e., $a_2 > a_1$) consistently reduce RE producer surplus, regardless of the degree of risk aversion, as the inflexibility increases first-stage bids.

Figure 4.4 (b) shows that the surplus of conventional producers increases under risk aversion. This is due to higher first-stage prices caused by RE producers' strategic withholding. As with RE producers, conventional producer surplus declines when supply curves are steeper in the second stage, reflecting higher adjustment costs and reduced flexibility. However, as the number of producers increases, the surplus converges across all cases, indicating that market power diminishes and price effects become negligible in the limit of perfect competition.

Consumer surplus

Following standard practice in electricity market modeling, we assume that consumer demand is inelastic. This implies that electricity is consumed in full up to a price threshold defined by the value of lost load (p^{VOLL}), which reflects the maximum willingness to pay for uninterrupted supply. Under this assumption, consumer surplus in the first stage is given by the product of the difference between the value of lost load and the market-clearing price, and the total demand level $((p^{VOLL} - p_1) \cdot d)$ (Knaut and Obermüller, 2016). By substituting the equilibrium first-stage price $p_1(q_1^*) = a_1 \cdot (d - q_1^*) + b$, consumer surplus can be expressed as:

$$CS = (p^{VOLL} - a_1 \cdot d - b + a_1 \cdot q_1^*) \cdot d \quad (4.39)$$

By further plugging in the optimal quantity q_1^* , we can quantify the consumer surplus. As earlier results have shown, the optimal quantity q_1^* , and hence the resulting consumer surplus, depends on the underlying market configuration, such as the degree of risk aversion or the slope asymmetry between the two market stages.

Figure 4.4 (c) illustrates the effects of risk aversion and market structure on consumer surplus. Risk-averse producers strategically withhold quantities in the

first stage to hedge against uncertainty. Prices then increase, leading to a decline in consumer surplus compared to the risk-neutral benchmark. However, consumer surplus increases with a larger number of RE producers, as increased competition reduces market power and puts downward pressure on first-stage prices. This relationship is particularly pronounced under inflexible supply conditions, consistent with findings by Knaut and Obermüller (2016), and it remains robust even when producers are risk-averse. Nevertheless, overall consumer surplus tends to be lower under risk aversion due to reduced first-stage supply and higher first-stage prices.

Welfare

Combining the effects on producer and consumer surplus allows us to assess the implications for overall welfare. Changes in total welfare indicate efficiency losses or gains due to strategic behavior, risk aversion, or market structure. The overall expected welfare can be defined as:

$$\mathbb{E}[W(q_1)] = \mathbb{E}[\Pi_R(q_1)] + \mathbb{E}[\Pi_C(q_1)] + \mathbb{E}[CS(q_1)] \quad (4.40)$$

Corollary 4. *When supply slopes are identical ($a_1 = a_2$), risk aversion has no effect on overall welfare compared to the risk-neutral case. A steeper second-stage supply curve ($a_2 > a_1$) reduces welfare relative to the flexible benchmark due to higher adjustment costs. Under risk aversion, welfare declines further in oligopolistic settings, as producers withhold more and amplify inefficiencies.*

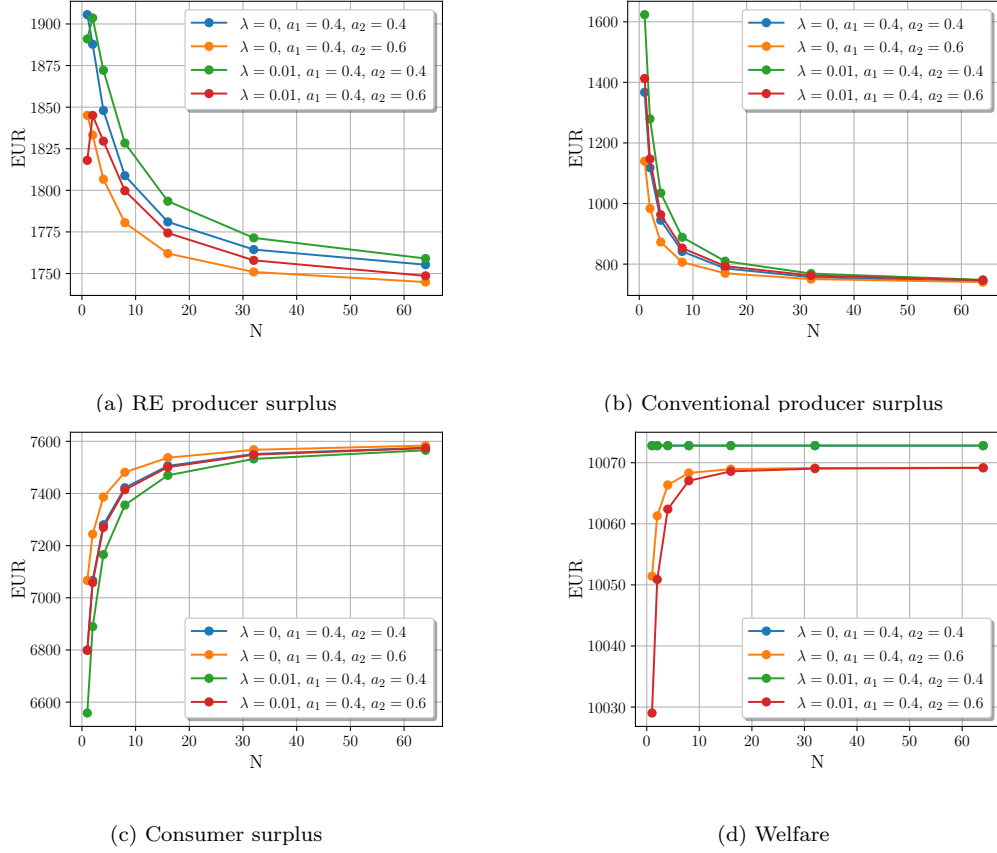


Figure 4.4.: Results under risk aversion and (in)flexible supply curve: producer surplus, consumer surplus, and welfare.

Note: N is the number of symmetric RE producers. λ is the coefficient of risk aversion. Results for an example with $a_1 = 0.4$, $a_2 = [0.4; 0.6]$, $b = 20$, $d = 100$, $\mu_Q = 40$, $\sigma_Q = 6$ and $p^{VOLL} = 120$.

Figure 4.4 (d) summarizes the effects on total welfare. In line with Knaut and Obermüller (2016), we find that when the supply slopes in both market stages are identical ($a_1 = a_2$), market power alone does not reduce welfare under risk neutrality. We extend this result by showing that this welfare invariance also holds under risk aversion: the blue (risk-neutral) and green (risk-averse) lines in the figure coincide, indicating that strategic withholding does not influence welfare as long as the conventional producers are fully flexible.

However, when conventional producers are inflexible ($a_2 > a_1$), total welfare declines. Since RE producers bid more in the first stage, prices decrease, increasing consumer surplus. RE and conventional producers' surplus decreases by a larger amount, decreasing overall welfare. Risk-averse behavior reinforces this effect by inducing greater quantity withholding in the first stage. As the number of producers decreases, these distortions intensify due to greater market power.

Thus, our results highlight that the interaction of risk aversion and supply-side inflexibility leads to welfare losses (red line) beyond those attributable to market power alone.

4.3.5. Rents and welfare implications of Case 3

This section explores the welfare and rent distribution through a heterogeneous market structure in the presence of risk aversion (Case 3). In particular, we analyze how strategic withholding by risk-averse and oligopolistic RE producers affects their surplus as well as the surplus of competitive fringe producers, conventional producers, and consumers. Figure 4.5 illustrates the distributional effects of risk aversion and flexible conventional producers in a setting with both oligopolistic and competitive RE producers.

The total producer surplus in this setup consists of the surpluses of oligopolistic RE producers, fringe RE producers, and conventional producers. The surplus of oligopolistic RE producers is given by the following equation:

$$\mathbb{E}[\Pi_{R,olig}(q_1)] = p_1 \cdot M \cdot q_{i1} + \mathbb{E}[p_2 \cdot (Q - M \cdot q_{i1})] \quad (4.41)$$

with:

$$p_1 = a_1 \cdot (d - \mu_Q - M \cdot q_{i1}) + b, \quad (4.42a)$$

$$p_2 = a_2 \cdot (d - 2 \cdot Q) + b \quad (4.42b)$$

As in Case 1 and Case 2, they face no marginal costs and operate under uncertainty. By plugging in the optimal bid quantity, we can quantify the producer surplus of oligopolistic RE producers. The expected producer surplus of fringe RE producers is given by:

$$\mathbb{E}[\Pi_{R,fringe}(q_1)] = p_1 \cdot \mu_Q + \mathbb{E}[p_2(Q - \mu_Q)] \quad (4.43)$$

where p_1 and p_2 are analogous to Eqs. 4.42. Fringe producers behave competitively and bid their expected output μ_Q in the first stage. Since they cannot influence the price strategically, their surplus depends entirely on price levels influenced strategically by the oligopolists. As risk aversion leads to more withholding by strategic producers, fringe producers indirectly benefit from the resulting price increase.

The expected conventional producer surplus is given by:

$$\mathbb{E}[\Pi_C(q_1)] = p_1 \cdot (d - M \cdot q_{i1} - \mu_Q) - C_1(q_1) + \mathbb{E}[p_2(M \cdot q_{i1} + \mu_Q - 2Q)] - \mathbb{E}[C_2(q_1)] \quad (4.44)$$

The cost function in the first stage and the expected cost function for the second stage are analogous to (4.37) and (4.38), respectively, with the substitution of $q_1 \mapsto m \cdot q_1 - \mu_Q$.

In the first stage, conventional producers supply the residual demand not covered by RE producers. In the second stage, they adjust output in response to deviations in renewable production.

Corollary 5. *Fringe RE producers benefit from the market power exerted by oligopolistic RE producers, as higher first-stage prices increase their revenues. This effect is amplified when oligopolistic producers are risk averse.*

A smaller number of strategic producers implies greater market power and more pronounced withholding in the first stage. This results in higher first-stage prices and larger expected forward premia. Consequently, fringe producers benefit from concentrated market structures: they bid their expected output without strategically influencing the price, yet receive higher prices due to the actions of the oligopolists. This relationship is reflected in Figure 4.5 (b), where fewer oligopolistic producers lead to a higher surplus for fringe suppliers. A similar pattern emerges for conventional producers in Figure 4.5 (c): lower competition among renewables leads to a higher first-stage price and a higher surplus. Thus, both fringe and conventional producers benefit from the exercise of market power by a few strategic RE producers. Comparing the risk-neutral and risk-averse cases reveals that the surplus of competitive RE producers is higher when the oligopolists are risk-averse (the orange line lies above the blue one). Again, more aggressive withholding of risk-averse RE producers raises first-stage prices and thereby increases the rents of price-taking producers.

Consumer surplus and total welfare are computed analogously to the previous cases. Specifically, the structure of the equations remains unchanged; only the relevant prices and quantities reflecting the heterogeneous market setup need to be substituted. For consumer surplus, Eq. (4.39) still applies, but the equilibrium price p_1 must reflect the pricing behavior of oligopolistic RE producers. Consumer surplus declines significantly with risk aversion, particularly in concentrated markets. This is consistent with previous findings and reflects the pass-through of price increases to consumers.

Likewise, the total welfare expression is the sum of the producer surplus of all market participants (oligopolistic RE producers, fringe RE producers, and conventional producers) and consumer surplus. By inserting the corresponding prices and quantities from this hybrid market structure, we obtain the welfare implications of strategic behavior under risk aversion in the presence of both competitive and dominant renewable producers. Figure 4.5 (d) shows that total welfare remains unchanged. This indicates that risk aversion primarily redistributes rents between producers and consumers, rather than generating allocative inefficiencies, if conventional producers are flexible.

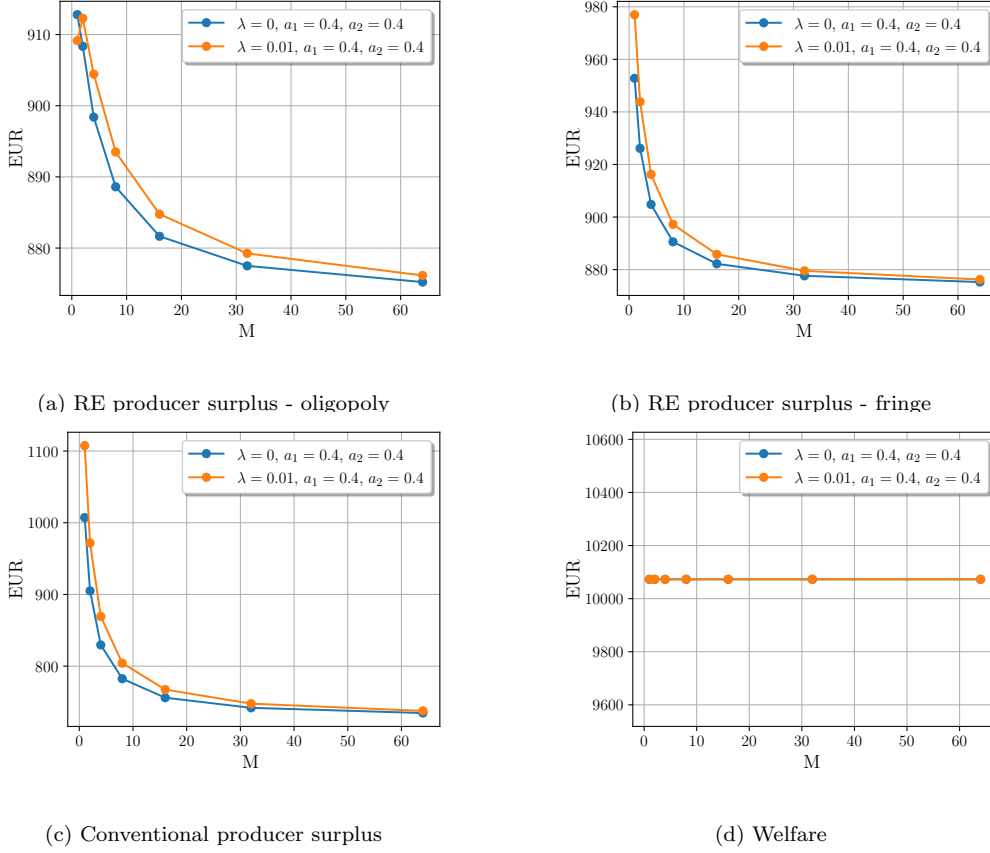


Figure 4.5.: Results under risk aversion, flexible supply curve, and heterogeneous RE producers: producer surplus, consumer surplus, and welfare.

