# Essays in Energy Economics: On Price Signals and Investments

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# 1. Introduction

## 1.1. Motivation

The imperative to decarbonize the global energy system represents one of the most profound and complex challenges of our era. Central to this endeavor is the electricity sector, which plays a pivotal role in decarbonizing the wider energy consumption. This transition involves a fundamental overhaul of the electricity generation, with a decisive shift towards renewable energy sources; a significant evolution in consumption patterns, driven by the electrification of end-use sectors; and a corresponding adaptation of the electricity transmission and distribution infrastructure to accommodate these new dynamics.

Such a fundamental transition relies on mobilizing substantial, timely, and strategically directed investments. The magnitude of these investments translates into a significant renewal and expansion of the capital stock. Given the vast financial resources involved, ensuring the economic efficiency of these investments is of great importance. Misallocation or suboptimal timing of capital deployment could lead to unnecessarily high transition costs, potentially jeopardizing public acceptance and the overall pace of decarbonization.

In largely liberalized electricity markets, investment decisions are primarily steered by price signals. These signals critically determine the type, location, scale, and ultimate economic viability of new energy projects. The price signals are multifaceted, comprising various components shaped by environmental policy instruments, electricity market mechanisms, and grid regulation. Carefully coordinating these price components is essential to ensure coherent investment incentives.

The effective coordination of the various price components presents a complex challenge due to their different origins and manifold interdependencies. The components are formulated by a diverse set of actors, including governmental bodies and regulatory agencies, each having potentially overlapping objectives. Furthermore, the structural unbundling of the electricity sector into distinct generation, transmission, distribution, and retail entities can impede holistic system planning and introduce additional layers of complexity. Ensuring that the decentralized investment decisions of diverse market participants align with the overarching system efficiency and decarbonization goals is a non-trivial regulatory task.

Compounding the coordination complexity is the pervasive uncertainty inherent in such a large-scale and long-term transition. Investment decisions, particularly those concerning long-lived, capital-intensive assets essential for decarbonization, are invariably made under conditions of uncertainty. Market participants and regulators alike are exposed to various risks. These include, but are not limited to, policy and regulatory risk, technological uncertainty regarding the cost and performance of emerging low-carbon solutions, and volatility in commodity and carbon markets. The perception and management of these risks are critical determinants of the investment behavior and the overall cost of the energy transition.

Against this backdrop, this thesis seeks to contribute to a deeper understanding of the interactions between different price components and their investment incentives within the transitioning electricity sector. Chapter 2 applies an analytical model to examine the interactions of different spot market pricing schemes and network tariff designs in light of dynamic investment incentives. Chapter 3 empirically investigates the impact of regionally differing electricity prices on residential PV investments. In Chapter 4, the grid connection sizing of utility-scale hybrid PV-Battery systems is investigated, considering risks in power prices and renewable production. Chapter 5 examines how different sources of risk affect the efficiency of Carbon Contracts for Differences (CCfDs) for incentivizing decarbonization investments. The four essays are self-contained and may be read in any order. Each chapter is based on a paper to which all the authors contributed equally:

1. Network Tariffs under Different Pricing Schemes in a Dynamically Consistent Framework. Joint work with Amelie Sitzmann. *EWI Working Paper 21/01* (Jeddi and Sitzmann, 2021)

2. How Prices Guide Investment Decisions under Net Purchasing – An Empirical Analysis on the Impact of Network Tariffs on Residential PV. Joint work with Fabian Arnold and Amelie Sitzmann. *EWI Working Paper 21/07* and published in *Energy Economics*, Vol. 112, 2022 (Arnold et al., 2022)

3. Grid Connection Sizing of Hybrid PV-Battery Systems: Navigating Market Volatility and Infrastructure Constraints. *EWI Working Paper 25/05* (Jeddi, 2025)

4. Complementing carbon prices with Carbon Contracts for Difference in the presence of risk – When is it beneficial and when not? Joint work with Dominic Lencz and Theresa Wildgrube. *EWI Working Paper 21/09* (Jeddi et al., 2021)

The remainder of the introduction outlines the content of the four essays (Section 1.2), discusses their methodological approaches, and hints at potential areas of further research (Section 1.3).

## 1.2. Outline of the Thesis

### 1.2.1. Network Tariffs under Different Pricing Schemes in a Dynamically Consistent Framework

Adequately designed prices are essential to achieve efficient coordination between the electricity network and market participants. However, consumer prices comprise several, possibly distorting price components. Applying an analytical model, **Chapter 2** examines different regulatory settings, consisting of alternative spot market pricing schemes and network tariff designs in a dynamic context. While a setting with zonal pricing, i.e., spatially differentiated prices, and fixed network tariffs achieves the highest welfare, a deviation of either the pricing scheme or the network tariff design leads to inefficiencies. The results show that two inefficiently designed price components can be better than one, especially if network tariffs correct for the static inefficiency of the pricing scheme. Besides the network tariff design, network operators must pay attention to the allocation of network costs. It affects spatial price signals and, therefore, the dynamic allocation of investment decisions. Considering these decisions in a dynamic framework increases the requirements for the configuration of network tariffs, especially with volume-based network tariffs.

### 1.2.2. How Prices Guide Investment Decisions under Net Purchasing - An Empirical Analysis on the Impact of Network Tariffs on Residential PV

Within the regulation of net purchasing, investment incentives for residential PV depend on the remuneration for grid feed-in and the consumption costs that households can save by self-consumption. Network tariffs constitute a substantial part of these consumption costs. **Chapter 3** uses postcode-level data for Germany between 2009 and 2017 and exploits the regional heterogeneity of network tariffs to investigate whether they encourage to invest in PV installations and evaluate how the nonlinear tariff structure impacts residential PV adoption. The results show that network tariffs do impact PV adoption. The effect has increased in recent years when self-consumption has become financially more attractive, and the results confirm the expectation that PV investments are driven by the volumetric tariff. Policy reforms that alter the share between the price components are, thus, likely to affect residential PV adoption. Further, with self-consumption becoming a key incentive, price signals can effectively support the coordination of electricity demand and supply in Germany.