Note: M is the number of oligopolistic RE producers. λ is the coefficient of risk aversion. Results for an example with $a_1 = a_2 = 0.4$, $b = 20$, $d = 100$, $p_{VOLL} = 120$, $\mu_Q = 40$ and $\sigma_Q = 6$.

4.4. Discussion

This work contributes to the literature on sequential electricity markets by introducing risk-averse behavior into an analytical framework of strategic bidding. While previous studies, such as Ito and Reguant (2016), emphasize the role of market power and limited arbitrage in generating forward price premia, they abstract from producers' risk preferences. We contribute by explicitly modeling how risk aversion affects market outcomes under flexible and inflexible supply. In addition, we extend the framework by distinguishing between oligopolistic and competitive renewable producers. The findings reveal that risk aversion, particularly under conditions of limited intraday flexibility, can magnify both price distortions and welfare losses, offering new insights into the interaction between market power, flexibility, and risk aversion.

A central finding is that risk aversion and concentrated markets lead to substantial welfare losses if intraday markets are inflexible, represented by a steeper marginal cost curve. An inflexible intraday market mirrors more realistic conditions, where conventional producers often lack the ability to adjust generation on short notice without incurring significant costs. This provides a further rationale for policy efforts aimed at improving short-term responsiveness through investments in storage, demand-side management, and flexible backup generation.

Our results further show that risk-averse producers strategically withhold more in the day-ahead market, driving up day-ahead prices and forward premia. While this effect vanishes under perfect competition, it becomes particularly problematic in oligopolistic markets with limited flexibility, amplifying price distortions and welfare losses. The interaction between risk aversion and market power suggests the need for closer examination of dominant producers' bidding behavior.

Beyond overall welfare, our results highlight important distributional implications. Strategic withholding increases producer surplus while reducing consumer surplus. Fringe renewable producers passively benefit from the market power of oligopolistic producers, with this effect becoming more pronounced under risk aversion. In the German regulatory setting, TSOs' bidding rationale mimics the behavior of fringe RE producers. If TSOs were to behave oligopolistically, they could increase the fringe's surplus, translating into lower subsidy costs, while consumer surplus would decrease. If conventional production is inflexible ($a_2 > a_1$), overall welfare would decline if TSOs bid strategically, as seen in Case 2. Further research could investigate a welfare-maximizing behavior of TSOs, which would require an alternative formulation of the utility function.

This analysis omits a potential Case 4, which would combine conventional producer inflexibility with RE producer heterogeneity. Since the fringe bid the expected production in the first stage, Case 2 can be adjusted analogously to the shift in residual demand in Case 3. Thus, the main effects of Cases 2 and 3 are jointly present: (i) a welfare loss due to $a_2 > a_1$ and strategic withholding, and (ii) an increase in rents for the fringe. However, the welfare loss found in Case 2 would, *ceteris paribus*, be reduced by the fringe's bidding behavior, as they reduce the amount that is strategically withheld in the first stage.

In sum, our findings show that market power, risk aversion, and flexibility constraints interact. A robust market design should jointly promote competition, reduce risk, and improve operational flexibility to ensure efficient and equitable electricity markets in a low-carbon future.

The role of short-term storage, such as batteries, is neglected in our analysis, as their inclusion would require intertemporal linking across hours, substantially increasing the complexity of the model. Assessing the impact of batteries on our results is challenging, since they can arbitrage price differences both within a market (e.g., the day-ahead price spread from morning peaks to midday troughs) and across markets (e.g., from the day-ahead price at 7 a.m. to the intraday price at 7 a.m.). If battery operators anticipate oligopolistic and risk-averse bidding

behavior of RE producers, they could take physical positions to arbitrage the positions of these producers, selling in the day-ahead market and repurchasing quantities in the intraday market. Such operations could mitigate the emergence of price premia. Moreover, if conventional production is inflexible, the activity of batteries could result in an overall welfare gain.

Several limitations must be considered when interpreting the results. We model risk aversion using profit variance, which is a simplification. While CVaR may better capture tail risks, it is analytically intractable in our setting. However, numerical results suggest profit variance remains a reasonable proxy for capturing aversion against uncertainty. Further, the model adopts a simplified structure to facilitate analytical tractability: it assumes linear costs, normally distributed uncertainty, and inelastic demand. While real-world cost curves are typically monotonically increasing and often approximated by convex functions, the assumption of linearity, following Knaut and Obermüller (2016), simplifies the analytical model. In principle, our results could be extended to convex cost functions, though this would significantly increase complexity.

A promising avenue for future research would involve an empirical examination of the analytical model. However, this is non-trivial, as empirically identifying risk aversion remains challenging given that it is not directly observable. Moreover, this would require disaggregating the withholding effect by market power and risk aversion. As capital-intensive, low-operating-cost technologies like renewables increasingly replace conventional power plants, understanding price formation and risk allocation in sequential electricity markets will become more critical.

4.5. Conclusion

This paper investigates the effects of risk aversion on market outcomes in sequential electricity markets, particularly focusing on the interaction between market power, flexibility, market structure, and producers' risk preferences. Our analytical framework builds upon Ito and Reguant (2016) and Knaut and Obermüller (2016), and is extended by incorporating risk-averse bidding behavior. We focus on strategic bidding of RE producers who face uncertainty about their production in the first stage, which must be sold completely in the second stage. We assume perfect competition among conventional producers that form a linear marginal cost curve.

We demonstrate that in an oligopolistic setting, risk-averse RE producers tend to withhold more in the first stage of the market to hedge against profit variance. This behavior leads to an additional forward premium, which is absent in perfectly competitive markets, where risk aversion has no effect. Moreover, the forward premium increases with the degree of risk aversion, particularly when demand is sufficiently high relative to expected RE generation. The impact of

risk aversion on the premium is further amplified by the slope of the second-stage supply curve: higher inflexibility in the second stage results in a larger forward premium.

When conventional producers have limited flexibility, risk-averse behavior in oligopolistic markets leads to additional welfare losses. Furthermore, fringe RE producers benefit from the market power of oligopolistic producers, with this effect becoming more pronounced when oligopolistic producers are risk-averse.

Beyond aggregate welfare effects, our analysis reveals important distributional implications. Strategic withholding, amplified by risk aversion, raises the surplus of both oligopolistic and fringe producers while lowering consumer surplus. These findings underscore the need for careful market design that promotes competition and enhances system flexibility. In a future with increasing renewable energy penetration, ensuring efficiency in electricity markets will require addressing these interactions between market power, risk aversion, and flexibility.

5. Bidding Wind and Solar: A Theory of Price Premia in Sequential Electricity Markets

5.1. Introduction

Electricity is predominantly traded through sequential wholesale markets. This market design allows market participants to adjust positions over time and thereby improve allocative efficiency relative to single-stage markets while simultaneously facilitating risk management. The sequential structure typically consists of forward and spot markets. Forward markets serve medium- to long-term hedging purposes, whereas spot markets determine short-term dispatch and prices close to delivery. The spot market itself is commonly organized as a day-ahead market followed by an intraday market, enabling market participants to incorporate updated information on supply and demand (Stoft, 2002).

Under frictionless conditions, economic theory states that prices across sequential markets should converge in expectation (Weber, 1981). Empirical evidence, however, documents persistent price differences between sequential markets, commonly referred to as price premia, contradicting this convergence (Bowden et al., 2009, Hadsell, 2008, Longstaff and Wang, 2004). The existing literature proposes several reasons that may explain the emergence of systematic¹² price premia between sequential markets. These include strategic behavior in the presence of market power (Ito and Reguant, 2016), risk aversion (Bessembinder and Lemmon, 2002), and differences in liquidity (Hagemann and Weber, 2013).

While these explanations focus primarily on market frictions or aggregate risk preferences, less attention has been paid to the bidding behavior of renewable producers and their risk preferences as a potential source of such systematic price premia. A first step in this direction is taken by Obermüller (2017) and Ashour Novirdoust et al. (2025), who derive optimal day-ahead bids in a competitive and non-competitive market under risk-neutral and risk-averse preferences, respectively. This perspective is specifically relevant in markets with a high share of variable renewable generation, with the German market providing a prominent example. For Germany, Schnaars (2021) and Paschmann (2017) demonstrate a characteristic diurnal pattern of price premia. While existing explanations tar-

¹²This work defines systematic price premia as recurring patterns that arise consistently across trading periods, rather than being driven by episodic shocks such as forecast errors or plant outages.

get average price premia between day-ahead and intraday markets, they remain largely silent on why these premia exhibit a pronounced diurnal structure, as observed in high-renewable systems such as Germany (cf. Figure 5.1).

Addressing this gap, this paper makes three contributions to the literature on price formation in sequential electricity markets. First, it provides a micro-founded analytical link between renewable producers' bidding behavior under uncertainty and the emergence of systematic day-ahead–intraday price premia in a perfectly competitive market setting. Second, it isolates the economic mechanism through which supply curve convexity and forecast uncertainty amplify the effect of risk preferences, thereby determining the magnitude of price premia across market stages. Third, by parameterizing a theoretical model with observed market data and differentiating bidding rationales across renewable technologies, the paper offers a novel structural explanation for the pronounced diurnal pattern of price premia observed in the German market.

To this end, this work applies a simplified two-stage model in which renewable producers choose day-ahead positions under three distinct bidding rationales: bidding expected production, risk-neutral bidding, and risk-averse bidding that accounts for tail risk. For each rationale, closed-form expressions are derived for the bids of renewable producers and for the resulting expected price premia between the two market stages. The analysis is complemented by differentiating the bidding rationales of PV and wind producers. The analytical framework is subsequently parameterized using observed market data, incorporating hourly information on demand, renewable production forecasts and their uncertainty, and supply curve price sensitivity to represent typical market situations in the diurnal cycle. This way, the analysis identifies how bidding rationales interact with time-varying supply curve convexity and forecast uncertainty, translating heterogeneous risk preferences into systematic price premia.

The remainder of this paper is structured as follows. Section 5.2 discusses the existing literature linked to this work. Section 5.3 introduces the theoretical model and analytical description of bidding rationales. Section 5.4 describes the parameterization of the theoretical model and compares the pattern of simulated premia to observed premia. Section 5.5 discusses the implications and limitations of this work, followed by a conclusion of the findings in Section 5.6.

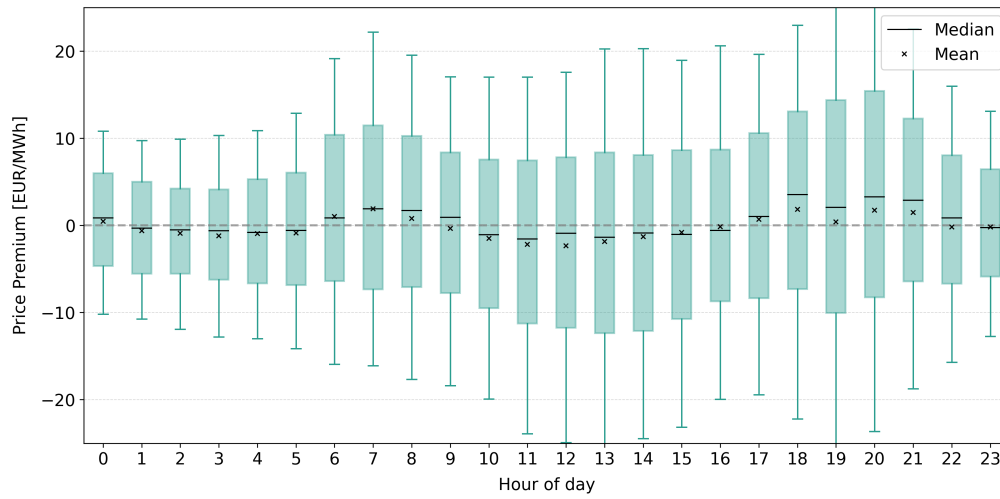


Figure 5.1.: Hourly price premium (day-ahead – ID3) in Germany for the period January 2024 to August 2025. Boxes represent the interquartile range (25th–75th percentile), while whiskers extend to the 10th and 90th percentiles. The sample is restricted to the 1st–99th percentiles to exclude extreme outliers.

5.2. Literature

In the following, the present work is positioned into several strands of literature analyzing price premia in sequential electricity markets.

A first reference is the foundational work by Bessembinder and Lemmon (2002), which builds on the theory of sequential markets developed by Allaz and Vila (1993) and analyzes equilibrium pricing and optimal hedging in electricity forward markets. In their framework, forward price premia depend on the variance and skewness of expected spot prices, which determine hedging pressure by risk-averse producers and retailers. While this contribution establishes a fundamental link between uncertainty, risk preferences, and price premia, it differs from the present analysis in several ways. In particular, uncertainty arises from stochastic renewable generation rather than demand, market participants are heterogeneous regarding risk preferences, and risk aversion is modeled using a Conditional Value-at-Risk criterion, allowing for an explicit treatment of tail risks.

A second strand of the literature emphasizes strategic behavior and imperfect competition as drivers of price premia in sequential markets. Ito and Reguant (2016) develop a two-stage model with limited arbitrage and show that market power in the first market stage can generate systematic price premia even in the absence of risk aversion. Their theoretical predictions are supported by empirical evidence from the Iberian electricity market. Related analytical work by Knaut and Obermüller (2016) shows that oligopolistic renewable producers

may strategically withhold supply in the first market stage, leading to higher prices. Ashour Novirdoust et al. (2025) extend this framework by introducing risk-averse renewable producers and show that mean–variance risk aversion amplifies withholding incentives and price premia under imperfect competition. In contrast to this literature, the present paper abstracts from market power and focuses exclusively on perfectly competitive settings.

Closely related are also Botterud et al. (2010) and Botterud et al. (2012), who derive day-ahead bidding strategies for wind producers under risk-seeking, risk-neutral, and risk-averse preferences. Despite relying on simplifying assumptions, most notably that prices are independent of wind realizations, their numerical results indicate that risk-averse preferences, modeled via Conditional Value-at-Risk, lead to lower day-ahead bids. Similar conclusions are reached by Bitar et al. (2012), who analytically derive optimal forward commitments of wind producers in a competitive two-settlement market. However, in their framework, imbalance prices are modeled as exogenous random variables independent of renewable realizations.

A smaller but closely related strand considers the role of supply curve characteristics and asymmetric price responses. Few studies explicitly analyze how the shape of the supply curve affects price premia. Kulakov and Ziel (2021) implicitly address this issue by modeling intraday prices as horizontal shifts of empirical day-ahead supply curves in response to wind and solar forecast errors. Because the local steepness of the merit order varies over time, their approach captures non-linear and asymmetric price responses without imposing a specific functional form. Hirsch and Ziel (2024) explicitly study how merit-order steepness affects intraday price volatility and tail behavior, finding that steep regimes are associated with higher volatility and heavier tails, although they abstract from asymmetries between positive and negative imbalances. Obermüller (2017) incorporates such asymmetries in a two-stage analytical model with a convex marginal cost curve and shows that competitive, risk-neutral renewable producers optimally withhold supply in the day-ahead market under forecast uncertainty. While empirical results suggest a positive relationship between renewable uncertainty and day-ahead–intraday price differences, the analysis does not address the pronounced diurnal pattern of price premia observed in practice. Paschmann (2017) offers an alternative explanation, arguing that non-convexities in subsets of sequential markets may also give rise to price premia.

Finally, a large forecasting-oriented strand of literature studies day-ahead and intraday price formation using econometric and statistical models (O’Connor et al., 2025). This strand primarily aims to predict prices or their distributions based on historical prices, forecast updates, trading volumes, and other market information (Hirsch and Ziel, 2024, Janke and Steinke, 2019, Narajewski and Ziel, 2020). Some studies explicitly model day-ahead–intraday price spreads, e.g., Maciejowska et al. (2019), but typically do not treat these premia as outcomes of bidding behavior. In contrast to this literature, the present paper does not aim to forecast prices but to provide a structural explanation for the emergence of

systematic price premia based on renewable producers' bidding decisions under uncertainty.

5.3. Theory

This chapter examines the emergence of price premia using a simplified two-stage model. First, the analytical framework is introduced. Then, the bidding rationales of renewable energy (RE) producers are discussed, followed by an analysis of how these rationales affect the expected price premia between the two market stages.

5.3.1. Model

The analytical model distinguishes two market stages, with the first stage representing the day-ahead market and the second stage representing the intraday market. The model captures the trading of RE producers with uncertain output, conventional producers, and retailers, and is formulated similar to the approach presented by Obermüller (2017). I assume that conventional producers are competitive and offer their production at marginal costs. Together, they form a marginal cost curve that is modeled as quadratic, thereby being convex and strictly monotonic: $MC(x) = ax^2 + bx + c$. The demand d is assumed to be deterministic and inelastic, with competitive retailers buying in the first stage. Additionally, RE producers with uncertain total production $Q \sim \mathcal{N}(\mu, \sigma^2)$ offer a quantity q in the first stage. It is assumed that total RE production must be sold in the second stage, where any deviations from the first-stage bid are balanced. RE producers are considered competitive, with symmetric production and production uncertainty. The model abstracts from pure financial arbitrage¹³. Prices in the two stages can be determined as described in Equation 5.1a and 5.1b, and the expected price premium Δp is given by Equation 5.1c.

$$p_1(q) = a \cdot (d - q)^2 + b \cdot (d - q) + c \quad (5.1a)$$

$$p_2(Q) = a \cdot (d - Q)^2 + b \cdot (d - Q) + c \quad (5.1b)$$

$$E(\Delta p) = a \cdot (q^2 - \mu^2 - \sigma^2) + (2ad + b) \cdot (\mu - q) \quad (5.1c)$$

¹³In practice, effective arbitrage between day-ahead and intraday markets can be limited by entry barriers for purely financial traders, transaction costs, credit limits, and the fact that physically active market participants primarily hedge their own positions and may lack complete information about RE producers' forecasts and risk exposures.

5.3.2. Bidding rationales

The following section investigates three distinct bidding rationales of RE producers in the first market stage, along with the expected price premia associated with these rationales. Subsequently, the bidding rationales of wind and PV producers are separated to examine heterogeneous bidding behavior and its impact on price premia. The cases under investigation are listed below:

1. Renewable producers bid the **expected production**.
2. Renewable producers bid **risk-neutrally**.
3. Renewable producers bid **risk-aversely**.
4. Separate bidding behavior:
 - a) **PV** producers bid **expected production**, while **wind** producers bid **risk-neutrally**.
 - b) **PV** producers bid **expected production**, while **wind** producers bid **risk-aversely**.

Expected production

An intuitive and simple bidding rationale is bidding the **expected production** μ . This rationale aims to minimize deviations in marketed quantities between the two market stages. Equation 5.2a formulates the bidding rationale, while Equation 5.2b describes the expected price premium if RE producers bid the expected production.

$$q_{ep} = \mu \tag{5.2a}$$

$$E(\Delta p_{ep}) = -a\sigma^2 \tag{5.2b}$$

This bidding rationale produces a negative price premium in expectation, increasing with supply curve convexity and the level of renewable production uncertainty. The premium arises from the convexity of the supply curve, which introduces an asymmetric price reaction to an imbalance in the second market stage.

Risk neutral

Another potential bidding rationale is the **risk-neutral bid**. A risk-neutral bidder maximizes expected profits. The aforementioned asymmetric price reaction in the second market stage must be considered in the risk-neutral bid leading to a withholding effect in the first market stage. The risk-neutral bid of competitive

RE producers has been derived in Obermüller (2017) and can be described as stated in Equation 5.3a. If there is no uncertainty ($\sigma = 0$), the first-stage bid is equal to the expected production. However, higher uncertainty reduces the risk-neutral bid. Intuitively, if RE producers are risk neutral in a competitive market setting, the expected price premium converges to zero (cf. Equation 5.3b).

$$q_{rn} = d + \frac{b}{2a} - \sqrt{\left[\left(d + \frac{b}{2a} - \mu \right)^2 + \sigma^2 \right]}. \quad (5.3a)$$

$$E(\Delta p_{rn}) = 0 \quad (5.3b)$$

Unlike the derivation of q_{rn} in Obermüller (2017), which relies on an equilibrium approach for individual market participants, the result can alternatively be derived using a representative agent approach. This approach aggregates the behavior of competitive market participants into a single decision-maker and assumes that market participants act as price takers in the first stage.

Formally, the representative agent's profit depends on the first- and second-stage quantity $\pi(q_1, Q)$. Let $f(q_1, Q) = d\pi/dq_1$ denote the marginal profit with respect to the first-stage bid. Then the maximum risk-neutral utility is given by the first-order condition of the utility function U_{rn} , as shown in Equation 5.4. From the second derivative of the utility function, it follows that $q_{rn} = q_{1-}^*$, as shown in the proof of Obermüller (2017).

$$\pi(q_1, Q) = p_1(q_1) \cdot q_1 + p_2(Q) \cdot (Q - q_1), \quad (5.4a)$$

$$\begin{aligned} f(q_1, Q) &:= \frac{d\pi(q_1, Q)}{dq_1} = p_1'(q_1) q_1 + p_1(q_1) - p_2(Q) \\ &\approx p_1(q_1) - p_2(Q) \quad (\text{representative agent}), \end{aligned} \quad (5.4b)$$

$$\frac{dU_{rn}}{dq_1} = \mathbb{E}[f(q_1, Q)] = 0. \quad (5.4c)$$

Computing the expectation term by term yields

$$\begin{aligned} \mathbb{E}[f(q_1, Q)] &= [a(d - q_1)^2 + b(d - q_1) + c] \\ &\quad - \mathbb{E}[a(d - Q)^2 + b(d - Q) + c] \end{aligned} \quad (5.4d)$$

$$= aq_1^2 - (2ad + b)q_1 + 2ad\mu + b\mu - a(\mu^2 + \sigma^2) \quad (5.4e)$$

$$= a \left[q_1^2 - \left(2d + \frac{b}{a} \right) q_1 + 2d\mu + \frac{b}{a}\mu - (\mu^2 + \sigma^2) \right]. \quad (5.4f)$$

Solving $\mathbb{E}[f(q_1, Q)] = 0$ gives

$$q_{1\pm}^* = d + \frac{b}{2a} \pm \sqrt{\left(d + \frac{b}{2a} - \mu\right)^2 + \sigma^2}. \quad (5.4g)$$

Risk averse

The third bidding rationale under investigation is the **risk-averse bid**. The asymmetry in the price response to imbalances in the intraday market introduces a tail to the profit distribution of RE producers. To visualize the tail risk, a Monte-Carlo-Simulation is conducted for the risk-neutral bidding rationale with a numerical example. Figure 5.2a illustrates the marginal cost curve together with uncertain RE production Q . Figure 5.2b shows the profit distribution of RE producers. Notably, the profit distribution is left-skewed, i.e., there is a risk exposure to low profits.

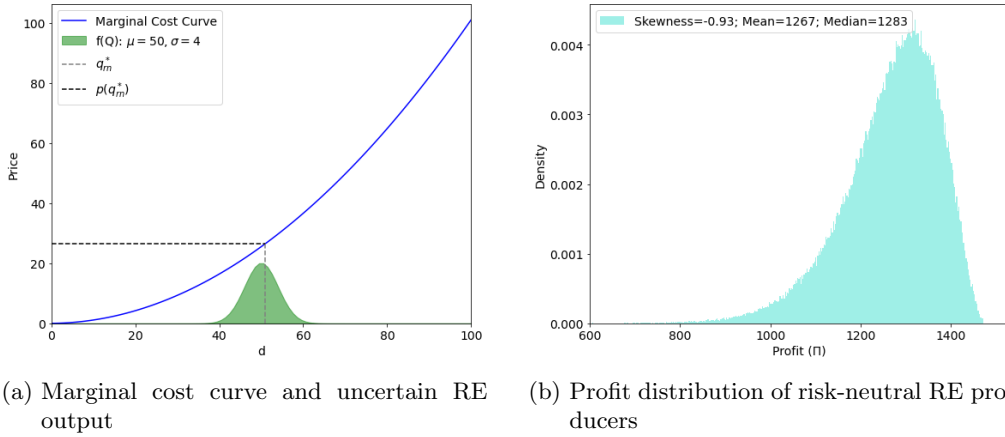


Figure 5.2.: Schematic marginal cost curve, RE production, and profit distribution of RE producers. Assumptions: $a=0.01$, $b=0.01$, $c=0$, $d=100$.

If RE producers are risk-averse, their bidding strategies account for their aversion to tail risks. A common approach to represent risk aversion is to incorporate the Conditional Value-at-Risk (CVaR) into the utility function U of market participants. This utility function jointly maximizes expected profits $\mathbb{E}[\pi]$ and minimizes exposure to tail risks, as shown in Equation 5.5. The degree of risk aversion is controlled by the parameter $\lambda \in [0, 1]$. Typically, risk aversion focuses on large losses; however, in this case, it targets low profits. Therefore, the left-sided α -quantile is used, and the $CVaR$ is added to expected profits and maximized.

$$U_{ra}(\pi) = (1 - \lambda) \cdot \mathbb{E}[\pi] + \lambda \cdot CVaR_{\alpha}(\pi), \quad (5.5)$$

This utility function cannot be solved analytically to derive the risk-averse bid of RE producers, as the inverse cumulative density function of profits would be required. Furthermore, an approximation using higher-order moments (e.g., skewness or kurtosis) is intractable, as terms above the fifth degree would need to be solved. Despite the unknown analytical solution for the risk-averse bid, the qualitative relationship between the risk-averse and risk-neutral optimal bids can be formally established.

To demonstrate this relation, the representative agent approach is adopted, such that market participants are modeled as price takers in the first stage. For the risk-averse representative agent, the utility function additionally accounts for tail risk via the CVaR. Equation 5.6 states the first-order condition with respect to the first-stage bid. Evaluating the derivative of the risk-averse utility at the risk-neutral optimum $q_1 = q_{rn}$ shows that the derivative is negative, i.e., a marginal increase of q_1 reduces the utility of the risk-averse representative agent. To fulfill the first-order condition for the risk-averse utility function, the first-stage bid must be decreased relative to the risk-neutral bid. Therefore, the risk-averse representative agent would choose a lower first-stage bid relative to the risk-neutral representative agent.

$$U_{ra} = (1 - \lambda) \mathbb{E}[\pi(q_1, Q)] + \lambda \text{CVaR}_\alpha(\pi(q_1, Q)), \quad (5.6a)$$

$$\begin{aligned} \frac{dU_{ra}}{dq_1} &= (1 - \lambda) \mathbb{E}[f(q_1, Q)] \\ &\quad + \lambda \mathbb{E}[f(q_1, Q) \mid \pi(q_1, Q) \leq \text{VaR}_\alpha(\pi)] = 0. \end{aligned} \quad (5.6b)$$

Evaluating the first-order condition at the risk-neutral optimum $q_1 = q_{rn}$:

$$\begin{aligned} \left. \frac{dU_{ra}}{dq_1} \right|_{q_{rn}} &= (1 - \lambda) \underbrace{\mathbb{E}[f(q_{rn}, Q)]}_{=0} \\ &\quad + \lambda \underbrace{\mathbb{E}[f(q_{rn}, Q) \mid \pi(q_{rn}, Q) \leq \text{VaR}_\alpha]}_{<0} < 0 \end{aligned} \quad (5.6c)$$

$$\implies q_{ra} < q_{rn}. \quad (5.6d)$$

The equality $\mathbb{E}[f(q_{rn}, Q)] = 0$ follows directly from the first-order condition of the risk-neutral representative agent. The inequality $\mathbb{E}[f(q_{rn}, Q) \mid \pi(q_{rn}, Q) \leq \text{VaR}_\alpha] < 0$ is established in Eq. (5.7).

Define the lower tail of profits:

$$\mathcal{T} := \{(q_{rn}, Q) \mid \pi(q_{rn}, Q) \leq \text{VaR}_\alpha(\pi)\}. \quad (5.7a)$$

For realizations in this tail, low profits are driven by low realized output:

$$Q \in \mathcal{T} \implies Q < q_{rn} \implies p_1 - p_2(Q) < 0. \quad (5.7b)$$

Applying the representative-agent approximation:

$$\begin{aligned} f(q_{rn}, Q) &= p'_1 q_{rn} + p_1 - p_2(Q) \\ &\approx p_1 - p_2(Q). \end{aligned} \quad (5.7c)$$

Taking the conditional expectation over the tail yields

$$\mathbb{E}[f(q_{rn}, Q) \mid (q_{rn}, Q) \in \mathcal{T}] < 0. \quad (5.7d)$$

Since an analytical representation of the utility-maximizing risk-averse bid is intractable, I propose an approximation of the risk-averse bid based on the information derived above. This approximation is based on the risk-factors a and σ that drive the risk-averse behavior. The approximate risk-averse first-stage bid is lower than the corresponding risk-neutral bid, with the extent of this reduction depending on the convexity of the marginal cost curve and the level of uncertainty in RE output. Equation 5.8a provides the approximate risk-averse first-stage bid q_{ra} , which is derived by adjusting the risk-neutral bid q_{rn} according to the parameters a and σ , and is scaled by a parameter k_λ to modulate the degree of risk aversion. Equation 5.8b expresses the expected price premium between the two market stages. Under a risk-averse bidding rationale, the expected price premium is positive if the supply curve is convex ($a > 0$) and renewable production is uncertain ($\sigma > 0$).

$$q_{ra} = q_{rn} - k_\lambda \cdot a\sigma \quad (5.8a)$$

$$E(\Delta p_{ra}) = k_\lambda a^2 \sigma \cdot (2 \sqrt{\left[\left(d + \frac{b}{2a} - \mu \right)^2 + \sigma^2 \right]} + k_\lambda a \sigma) \quad (5.8b)$$

Separate bidding rationale

The fourth bidding rationale assumes that wind and PV producers follow separate bidding rationales, introducing heterogeneity among RE producers. In the German market, a large stake of PV production is sold by transmission system operators (TSOs), who are legally obliged (§2 EEG) to minimize deviations between marketed and produced quantities (BMJV, 2025). In contrast, wind production is largely sold by direct marketers, who might be risk averse. The following analysis assumes that PV production is marketed in the first stage at its expected value, while wind production is marketed either risk-neutrally (*Case a*) or risk-aversely (*Case b*).

The approximated risk-averse bid derived in Section 5.3.2 is based on the risk-neutral bid with an adjustment to tail risk. To avoid an unintended “cross-hedging” that arises when risk-neutral wind producers internalize the suboptimal PV producer position, I impose an idiosyncratic risk-neutral bidding rule for wind’s first-stage bid q_{rn}^{wind} . Here, the PV production is treated as a fixed parameter equal to its expected production in both market stages ($q_{pv} = \mu_{pv}$), and the wind objective takes expectations only over wind’s own production uncertainty. Under this formulation, wind optimizes against its own imbalance exposure, while PV’s commitments are exogenous, preventing wind from implicitly hedging PV’s position, which would imply financial arbitrage. The bid is derived using the approach in Equation 5.4, after adjusting the problem to account for expected PV production, effectively replacing q_1 with $q_1 - \mu_{pv}$. The competitive risk-neutral first-stage bid of wind producers is stated in Equation 5.9a. This bid considers the expected production of both wind and PV while only considering the risk exposure of its own production (σ_{wind}). Equation 5.10a describes the approximated risk-averse first-stage bid of wind producers, which is based on the risk-neutral bid and adjusted to account for wind’s tail risk via $k_\lambda a \sigma_{wind}$. Equations 5.9b and 5.10b describe the expected price premium for *Case a* and *Case b*.

$$q_{rn}^{wind} = d - \mu_{pv} + \frac{b}{2a} - \sqrt{\left(\mu_{wind} - d + \mu_{pv} - \frac{b}{2a}\right)^2 + \sigma_{wind}^2} \quad (5.9a)$$

$$E(\Delta p_{separate, rn}) = -2a \cdot \text{Cov}(Q_{pv}, Q_{wind}) - a\sigma_{pv}^2 \quad (5.9b)$$

$$q_{ra}^{wind} = q_{rn}^{wind} - k_\lambda a \sigma_{wind} \quad (5.10a)$$

$$\begin{aligned} E(\Delta p_{separate, ra}) = & -2a \text{Cov}(Q_{pv}, Q_{wind}) - a\sigma_{pv}^2 + a^3 k_\lambda^2 \sigma_{wind}^2 \\ & + 2a^2 k_\lambda \sigma_{wind} \sqrt{\left(\mu_{wind} - d + \mu_{pv} - \frac{b}{2a}\right)^2 + \sigma_{wind}^2} \end{aligned} \quad (5.10b)$$

5.4. Numerical application of the theoretical model

This section applies the theoretical framework to actual market conditions. Market conditions vary substantially across hours, reflecting systematic changes in demand, renewable generation, forecast uncertainty, and supply-side price sensitivity. As a result, identical bidding rationales may lead to different price premia

depending on the prevailing market environment. To capture this interaction, the theoretical model is parameterized using observed market data and simulated for an average diurnal cycle representing typical hourly market conditions. The objective is not to precisely reproduce realized price premia, but to illustrate how the interaction between market conditions and bidding behavior can give rise to diurnal patterns in expected price premia. The resulting simulated patterns are subsequently compared with observed premia to assess whether the mechanisms highlighted by the model are consistent with observed regularities, providing an indication, though not proof, of how such patterns may emerge in practice.

The section proceeds as follows. First, observed price premia are presented. Then the data used to parameterize the theoretical model are introduced. Next, the model is simulated for an average daily market profile, and the resulting price premia for various bidding rationales of RE producers are compared with observed patterns in the German market.

5.4.1. Observed price premia

The following section introduces observed price premia between the day-ahead and intraday market in Germany. The price premium is calculated as the difference between hourly day-ahead prices and the corresponding ID3 prices from EPEX SPOT SE (2025b). The ID3 index represents the continuous intraday market and reflects the volume-weighted average price of all 15-minute transactions executed within the three hours prior to delivery. Hence, the index serves as a suitable proxy for real-time prices.

The analysis draws on recent market data covering the period from January 2024 to August 2025, comprising a total of about 16,500 hourly observations. Each hour of the diurnal cycle contains around 688 individual data points. The dataset is subsequently corrected for outliers by retaining observations of price premia within the 1st to 99th percentile range, thereby excluding extreme events and data inconsistencies. Figure 5.1 illustrates the distribution of hourly price premia.

The distribution of price premia reveals a distinct diurnal pattern. During nighttime and early morning hours, mean price premia hover around zero, with an interquartile range (25th–75th percentile) of approximately 10 €/MWh. A pronounced increase in premia is observed during the morning (6–8 a.m.) and evening (6–9 p.m.) hours, where mean price premia range around +2 €/MWh. In contrast, during midday hours (10 a.m.–3 p.m.), premia are predominantly negative, with average values around -2 €/MWh. A one-sample mean comparison test against zero, applied hour-wise after excluding extreme observations, indicates that price premia are statistically different from zero for all hours except 0, 1, 5, 8, 9, 15, 16, 17, 19, 22, and 23.

5.4.2. Data and parameterization

This section introduces the data used for the parameterization of the theoretical model. The relevant data includes renewable production and its forecast uncertainty, demand forecast, and the shape of the hourly marginal cost curve, particularly its convexity.

Renewable production and demand

The parameterization of the theoretical model is based on hourly means of renewable production forecast and the demand forecast. As a proxy for the ex-ante renewable production uncertainty, the standard deviation of the hourly forecast error is used. As the mean forecast error is close to zero (49 MW), the mean forecast is an unbiased predictor of mean realized production. The data are obtained from the SMARD electricity market data platform of the Federal Network Agency (BNetzA, 2025). Figure 5.3 illustrates the resulting mean hourly values.

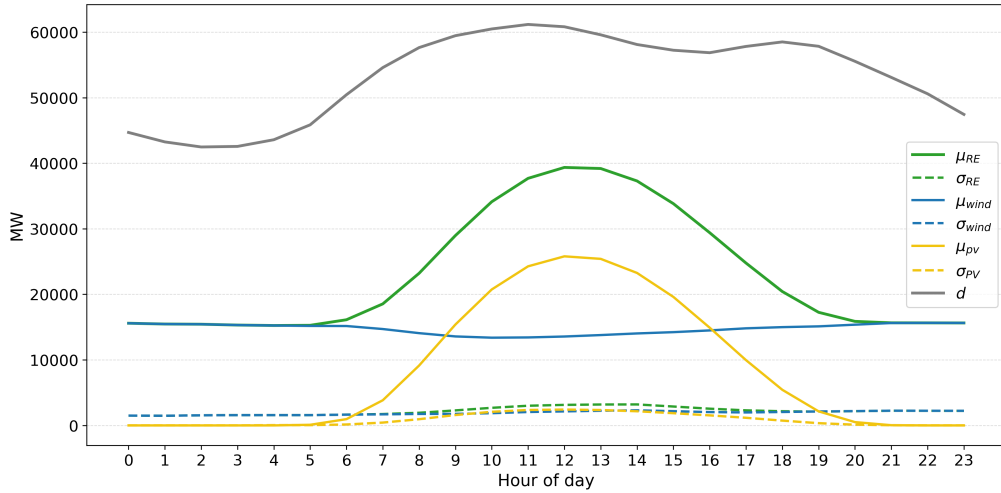


Figure 5.3.: Hourly means of RE forecast (μ_{RE}), RE standard deviation (σ_{RE}), wind forecast (μ_{wind}), wind standard deviation (σ_{wind}), PV forecast (μ_{PV}), PV standard deviation (σ_{PV}), and load forecast (d) from January 2024 to August 2025.

Marginal cost curve

This section derives a numerical measure of the hourly convexity of the marginal cost curve based on observed day-ahead bid curves. To ensure that the slopes around the market-clearing point reflect supply-side price sensitivities alone, the bid curves are first transformed into a representation with perfectly inelastic demand. The transformed curves are then used to numerically derive hourly

convexity measures, which serve to parameterize the marginal cost curve in the theoretical model.

To approximate the convexity of the marginal cost curve, it is essential that the slope around the day-ahead clearing point reflects supply-side price sensitivities alone. However, slopes computed directly from the raw auction curves embed demand-side elasticity that is unrelated to producers' cost structures, which creates an inconsistency when such slopes are used to parameterize an analytical model with inelastic demand. To obtain a meaningful measure of hourly convexity, the day-ahead bid curves are therefore transformed into a representation with perfectly inelastic demand. This transformation was first introduced in Kulakov and Ziel (2019) and has been applied in Hirsch and Ziel (2024). The transformation preserves the original market-clearing price but reallocates the observed demand elasticity to the supply side. This reallocation is economically justified by the fact that demand-side bids in the day-ahead auction do not solely reflect short-run price responsiveness of final electricity consumers but rather the portfolio decisions and arbitrage activities of market participants who are active across multiple trading venues. In particular, utilities and trading firms can balance their positions between the day-ahead auction, intraday markets, and over-the-counter contracts, such that a buy order at a given price in the auction can equivalently be interpreted as a sell position at a slightly higher price in an alternative market. As a result, the elasticity observed on the demand side of the auction can be shifted to the supply side without altering the equilibrium outcome.

The transformed supply curve provides a representation in which local slopes around the clearing point can be interpreted as supply-side marginal price responses. This is consistent with the theoretical framework employed in this paper, where demand is assumed to be deterministic and inelastic, and producers face a strictly convex marginal cost function. Figure 5.4 visualizes the day-ahead bid curves for the delivery day November 18th in 2024 at 9 p.m. in their original and transformed forms. The formal approach to the transformation is described in Appendix D.1.

5.4. Numerical application of the theoretical model

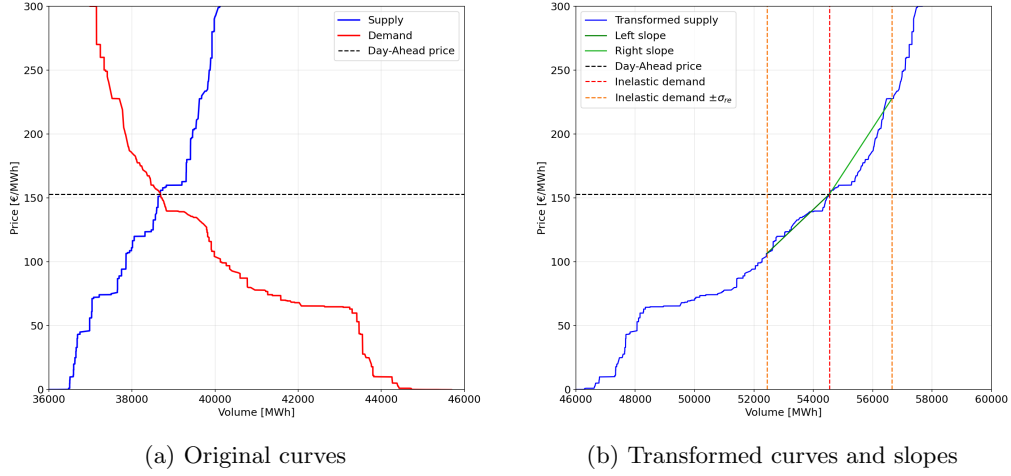


Figure 5.4.: Original and transformed day-ahead bid curves from 11/18/2024 at 9 p.m. and derived slopes.

The slopes around the clearing point in the transformed day-ahead supply curve form the basis for the subsequent construction of the hourly convexity parameter used in the theoretical model. The convexity of the marginal cost curve is approximated by a^{linear} , which expresses the relationship between the left- and right-sided slopes, s^l and s^r (s. Equation 5.11a), originating from the market clearing point at $MC(d^{inelastic})$. The left- and right-sided gradients are computed over an interval defined by the mean hourly standard deviation of the RE forecast errors $\bar{\sigma}_h$, as stated in Equation 5.11c and 5.11b. This way, the convexity is determined on an interval of the supply curve, which is likely relevant in determining second-stage prices. To obtain a suitable convexity parameter a_h for the theoretical model, the linearly approximated convexity a^{linear} is scaled to ensure a realistic price level within the stylized marginal cost specification while preserving the observed hourly variation in convexity. Again, the dataset covers every hour of a 20-month period, from January 2024 to August 2025, and the day-ahead bid curves are based on EPEX SPOT SE (2025b).

$$a_{d,h}^{linear} = \frac{s_{d,h}^r}{s_{d,h}^l} \quad (5.11a)$$

$$s_{d,h}^r = \frac{MC_{d,h}(d_{d,h}^{inelastic} + \bar{\sigma}_h) - MC_{d,h}(d_{d,h}^{inelastic})}{\bar{\sigma}_h} \quad (5.11b)$$

$$s_{d,h}^l = \frac{MC_{d,h}(d_{d,h}^{inelastic}) - MC_{d,h}(d_{d,h}^{inelastic} - \bar{\sigma}_h)}{\bar{\sigma}_h} \quad (5.11c)$$

Figure 5.5 summarizes all linear approximations $a_{d,h}^{linear}$ of the convexity of the marginal cost curve for the time horizon under investigation.

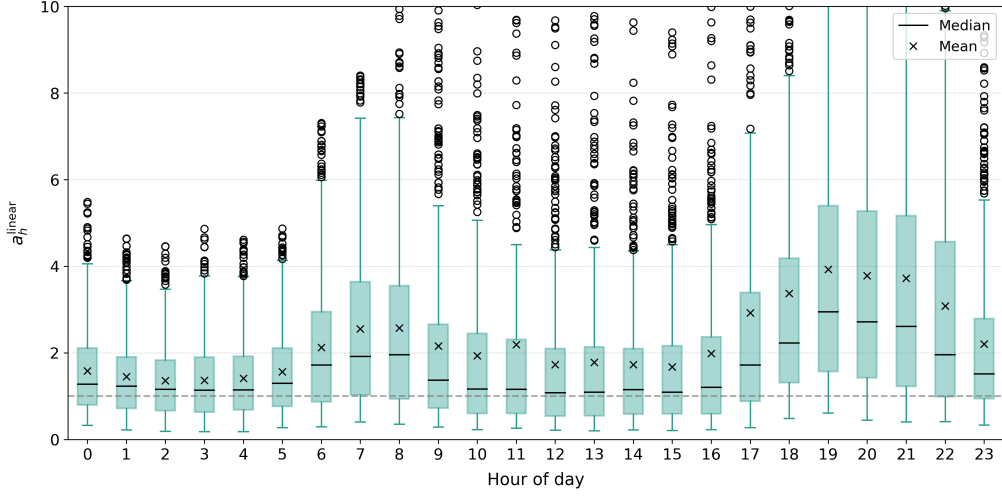


Figure 5.5.: Hourly slope ratios a_h^{linear} from January 2024 to August 2025 of the day-ahead auction.

5.4.3. Simulation of price premia

This section analyzes how different first-stage bidding rationales affect the expected hourly price premium between the two market stages in the diurnal cycle and compares the pattern of simulated premia to the pattern of observed premia. The bidding rationales (cf. Section 5.3.2) are applied within the theoretical model (cf. Section 5.3.1) that is parameterized according to the data in Section 5.4.2.

Although the marginal cost function in the theoretical model is based on observed supply curves, the empirical approximation only recovers the diurnal pattern of convexity rather than its exact magnitude. Therefore, the convexity parameter derived from the transformed day-ahead supply curves is scaled with a scalar $s = 0.2$ to obtain a realistic level of premia within the theoretical model while preserving the diurnal variation in convexity. As a result, the calibration affects only the magnitude of simulated price premia but does not impose their diurnal structure. Similarly, the degree of risk aversion of RE producers cannot be directly observed and is therefore calibrated with $k_\lambda = 0.05$. Again, altering this scalar would generally influence the magnitude but not the overall pattern in price premia. The remaining linear components of the marginal cost function are set to constant values ($b = 0.1$ and $c = 0$), as they primarily affect the overall price level but do not influence the mechanisms determining price premia within the model.

Figure 5.6 illustrates the simulated hourly price premia for the three cases with homogeneous bidding rationales among RE producers, expressed relative to the average simulated day-ahead price. For a risk-neutral first-stage bid, the expected price premia are consistently zero. Risk-neutral RE producers consider

both the asymmetric price reaction to RE forecast errors and the uncertainty in their expected production, resulting in expected prices that converge.

When RE producers bid their expected production, the price premia correlate negatively with the convexity of the marginal cost curve. This bidding rationale neglects the asymmetric price reaction in the second stage, causing negative expected price premia, which are particularly pronounced in hours with higher production uncertainty (cf. Figure 5.3) and higher convexity (cf. Figure 5.5) .

In contrast, risk-averse RE producers adjust their bids to account for the asymmetric price response in the second stage while also incorporating expected tail risk. As this risk increases with the convexity of the marginal cost curve and the uncertainty in RE production, the expected price premia are higher in these hours (e.g., hours 7 or 19). Notably, the systematic pattern of price premia resulting from risk-averse bidding vaguely resembles the observed pattern of actual price premia observed in market data (cf. Figure 5.1). However, particularly the negative price premia around midday hours cannot be explained with this homogeneous bidding rationale.

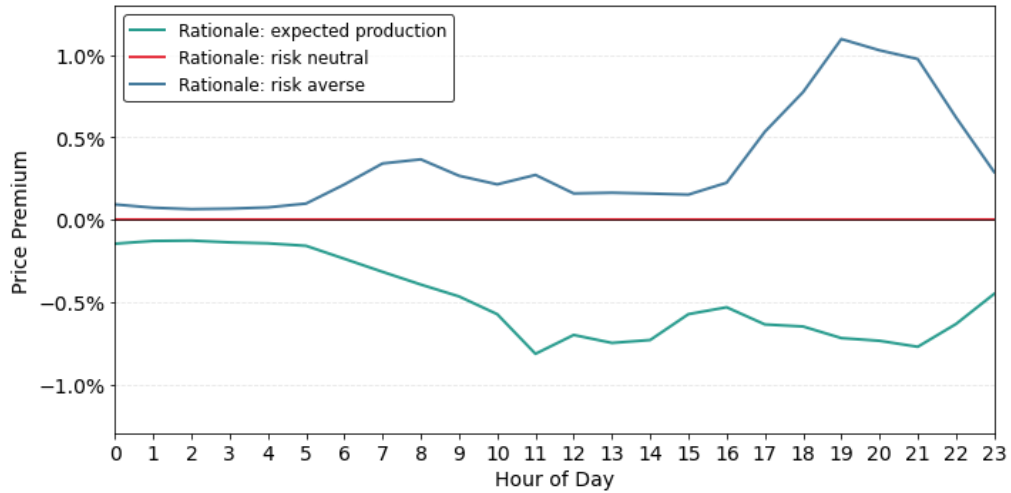


Figure 5.6.: Simulated price premia relative to average day-ahead prices for homogeneous bidding rationales among RE producers.

Subsequently, the parameterized theoretical model is computed with separate bidding rationales for wind and PV producers. Two cases are analyzed, as described in Section 5.3.2, assuming PV production to be marketed with expected production and wind production to be marketed risk-neutrally (*Case a*) and risk-aversely (*Case b*), respectively. In both cases, the expected price premium also depends on the covariance between uncertain wind and PV production (cf. Equations 5.9b and 5.10b). An analysis of PV and wind forecast errors yields a covariance close to zero; thus, its impact on expected price premia is negligible.

The results of the simulated price premia for the two cases are illustrated in Figure 5.7 together with observed premia. The premia are shown relative to their underlying mean day-ahead price. If PV production is zero, the risk-neutral bidding rationale of wind (*Case a*) results in a convergence of first- and second-stage prices, consistent with Equation 5.3b. When PV production is positive, the first-stage bid of PV ($q_{pv} = \mu_{pv}$) leads to negative expected price premia, as derived in Equation 5.2b. This effect intensifies with increasing PV production and is particularly pronounced around midday.

Under a risk-averse bidding rationale of wind production (*Case b*), the sign and magnitude of the expected price premium depend on which RE source dominates. The risk-averse bid of wind tends to induce positive premia, especially when the convexity of the marginal cost curve (a) is high, whereas the opposite holds for PV. Consequently, the interaction between the time-varying convexity of the marginal cost curve and the diurnal composition of wind and PV production determines both the sign and the magnitude of the expected price premium. Notably, the separate bidding rationale with risk-averse wind producers exhibits both a negative trough around midday and two peaks around morning and evening hours.

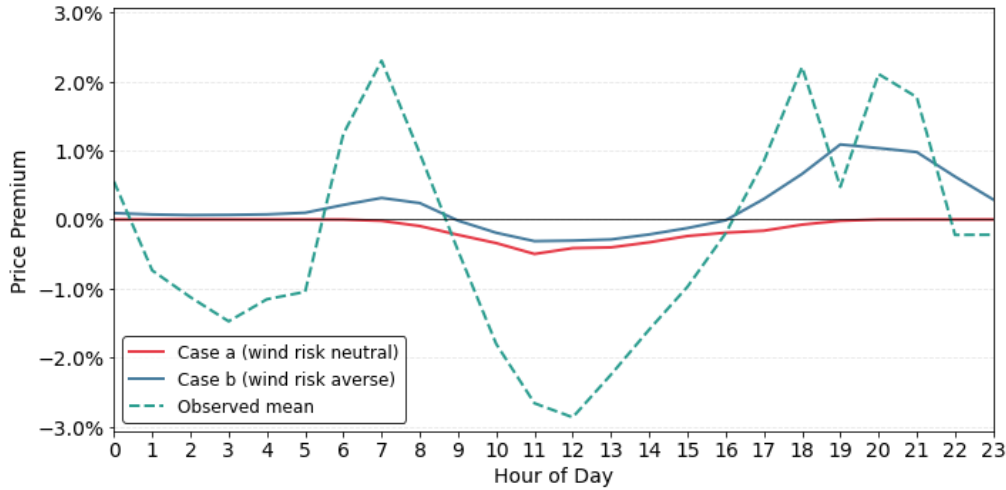


Figure 5.7.: Simulated price premia relative to average day-ahead prices for separate bidding rationales between wind and PV producers, and mean observed price premia.

A comparison with observed premia indicates that the characteristic structure of observed price premia is best explained by *Case b*. In both graphs, there is a positive premium around morning and evening hours, with a higher level in the evening hours in *Case b*, which can be explained by a higher convexity stemming from higher residual load together with higher forecast uncertainty relative to the morning peak. Moreover, *Case b* resembles the low around midday, when PV production typically reaches its high and turns out higher than wind production

(cf. Figure 5.3). Conversely, the negative observed premia around nighttime are not resembled by *Case b* but turn out slightly positive instead. By definition of the model, when PV production is zero, price premia can only turn out positive, while actual price premia might be driven by factors beyond the scope of the model.

5.5. Discussion

This paper investigates the emergence of systematic price premia between the day-ahead and intraday markets as a consequence of the bidding behavior of renewable energy producers. In particular, the analysis examines how different bidding rationales translate into diurnal patterns of price premia when market conditions vary over the course of the day. To address this question, a theoretical framework is developed in which closed-form expressions for day-ahead bids are derived under different bidding rationales. The theoretical model is subsequently parameterized using observed market data from Germany and simulated for an average diurnal cycle. Comparing the resulting simulated premia with the observed pattern provides an indication of how the mechanisms highlighted by the model may contribute to the emergence of price premia in actual markets.

The discussion proceeds as follows. First, stylized facts of the German electricity market are outlined. Second, the model results are interpreted in light of these stylized facts. Third, the findings are related to the existing literature, and their economic implications are discussed. Finally, limitations of the analysis and directions for future research are addressed.

5.5.1. Stylized facts

To structure the discussion, the following stylized facts of the German electricity market are summarized:

- **SF1 - Supply curve convexity:** The price response to renewable forecast errors is asymmetric due to convex marginal costs. This asymmetry tends to be more pronounced at times of high residual demand, when the supply curve is steeper.
- **SF2 - Renewable generation profiles:** PV generation is strongly concentrated around midday, whereas wind generation exhibits a less pronounced and more dispersed diurnal pattern.
- **SF3 - Forecast uncertainty:** Forecast errors for renewable generation increase in absolute terms with expected output and forecast horizon. As a result, periods with high renewable generation, particularly around midday for PV, are associated with larger potential quantity deviations.

- **SF4 - Institutional setting:** A substantial share of PV generation under public support schemes is marketed by TSOs that are obligated to minimize quantity deviations between the day-ahead and intraday market, whereas wind generation is more frequently exposed to market-based and potentially risk-sensitive bidding strategies.

5.5.2. Economic interpretation of model results

The theoretical analysis shows that bidding rationales shape expected price premia between the two market stages. When renewable energy producers bid their expected production, expected price premia become negative due to the asymmetric price response to forecast errors in the intraday market (SF1). In this case, producers neglect that downward revisions of renewable output tend to have a stronger price impact than upward revisions. Conversely, when producers follow a risk-neutral bidding rationale, this asymmetry is fully anticipated. Producers adjust their day-ahead bids accordingly, leading to a convergence of expected prices between the two market stages.

A novel contribution of this paper is the derivation of a closed-form expression for a risk-averse bidding strategy. To derive the expression, risk aversion is modeled through a CVaR-based representation of tail risk. In this case, producers account not only for the asymmetric price response (SF1), but also for exposure to adverse outcomes with particularly low profits. The analysis shows that risk-averse bidding can give rise to positive expected price premia, as producers reduce their day-ahead positions to limit exposure to unfavorable outcomes in the intraday market. Importantly, the magnitude of these premia depends on the interaction between renewable production uncertainty (SF3) and the convexity of the marginal cost curve (SF1). In addition, the theoretical analysis derives premia that emerge from technology-specific bidding rationales that only consider idiosyncratic risk.

The application of the bidding rationales in the parameterized theoretical model, which represents changing market conditions over the course of a day, reveals distinct patterns in price premia that emerge from the interaction between bidding behavior and market conditions. Most prominently, a configuration in which PV bids its expected production while wind is marketed risk-aversely in the day-ahead market produces a pattern with positive premia during morning and evening hours and negative premia around midday. This pattern closely resembles the structure observed in market data, indicating that heterogeneity in bidding rationales across renewable technologies (SF2, SF4) can rationalize the observed diurnal structure of price premia in the German market.

5.5.3. Relation to the literature and economic implications

These findings contribute to the literature on price premia in sequential electricity markets. Previous analyses have identified several mechanisms that may give rise to price differences across market stages. Some contributions emphasize the role of market frictions, such as transaction costs, while others highlight the impact of market power and strategic behavior by dominant market participants that leads to persistent price premia (Ashour Novirdoust et al., 2025, Ito and Reguant, 2016). A further explanation relates premia to hedging pressure among risk-averse market participants, where differences in the willingness to bear risk between producers and consumers generate equilibrium risk premia (Bessembinder and Lemmon, 2002). The results of this paper identify a related mechanism through which systematic price premia can arise. Even in the absence of market power or market frictions, bidding rationales of renewable producers facing production uncertainty can generate price premia between market stages. In this sense, systematic premia do not necessarily indicate market inefficiencies but may reflect equilibrium outcomes driven by risk preferences and market structure.

From an economic perspective, the results raise the question of why such premia are not fully arbitrated away. One possible explanation is that arbitrage opportunities involve substantial exposure to price risk, which market participants may be unwilling to assume. Even if premia are partially arbitrated, risk considerations may prevent their complete elimination. In this context, the increasing deployment of storage technologies could play an important role in the future. Batteries can react to forecast errors at very short time horizons and may therefore act as a physical hedge against balancing risks faced by renewable producers (Zhao et al., 2023). A portfolio combining renewable generation and storage could allow market participants to reduce exposure to unfavorable intra-day price realizations, potentially affecting bidding incentives and the resulting structure of price premia.

Further, the results have implications for the institutional design of renewable energy marketing. The analysis shows that an expected-production bidding rationale, as implied by the institutional setting in SF4, can lead to negative price premia and avoidable revenue losses. Such outcomes may increase the costs of renewable support schemes that are ultimately borne by the state. The findings therefore suggest that current renewable marketing rules may lead to suboptimal outcomes and could warrant reconsideration, particularly regarding the flexibility given to TSOs.

The analysis also highlights the importance of forecast accuracy for market outcomes. In the theoretical model, the magnitude of expected price premia increases with the variance of renewable production forecasts (SF3) under both expected-production and risk-averse bidding rationales. Improvements in forecast accuracy therefore reduce production uncertainty and weaken the role of risk considerations in day-ahead bidding behavior. In the context of the present

analysis, improved forecasting would dampen the emergence of systematic price premia that arise from risk-sensitive bidding behavior. This interpretation is consistent with previous research showing that improvements in forecast quality are particularly valuable for risk-prone and risk-averse market participants, as they directly reduce the uncertainty underlying their bidding decisions (Wang et al., 2022).

Beyond forecast accuracy, the analysis also suggests that the magnitude of price premia depends on the prevailing market environment through its effect on the convexity of the supply curve. In particular, the steepness of the supply curve may change with fuel prices or the availability of flexible generation. For instance, higher gas prices or tighter capacity margins can increase supply curve convexity and thereby amplify the price response to renewable forecast errors. In the framework of this paper, such changes would lead to larger price premia, whereas additional flexibility, for example from battery storage, could dampen these effects. As a result, the magnitude of premia may vary with broader market conditions, which is relevant for understanding how structural changes in power systems can affect market outcomes.

5.5.4. Limitations and future research

Several limitations of the analysis should be acknowledged. First, the theoretical framework provides a stylized representation of electricity markets with two trading stages. In practice, electricity markets feature multiple trading opportunities. In particular, the risk of imbalance prices is not explicitly represented in the model. Moreover, the steepness of the marginal cost curve may change between market stages due to different participation constraints or technological response times in the intraday market. While market participants may anticipate such effects when forming expectations, these dynamics are not explicitly modeled in this work. Second, the risk-averse bidding rule derived in the theoretical model is represented by a closed-form approximation. While this approach allows for analytical insights and tractable numerical simulations, it necessarily simplifies the underlying optimization problem faced by market participants. Third, the numerical application of the theoretical model uses average diurnal market conditions. Extending the analysis to different seasons or market regimes could provide additional insights into how market conditions affect the emergence of price premia.

Future research could focus on empirically testing the mechanisms proposed in this work. While directly identifying risk preferences in bidding behavior may be challenging, empirical analyses could examine how observable risk factors, such as supply curve convexity, affect the magnitude of price premia. Extending the framework to additional electricity markets or incorporating additional trading stages could further help to assess the generality of the results.

5.6. Conclusion

The German electricity market exhibits a diurnal pattern in price premia between the day-ahead and intraday markets. Explaining the emergence of such temporal patterns remains challenging, as existing explanations for price premia in sequential electricity markets mainly focus on average premia rather than their diurnal structure.

This paper proposes a mechanism that links the observed pattern of price premia to the bidding behavior of renewable energy producers under production uncertainty. To this end, a stylized two-stage model is developed in which renewable producers determine their day-ahead positions under different bidding rationales. Closed-form expressions for the bids are derived and embedded in the theoretical model, parameterized with observed market data representing typical market conditions over the course of a day.

The analysis reveals that different bidding rationales systematically translate renewable production uncertainty into price premia between the two market stages in the absence of complete financial arbitrage. When producers bid their expected production, the asymmetric price response to forecast errors leads to negative expected premia. Under risk-neutral bidding, producers anticipate this asymmetry, resulting in a convergence of expected prices across market stages. By contrast, risk-averse bidding under consideration of tail risk can generate positive price premia, as producers reduce their day-ahead exposure to limit unfavorable outcomes in the intraday market.

Differentiating bidding rationales across renewable technologies further shows that heterogeneous strategies between wind and photovoltaic producers can generate a pronounced diurnal pattern of price premia. In particular, a configuration in which PV bids expected production while wind producers behave in a risk-averse manner produces a pattern that closely resembles the structure observed in the German market.

The results therefore suggest that systematic price premia in sequential electricity markets do not necessarily indicate market inefficiencies but may reflect risk preferences of market participants and institutional incentives of renewable energy marketing. In the German electricity market, a large share of PV generation supported under public support schemes is marketed by TSOs who are obligated to minimize quantity deviations rather than to optimize market revenues. Such a bidding rationale can lead to negative price premia and increase the costs of renewable support schemes, suggesting that renewable marketing rules may warrant reconsideration.

At the same time, the explanatory power of this work is subject to limitations. While the model reproduces the main diurnal structure of observed premia, it does not account for the slightly negative premia observed during nighttime hours in the German market. Moreover, the theoretical framework provides a stylized

representation of electricity markets limited to two trading stages. The results should therefore be interpreted as illustrating plausible mechanisms rather than providing direct empirical evidence.

A. Supplementary Material for Chapter 2

A.1. Notation

Table A.1.: Model sets, parameters, variables, and indices.

Name	Unit	Definition
Sets		
$d \in D$		Representative days
$h \in H$		Hours
$n, m \in N$		Nodes
$tech \in Tech$		Technologies
Parameters		
η	%	Efficiency
δ	%	Losses
p	-	Price
$timesteps$	-	Number of representative days
top	%	Minimum annual utilization of aggregate European hydrogen terminals
Variables		
TC	tEUR	Total system costs
$OPEX$	tEUR	Variable cost
FOM	tEUR	Fixed operating and maintenance cost
$CAPEX$	tEUR	Annualized capital cost
IC	tEUR	Import cost
S	GWh	Supply
D	GWh	Demand
$TRADEBAL$	GWh	Net trade balance
I	GWh	Imports
C	GW	Capacity
ST	GWh	Storage volume
L	GWh	Uncovered demand
Indices		
IMP		Import
$STOR$		Storage
ELY		Electrolysis
EL		Electricity
$H2$		Hydrogen

A.2. Assumptions

Table A.2.: Techno-economic assumptions as inputs for the energy system model.

Technology	Parameter	Unit	Value	Ref.
H2 storage capacity	CAPEX - New	tEUR/GWh	1,454	27, 35, 48, 89, 141
	CAPEX - Retrofit	tEUR/GWh	727	27, 35, 42, 48, 89, 141
	OPEX	tEUR/GWh	6.03	35, 48, 101, 141, 145
	FOM	% of CAPEX	4	101, 141
	Conversion H2/CH4	%	20	26, 103
	Round-trip eff.	%	90	138
	Lifetime	a	33	125
H2 storage inj. & with. capacity	CAPEX - New	tEUR/GWh/d	3,841	141
H2 pipeline	Conversion H2/CH4	%	75	56
	Losses	%	1	
H2 import terminal	CAPEX - New	tEUR/GWh/d	14,447	96
	OPEX	tEUR/GWh/d incl. in IC		138
	FOM	% of CAPEX	2.5	138
	Lifetime	a	33	
Electrolysis	CAPEX	tEUR/GW	392,243	67
	FOM	tEUR/GW	10,000	42
	Efficiency	%	74	
	Lifetime	a	25	
Battery	CAPEX	tEUR/GW	384,626	67
	FOM	tEUR/GW	13,100	42
	Efficiency	%	90	
	Lifetime	a	10	
Wind onshore	CAPEX	tEUR/GW	1,117,000	42
	FOM	tEUR/GW	13,140	42
	Efficiency	%	100	
	Lifetime	a	25	
Wind offshore	CAPEX	tEUR/GW	2,036,000	42
	FOM	tEUR/GW	26,280	42
	Efficiency	%	100	
	Lifetime	a	25	
Photovoltaics	CAPEX	tEUR/GW	682,000	42
	FOM	tEUR/GW	9,330	42
	Efficiency	%	100	
	Lifetime	a	25	
H2-to-power CCGT	CAPEX	tEUR/GW	762,000	42
	FOM	tEUR/GW	26,000	[1]
	Efficiency	%	60	

Technology	Parameter	Unit	Value	Ref.
	Lifetime	a	30	
H2-to-power OCGT	CAPEX	tEUR/GW	412,000	⁴²
	FOM	tEUR/GW	7,400	⁴²
	Efficiency	%	40	
	Lifetime	a	30	

¹ Where multiple sources are referenced, values represent the average across sources. Blank references indicate own assumptions.

A.3. Results of the investment decisions

Table A.3.: Investment decisions under varying TOP rates for the representative weather year 1989.

Technology	Unit	TOP 0%	TOP 20%	TOP 40%	TOP 60%	TOP 80%	TOP 100%
H2 terminal capacity	GWh/d	1716	1716	1716	1659	1310	1183
H2 storage capacity	TWh	63.4	63.4	63.4	64.7	72.6	81.2
H2 withdrawal capacity	GWh/d	7758	7758	7758	7819	8149	8243
H2 injection capacity	GWh/d	4284	4284	4284	4311	4529	5344
Electrolysis capacity	GW	617	617	617	617	614	600
Available wind and PV	TWh	5577	5577	5577	5570	5551	5521
Battery capacity	GW	43.7	43.7	43.7	43.7	43.9	43.9
H2-to-power capacity	GW	188	188	188	188	187	190

B. Supplementary Material for Chapter 3

B.1. Capacity factors for the calculation of LCOH

The calculation of stochastic LCOH requires hourly capacity factors of renewable energy classes for each weather year under consideration. The meteorological data used in Moritz et al. (2023) is based on hourly capacity factors from Pfenninger and Staffell (2016) which are scaled to annual capacity factors stemming from Pietzcker et al. (2014). The inclusion of Pietzcker et al. (2014) allows us to disaggregate renewable technologies into resource classes with different qualities and technical potentials restricting the output of hydrogen production. However, renewable energy potentials and capacity factors from Pietzcker et al. (2014) do not exhibit an hourly profile. Therefore, Brändle et al. (2021) conduct an exponential scaling to generate synthetic hourly profiles matching the capacity factors and potentials outlined in Pietzcker et al. (2014).

To incorporate multiple weather years in our analysis, we adjust the approach in the following way. First, we calculate the annual capacity factor cfa of individual weather years per node n and res tech r based on the time series from Pfenninger and Staffell (2016).

$$cfa_{n,s}^{res} = \sum_h cft_{n,h,s}^{res} / 8760 \quad (\text{B.1})$$

Second, we determine the relative deviation $delta$ of capacity factors per weather year to the mean annual capacity factor $cfma$.

$$delta_{n,s}^{res} = \frac{cfa_{n,s}^{res}}{cfma_n^{res}} \quad (\text{B.2})$$

Then we define an annual target capacity factor cft for each year as the original capacity factor cfo from Pietzcker et al. (2014) multiplied by the relative deviation of individual years to the mean.

$$cft_{n,r,s}^{res} = cfo_{n,r}^{res} \cdot delta_{n,s}^{res} \quad (\text{B.3})$$

Lastly, we define a final capacity factor cff , which reflects the targeted annual capacity factor while keeping the temporal structure of the initial hourly time series. This is done by using an exponential scaling factor σ for each combination

of node, resource class, res class, and scenario s , similar to the approach used in Brändle et al. (2021).

$$\frac{\sum_{h=1}^{8760} c f_{n,h,r,s}^{res}}{8760} = c f_{n,r,s}^{res} \quad (\text{B.4})$$

$$(c f_{n,r,h}^{res})^{\sigma_{n,r,s}^{res}} = c f_{n,h,r,s}^{res} \quad (\text{B.5})$$

The values for the exponential scaling factor σ are derived using a non-linear optimization model, minimizing deviations of the scaled original profile to the targeted capacity factor. The objective function and constraint are described in Equations B.6 and B.7

$$\min OBJ = slack_{up} + slack_{down} \quad (\text{B.6})$$

s.t.

$$c f_{n,r,s}^{res} = \frac{\sum_{h=1}^{8760} (c f_{n,r,h}^{res})^{\sigma_{n,r,s}^{res}}}{8760} + slack_{up} - slack_{down} \quad (\text{B.7})$$

This adjusted approach allows us to keep the information on the original intra- and inter-annual weather variability from Pfenninger and Staffell (2016) as well as the relation between capacity factors for each resource class from Pietzcker et al. (2014).

B.2. Comparison of LCOH

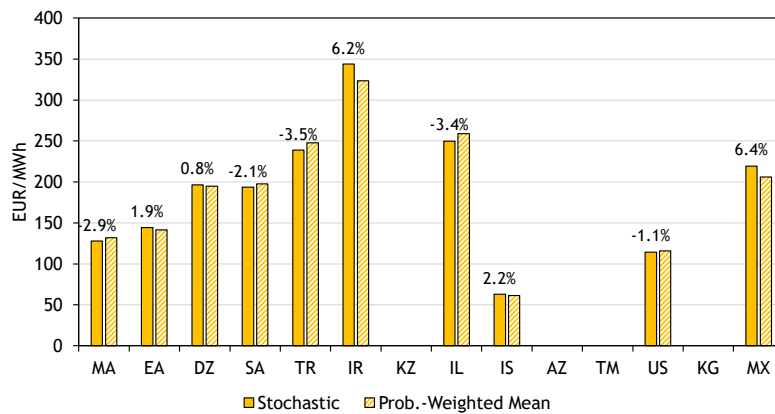


Figure B.1.: Comparison of stochastic LCOH and probability-weighted mean LCOH for wind offshore across various exporting countries. Percentages indicate the differences between both methodological approaches.

B.3. Wind correlation before and after clustering of weather years

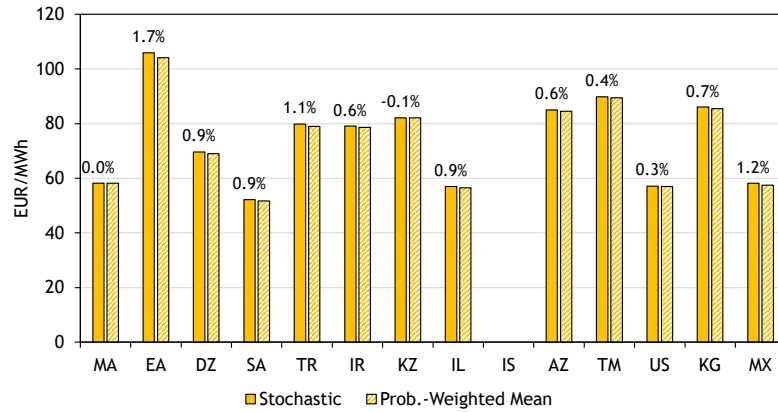


Figure B.2.: Comparison of stochastic LCOH and probability-weighted mean LCOH for PV across various exporting countries. Percentages indicate the differences between both methodological approaches.

B.3. Wind correlation before and after clustering of weather years

Figure B.3 shows the correlation of wind onshore¹⁴ capacity factors between Europe (capacity-weighted mean over countries) and each exporter for the full dataset of 27 weather years (*before Clustering*) and for the five clustered weather years (*after Clustering*). Although the clustering methodology does not explicitly include correlation as a criterion, both the magnitude and the direction of the correlations are largely preserved, indicating that the clustering adequately retains the interregional dependence structure.

¹⁴We abstract from an evaluation of PV capacity factors, as hydrogen exports based on PV generation play only a subordinate role in our model.

B. Supplementary Material for Chapter 3

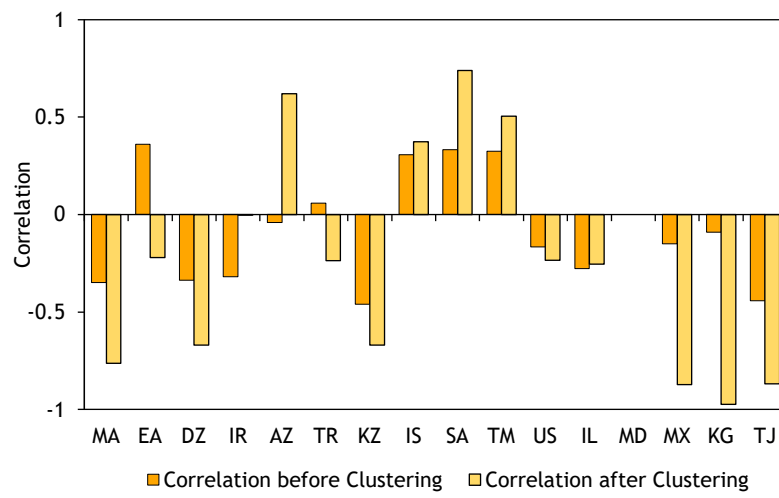


Figure B.3.: Correlation of wind onshore capacity factors between Europe and exporters.

B.4. Assumptions

Table B.1.: Techno-economic assumptions as inputs for the energy system model.

Technology	Parameter	Unit	Value	Ref.
H2 storage capacity	CAPEX - New	tEUR/GWh	350	54, 128, 141
	CAPEX - Retrofit	tEUR/GWh	300	
	OPEX	tEUR/GWh	6.03	35, 48, 101, 141, 145
	FOM	% of CAPEX	4	101, 141
	Conversion H2/CH4	%	20	26, 103
	Round-trip eff.	%	90	138
	Lifetime	a	33	125
H2 storage inj. & with. capacity	CAPEX - New	tEUR/GWh/d	6,126	128, 141
H2 pipeline	Conversion H2/CH4	%	75	56
	Losses	%	1	
Electrolysis	CAPEX	tEUR/GW	392,243	67
	FOM	tEUR/GW	10,000	42
	Efficiency	%	74	
	Lifetime	a	25	
Battery	CAPEX	tEUR/GW	384,626	67
	FOM	tEUR/GW	13,100	42
	Efficiency	%	90	
	Lifetime	a	10	
Wind onshore	CAPEX	tEUR/GW	1,117,000	42
	FOM	tEUR/GW	13,140	42
	Efficiency	%	100	
	Lifetime	a	25	
Wind offshore	CAPEX	tEUR/GW	2,036,000	42
	FOM	tEUR/GW	26,280	42
	Efficiency	%	100	
	Lifetime	a	25	
Photovoltaics	CAPEX	tEUR/GW	500,000	
	FOM	tEUR/GW	9,330	42
	Efficiency	%	100	
	Lifetime	a	25	
H2-to-power CCGT	CAPEX	tEUR/GW	762,000	42
	FOM	tEUR/GW	26,000	[1]
	Efficiency	%	60	
	Lifetime	a	30	
H2-to-power OCGT	CAPEX	tEUR/GW	412,000	42
	FOM	tEUR/GW	7,400	42
	Efficiency	%	40	

Technology	Parameter	Unit	Value	Ref.
	Lifetime	a	30	

¹ Where multiple sources are referenced, values represent the average across sources. Blank references indicate own assumptions.

B.5. LTC prices

Table B.2 summarizes LTC prices based on LCOH that vary by importing country due to differences in transport distances and available transport options (pipeline-based or seaborne).

Table B.2.: LCOH including transport costs (EUR/MWh) to selected European countries from various exporters.

Exporter	Technology	DE	NL	GB	IT	ES	PL
MA	Wind onshore	83.2	76.5	83.2	85.1	60.0	86.1
	Wind offshore	161.3	154.0	161.1	163.5	135.9	164.5
	PV	88.9	82.1	88.9	90.9	65.6	91.8
EA	Wind onshore	81.3	88.0	107.7	94.8	101.7	79.4
	Wind offshore	161.7	169.0	189.5	176.4	183.9	159.6
	PV	122.6	129.7	149.8	136.8	144.0	120.6
DZ	Wind onshore	95.8	93.3	97.4	85.5	74.0	101.1
	Wind offshore	236.0	233.1	237.5	224.4	211.0	242.5
	PV	104.5	102.0	106.1	94.1	82.5	110.0
SA	Wind onshore	144.5	138.8	137.4	127.9	134.3	145.6
	Wind offshore	301.6	294.0	292.3	278.0	286.2	303.3
	PV	132.9	127.4	126.0	116.9	123.2	134.0
TR	Wind onshore	114.7	125.0	126.9	112.4	128.6	115.6
	Wind offshore	266.7	278.8	280.8	263.8	283.2	267.9
	PV	103.0	113.2	115.0	100.7	116.7	103.9
IR	Wind onshore	108.1	115.0	127.0	110.7	130.6	114.1
	Wind offshore	395.4	404.3	419.1	398.4	424.7	403.2
	PV	119.4	126.3	138.4	122.0	142.2	125.5
KZ	Wind onshore	113.1	119.2	121.8	117.7	132.1	108.0
	Wind offshore	—	—	—	—	—	—
	PV	141.9	148.2	150.8	146.6	161.4	136.6
IL	Wind onshore	178.6	172.4	171.0	160.4	167.2	179.8
	Wind offshore	357.7	349.3	347.5	331.1	340.1	359.7
	PV	133.7	128.1	126.8	117.6	123.9	134.7
IS	Wind onshore	133.0	130.0	129.2	139.5	140.8	134.1
	Wind offshore	128.7	125.7	124.9	135.1	136.3	129.7
	PV	—	—	—	—	—	—
AZ	Wind onshore	115.4	122.8	127.7	117.2	134.2	120.9
	Wind offshore	—	—	—	—	—	—
	PV	119.2	126.7	131.6	121.0	138.1	124.8
TM	Wind onshore	132.5	137.7	147.3	139.8	163.6	128.9
	Wind offshore	—	—	—	—	—	—
	PV	138.5	143.8	153.5	145.9	169.8	134.9

Exporter	Technology	DE	NL	GB	IT	ES	PL
US	Wind onshore	144.7	140.4	139.0	144.8	146.0	145.7
	Wind offshore	202.7	197.9	196.5	202.9	204.0	204.0
	PV	136.7	132.5	131.2	136.8	138.1	137.8
KG	Wind onshore	205.8	213.1	217.5	209.8	233.5	198.1
	Wind offshore	—	—	—	—	—	—
	PV	141.8	148.6	152.8	145.5	167.8	134.5
MX	Wind onshore	161.5	156.8	155.5	160.2	161.4	162.6
	Wind offshore	328.4	322.4	320.8	326.8	327.6	330.1
	PV	140.8	136.4	135.0	139.5	140.8	141.9

C. Supplementary Material for Chapter 4

C.1. Use of variance as a risk metric

In the ex-post evaluation of profit risk, assuming normally distributed realizations of Q , we find that profit variance decreases under risk aversion ($\lambda > 0$), as expected. While the CVaR is often preferred for capturing tail risks in asymmetric distributions, it is analytically intractable in our setting. Approximations based on higher moments (e.g., skewness or kurtosis) are also impractical, as they would involve solving high-degree expressions. Despite the asymmetry in profits, we therefore adopt variance as a risk proxy within the mean-variance utility framework.

This choice is supported by our simulation results, which show a strong inverse correlation between profit variance and CVaR (see Figures C.1 and C.2). Since profits are strictly positive, a higher CVaR is favored. A maximization of the CVaR corresponds to a maximization of the lowest profits to an alpha-quantile ($\alpha = 0.05$). Hence, reducing variance can be interpreted as a reasonable approximation of maximizing the CVaR.

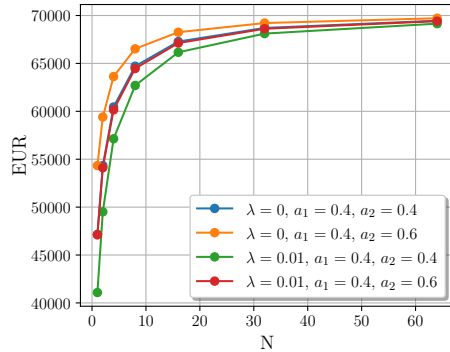


Figure C.1.: Variance of RE producer profits

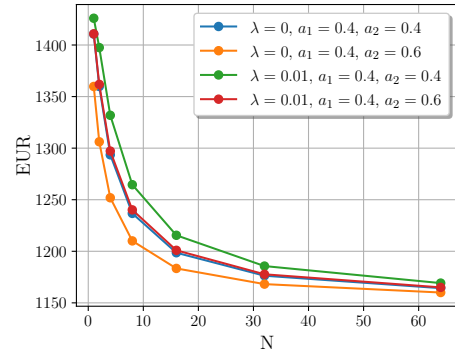


Figure C.2.: Conditional Value at Risk of RE producer profits

C.2. Choice of lambda

To calibrate a reasonable value for the degree of risk aversion λ , we assume that a risk-averse RE producer is indifferent between a certain profit (π_{gi}) equal to the expected profit minus one standard deviation of the uncertain profit π_i . That is, the certainty equivalent is given by:

$$\pi_{gi} = \mathbb{E}[\pi_i] - \sigma_{\pi_i} = \mathbb{E}[\pi_i] - \frac{\lambda}{2} \cdot \text{Var}(\pi_i) \quad (\text{C.1})$$

Solving for λ gives:

$$\lambda = \frac{2 \cdot \sigma_{\pi_i}}{\text{Var}(\pi_i)} \quad (\text{C.2})$$

Using this method and the numerical assumptions from Table 4.2, we derive the following estimates:

For a monopolistic setting ($N = 1$), we obtain $\mathbb{E}[\pi] = 1910$, $\text{Var}(\pi) = 32,658$, and $\sigma(\pi) = 180.3$. This results in $\lambda_1 \approx 0.011$.

For a more competitive market ($N = 64$), we find $\mathbb{E}[\pi] = 1760$, $\text{Var}(\pi) = 48,145$, and $\sigma(\pi) = 219.4$. Accordingly, $\lambda_{64} \approx 0.0091$.

While the precise value of λ plays a secondary role in our analysis, mainly serving for the visualization of effects, we choose $\lambda = 0.01$ as a consistent and reasonable estimate across different market settings.

C.3. Proofs

C.3.1. Proof of Proposition 2

The profit function of an RE producer for varying marginal cost functions is described in Eq. (4.3). The first derivative results in:

$$\frac{d\mathbb{U}}{dq_{i1}} = \frac{d\mathbb{E}(\text{profit})}{dq_{i1}} - \frac{\lambda}{2} \frac{d\text{Var}(\text{profit})}{dq_{i1}} \quad (\text{C.3})$$

with

$$\begin{aligned} \frac{d\mathbb{E}(\text{profit})}{dq_{i1}} &= \mu_{Q_i} N a_2 - \mu_{Q_i} a_1 + \mu_{Q_i} a_2 \\ &\quad - N a_2 q_{j1} - 2 a_2 q_{i1} + a_2 q_{j1} \end{aligned} \quad (\text{C.4})$$

and

$$\begin{aligned} \frac{d\text{Var}(\text{profit})}{dq_{i1}} &= 2 \sigma_{Q_i}^2 \left(-2 \mu_{Q_i} N^2 a_2^2 + 2 \mu_{Q_i} N a_1 a_2 - 2 \mu_{Q_i} N a_2^2 \right. \\ &\quad - N^2 a_1 a_2 q_{j1} + N^2 a_2^2 q_{i1} + N^2 a_2^2 q_{j1} \\ &\quad + N a_1^2 q_{j1} + N a_1 a_2 d - 2 N a_1 a_2 q_{i1} - N a_1 a_2 q_{j1} \\ &\quad + 2 N a_2^2 q_{i1} + N a_2 b - a_1^2 d + a_1^2 q_{i1} - a_1^2 q_{j1} \\ &\quad + a_1 a_2 d - 2 a_1 a_2 q_{i1} + 2 a_1 a_2 q_{j1} \\ &\quad \left. - a_1 b + a_2^2 q_{i1} - a_2^2 q_{j1} + a_2 b \right) \end{aligned} \quad (\text{C.5})$$

Setting the derivative of the utility function to zero and solving for q_{i1}^* results in the profit-maximizing first-stage bid of the RE producer i :

$$\begin{aligned}
& 2\mu_{Q_i}N^2\sigma_{Q_i}^2a_2^2\lambda - 2\mu_{Q_i}N\sigma_{Q_i}^2a_1a_2\lambda \\
& + 2\mu_{Q_i}N\sigma_{Q_i}^2a_2^2\lambda + \mu_{Q_i}Na_2 - \mu_{Q_i}a_1 + \mu_{Q_i}a_2 \\
& + N^2\sigma_{Q_i}^2a_1a_2\lambda q_{j1} - N^2\sigma_{Q_i}^2a_2^2\lambda q_{j1} \\
& - N\sigma_{Q_i}^2a_1^2\lambda q_{j1} - N\sigma_{Q_i}^2a_1a_2d\lambda + N\sigma_{Q_i}^2a_1a_2\lambda q_{j1} \\
& - N\sigma_{Q_i}^2a_2b\lambda - Na_2q_{j1} + \sigma_{Q_i}^2a_1^2d\lambda \\
q_{i1}^* = & \frac{N^2\sigma_{Q_i}^2a_2^2\lambda - 2N\sigma_{Q_i}^2a_1a_2\lambda + 2N\sigma_{Q_i}^2a_2^2\lambda}{N^2\sigma_{Q_i}^2a_2^2\lambda - 2N\sigma_{Q_i}^2a_1a_2\lambda + 2N\sigma_{Q_i}^2a_2^2\lambda} \\
& + \sigma_{Q_i}^2a_1^2\lambda - 2\sigma_{Q_i}^2a_1a_2\lambda + \sigma_{Q_i}^2a_2^2\lambda + 2a_2 \\
& + \frac{\sigma_{Q_i}^2a_1^2\lambda q_{j1} - \sigma_{Q_i}^2a_1a_2d\lambda - 2\sigma_{Q_i}^2a_1a_2\lambda q_{j1}}{N^2\sigma_{Q_i}^2a_2^2\lambda - 2N\sigma_{Q_i}^2a_1a_2\lambda + 2N\sigma_{Q_i}^2a_2^2\lambda} \\
& + \frac{\sigma_{Q_i}^2a_1b\lambda + \sigma_{Q_i}^2a_2^2\lambda q_{j1} - \sigma_{Q_i}^2a_2b\lambda + a_2q_{j1}}{N^2\sigma_{Q_i}^2a_2^2\lambda - 2N\sigma_{Q_i}^2a_1a_2\lambda + 2N\sigma_{Q_i}^2a_2^2\lambda} \\
& + \sigma_{Q_i}^2a_1^2\lambda - 2\sigma_{Q_i}^2a_1a_2\lambda + \sigma_{Q_i}^2a_2^2\lambda + 2a_2
\end{aligned} \tag{C.6}$$

Apply the symmetry assumption $q_{i1} = q_{j1}$, $\mu_Q = \mu_{Q_i} * N$, and $\sigma_Q = \sigma_{Q_i} * N$, and solve for q_{i1}^* :

$$q_{i1}^* = \frac{A + \lambda B}{C + \lambda D} \tag{C.7}$$

where the components are defined as follows:

$$\begin{aligned}
A &= \mu_Q N(Na_2 + a_2 - a_1) \\
B &= \sigma_Q^2 \left(2\mu_Q Na_2^2 - 2\mu_Q a_1a_2 + 2\mu_Q a_2^2 - Na_1da_2 - Nba_2 + a_1^2d + a_1b - a_1da_2 - ba_2 \right) \\
C &= N(N^2a_2 + Na_2) \\
D &= N \left(\sigma_Q^2 \left(-Na_1a_2 + 2Na_2^2 + a_1^2 - 3a_1a_2 + 2a_2^2 \right) \right)
\end{aligned}$$

C.3.2. Proof of Corollary 2

In the following, we reformulate $\frac{dq_{i1}^*}{d\lambda} = \frac{BC-AD}{(2a_2+\lambda D)^2}$ to prove Corollary 2. The numerator of Eq. (4.25) is:

$$BC - AD = \sigma_Q^2 \left[2a_2 \left(\mu_Q (4a_2^2 - 2a_1a_2) + (-2a_1da_2 - 2ba_2 + a_1^2d + a_1b) \right) - \mu_Q (2a_2 - a_1)(2a_2 - a_1)^2 \right].$$

Reformulate to:

$$BC - AD = \sigma_Q^2 \cdot (a_1 - 2a_2) \left(a_1(a_1 - 4a_2)\mu_Q + 2a_2(a_1d + b) \right).$$

Since $\sigma_Q^2 > 0$, $BC - AD < 0$ is equivalent to:

$$(a_1 - 2a_2) \left(a_1(a_1 - 4a_2)\mu_Q + 2a_2(a_1d + b) \right) < 0$$

Reformulate to:

C. Supplementary Material for Chapter 4

$$a_1(a_1 - 4a_2)\mu_Q > -2a_2(a_1d + b),$$

Solve for μ_Q :

$$\mu_Q < \frac{2a_2(a_1d + b)}{a_1(4a_2 - a_1)}.$$

D. Supplementary Material for Chapter 5

D.1. Transformation of bid curves

This section formally describes the transformation of the day-ahead bid curves. The approach and the notation follow Kulakov and Ziel (2019).

For a given delivery day d and hour s , the aggregated day-ahead auction results can be represented by a supply curve and a demand curve. Both curves relate traded volumes to prices and are defined on a common price domain bounded by the market price limits.

Let the wholesale supply curve be denoted by

$$\text{SUP}_{d,s}^{WS} : q \mapsto P, \quad (\text{D.1})$$

and the wholesale demand curve by

$$\text{DEM}_{d,s}^{WS} : q \mapsto P, \quad (\text{D.2})$$

where $q \in (0, \infty)$ denotes the cumulative volume and $P \in [P_{\min}, P_{\max}]$ the corresponding bid price.

Due to the strict monotonicity of both curves, their inverse functions exist and are given by

$$\text{SUP}_{d,s}^{WS,-1} : P \mapsto q, \quad \text{DEM}_{d,s}^{WS,-1} : P \mapsto q. \quad (\text{D.3})$$

The inverse curves map prices to cumulative quantities.

In the day-ahead auction, prices are bounded by a minimum admissible price $P_{\min} = -500$ EUR/MWh. The perfectly inelastic demand level for delivery day d and hour s is defined as the cumulative demand evaluated at the minimum price.

$$\text{DEM}_{d,s}^{\text{inelastic}} = \text{DEM}_{d,s}^{WS,-1}(P_{\min}). \quad (\text{D.4})$$

This quantity represents the total volume that is demanded at the lowest admissible price and serves as the fixed demand level in the transformed representation.

To obtain a representation with perfectly inelastic demand, the elasticity originally embedded in the demand curve is transferred to the supply side. This is achieved by combining the inverse wholesale supply curve with a mirrored version of the inverse wholesale demand curve.

The transformed inverse supply curve is defined as

$$\text{SUP}_{d,s}^{-1}(P) = \text{SUP}_{d,s}^{WS,-1}(P) + \left(\text{DEM}_{d,s}^{\text{inelastic}} - \text{DEM}_{d,s}^{WS,-1}(P) \right). \quad (\text{D.5})$$

The first term corresponds to the original inverse wholesale supply curve, while the second term reflects the demand-side elasticity mirrored around the perfectly inelastic

demand level. Since both inverse curves are monotonic, the transformed inverse supply curve is also monotonic.

The original day-ahead market-clearing price $P_{d,s}^{DA}$ satisfies

$$P_{d,s}^{DA} = \text{SUP}_{d,s}(DEM_{d,s}^{\text{inelastic}}), \quad (\text{D.6})$$

such that the transformed representation preserves the original equilibrium price.

Under the transformed representation, demand is perfectly inelastic and fixed at $DEM_{d,s}^{\text{inelastic}}$. Any quantity deviation x around this demand level corresponds to an equal and opposite horizontal shift of the transformed inverse supply curve. As a consequence, price adjustments resulting from quantity deviations can be interpreted exclusively as supply-side responses.

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Curriculum Vitae

CURRICULUM VITAE

Julian Keutz

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10/2018 - 10/2020	RWTH Aachen University Master of Science in Business Administration and Engineering: Electrical Energy Technology
10/2015 - 09/2018	RWTH Aachen University Bachelor of Science in Business Administration and Engineering: Electrical Energy Technology
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WORKING EXPERIENCE

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10/2018 - 02/2020	Institute for High Voltage Equipment and Grids, Digitalization and Energy Economics, RWTH Aachen University Working Student
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LANGUAGES

German	Native
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PUBLICATIONS

Research Articles:

- Keutz, J. (2026). Bidding Wind and Solar: A Theory of Price Premia in Sequential Electricity Markets. *EWI Working Paper* No. 26/02.
- Ashour Novirdoust, A., Hoffmann-Willers, P., Keutz, J. (2025). Optimal Bidding of Uncertain Renewable Electricity in Sequential Markets – Implications of Risk Aversion and Imperfect Competition. *EWI Working Paper* No. 25/10.
- Keutz, J., Kopp, J.H. (2025). The Cost of Security: Analyzing Strategies to Hedge Hydrogen Import Disruption under Stochastic Representation of Weather. *EWI Working Paper* No. 25/12.
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Selected Further Publications:

- Klaas, A.-K., Diehl, M., Fadl, N., Keutz, J., Leibfritz, T., Schäfer, F., Wohlleben, D. (2025). Green hydrogen production under RFNBO criteria. *Study on behalf of Förderinitiative Wasserstoff und Moleküle der Gesellschaft zur Förderung des Energiewirtschaftlichen Instituts an der Universität zu Köln e.V.*
- Dressler, M., Lilienkamp, A., Keutz, J., Just, L., Ruhnau, O. (2025). Assessment of energy-limited flexibilities in capacity mechanisms. *Study on behalf of Förderinitiative Integriertes Strommarktdesign der Gesellschaft zur Förderung des Energiewirtschaftlichen Instituts an der Universität zu Köln e.V.*
- Czock, B., Dressler, M., Keutz, J., Restel, L., Ruhnau, O., Schnaars, P. (2025). Optimized grid connections for wind and PV: How grid expansion costs can be saved via reduced grid connection capacity. *Study on behalf of Förderinitiative Integriertes Strommarktdesign der Gesellschaft zur Förderung des Energiewirtschaftlichen Instituts an der Universität zu Köln e.V.*
- Schnaars, P., Klaas, A.-K., Keutz, J., Walde, M., Restel, L., Emelianova, P., Schäfer, F., Schrader, E. (2024). Wasserstoffspeicher in Deutschland und Europa: Modellbasierte Analyse bis 2050. *Study on behalf of RWE Gas Storage West GmbH.*
- Fernandez Alvarez, C., Diers, H., Keutz, J. (2024). Coal 2024 - Analysis and forecast to 2027. *International Energy Agency (IEA)/OECD.*
- Sprenger, T., Keutz, J., Terhorst, S., Walde, M., Wild, P. (2024). Facilitating China's Industrial Transformation with CCU/S. *Study on behalf of Deutsche Energieagentur (dena).*
- Fernandez Alvarez, C., Keutz, J., Lilienkamp, A. (2023). Coal 2023 - Analysis and forecast to 2026. *International Energy Agency (IEA)/OECD.*
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- Kienscherf, P. A., Keutz, J., Diers, H. (2023). Versorgungssicherheit für NRW in 2030. *Study on behalf of IHK NRW.*
- Wagner, J., Schnaars, P., Namockel, N., Diers, H., Keutz, J. (2022). Gasverstromung im Winter 2022/2023. *Study on behalf of Gesellschaft zur Förderung des Energiewirtschaftlichen Instituts an der Universität zu Köln e.V.*
- Schnaars, P., Sprenger, T., Wild, P., Keutz, J. (2022). Politikoptionen zur Steigerung von Demand Side Management und Energieeffizienz in der deutschen und chinesischen Industrie. *et - Energiewirtschaftliche Tagesfragen, Vol. 72 (12), 2022, pp. 67-70.*

PRESENTATIONS AND TALKS

- Resiliente Energiewende trotz Wirtschaftsdruck - Systemintegration & Flexibilität als Wettbewerbsfaktor und gesellschaftliche Aufgabe. *Berliner Energietage*. April 2026. Berlin (online).
- Navigating uncertainty: Renewable bidding and price premia in sequential electricity markets. *ENERDAY 2026 - 20th International Conference on Energy Economics and Technology*. March 2026. Dresden.
- The Cost of Security: Analyzing Strategies to Hedge Hydrogen Import Disruption under Stochastic Representation of Weather. *9th AIEE Energy Symposium - Current and Future Challenges to Energy Security*. November 2025. Rome.
- Weather in energy system modeling. *HErZ Seminar Series*. July 2025. Cologne.

Declaration on the Use of AI Tools

Artificial intelligence-based tools, including ChatGPT (OpenAI) and Claude (Anthropic), were used during the preparation of this thesis. These tools were employed for language-related support, including grammar correction, stylistic refinement, and improvements in sentence structure and readability.

All scientific content, analyses, modeling approaches, interpretations, and conclusions presented in this dissertation are the sole work of the author. The author takes full responsibility for the accuracy and originality of the submitted work.