### 1.2.3. Grid Connection Sizing of Hybrid PV-Battery Systems: Navigating Market Volatility and Infrastructure Constraints

The increasing share of intermittent renewable energy generation amplifies power price volatility, raising the need for storage technologies such as battery energy storage systems (BESS). However, limited transmission infrastructure, particularly constrained grid connections, poses a major barrier to the deployment of both BESS and further renewable generation. Co-locating BESS with wind and solar assets can increase grid connection utilization and lower project costs. **Chapter 4** examines the effects of grid connection rationing on hybrid PV-BESS systems, accounting for weather-induced generation uncertainty and price fluctuations. The results indicate that PV and BESS margins exhibit a strong negative correlation, leading to risk diversification. Grid withdrawal constraints substantially reduce contribution margins and increase risk exposure by lowering the diversification effect. In contrast, hybrid PV-BESS systems can reduce their grid injection capacity by up to 60% of their nameplate capacity without significantly affecting contribution margins or risk, as peak solar generation coincides with low power prices. A market premium payment diminishes the diversification benefits of hybrid PV-BESS systems and encourages greater grid connections by inflating the value of generation during low-price periods. These findings suggest that the central features of the German EEG innovation tender scheme for hybrid BESS systems - grid withdrawal constraints and a market premium - created an unnecessary excess burden for taxpayers.

### 1.2.4. Complementing carbon prices with Carbon Contracts for Difference in the presence of risk - When is it beneficial and when not?

Deep decarbonization requires large-scale irreversible investments throughout the next decade. Policymakers propose CCfDs to incentivize such investments in the industry sector. CCfDs are contracts between a regulator and a firm that pay out the difference between a guaranteed strike price and the actual carbon price per abated emissions by an investment. **Chapter 5** develops an analytical model to assess the welfare effects of CCfDs and compare it to other carbon pricing regimes. In the model, a regulator can offer CCfDs to risk-averse firms that decide upon irreversible investments into an emission-free technology in the presence of risk. Risk can originate from the environmental damage or the variable costs of the emission-free technology. The results show that CCfDs can be beneficial policy instruments, as they hedge firms' risk, encouraging investments when firms' risk aversion would otherwise inhibit them. In contrast to mitigating firms' risk by an early carbon price commitment, CCfDs maintain the regulator's flexibility to adjust the carbon price if new information reveals. However, as CCfDs hedge the firms' revenues, they might safeguard production with the emission-free technology, even if it is ex-post socially not optimal. In this case, regulatory flexibility can be welfare superior to offering a CCfD.

## 1.3. Methodological Approaches, Limitations and Future Research

Each chapter of this thesis deals with a specific aspect of energy economic research. Therefore, different methodological approaches are applied, each tailored to answer the specific research question of each chapter.

**Chapter 2** establishes a stylized analytical model framework of the electricity system. The analysis employs a two-node model that incorporates a spot market and the network tariff structure implemented by a transmission system operator (TSO). The model framework is capable of representing various spot market pricing schemes and different network tariff designs. Through this theoretical approach, insights are gained regarding the interaction between these two price components, their potential for creating inefficiencies, and the conditions necessary for a dynamically consistent coordination of investments on the demand side. The stylized model utilizes several stringent assumptions, such as perfect competition, perfect foresight, constant marginal costs on the supply side, and identical consumers on the demand side. The assumptions incorporated into the model facilitate the derivation of tractable results, though they also introduce a significant level of abstraction and consequently limit the general applicability of the findings. Therefore, loosening critical assumptions, for instance, by moving away from the assumption of constant marginal costs or by including uncertainty in the decision problem, represents promising directions for future research. Additional empirical or numerical analyses could supplement the theoretical insights.

**Chapter 3** applies an econometric approach to analyze how price signals impact residential PV investments in Germany. The study employs a panel dataset encompassing PV installations, network tariffs, and socioeconomic variables at the postcode level from 2009 to 2017. The methodology leverages the network tariffs' regional heterogeneity to estimate how a nonlinear tariff structure encourages households to invest in PV systems. To this end, a Poisson quasi-maximum likelihood estimator (PQMLE) with fixed effects is applied, which allows for controlling for unobserved heterogeneity across regions and time. However, the use of fixed effects absorbs a substantial part of the within-variance, and hence, the analysis is limited in explaining the present heterogeneity of PV installations in Germany. Further research could explore alternative model frameworks to investigate the impact of economic and socioeconomic factors in more detail.

In **Chapter 4**, a mixed-integer linear program is developed, which simulates the dispatch of a single hybrid PV-battery system in different economic and regulatory environments. The dispatch is optimized for exogenous PV generation profiles and corresponding electricity price samples, generated with dedicated stochastic processes. Two parametric models for day-ahead and intraday markets capture the relationship between wind and solar generation and electricity prices. The model framework is applied to a case study of the German electricity market. By systematically varying the grid connection configuration, the analysis derives the change in contribution margins and associated risks resulting from incremental constraints on grid access. This framework enables investors to identify the optimal grid withdrawal and injection capacities by comparing the risk-return profiles of grid cost-adjusted contribution margins. The model only reflects the dispatch decisions of a single asset and does not cover system-wide effects. Additionally, the case study is carried out for an exemplary year and does not capture future energy system developments. These effects could become accessible using energy system optimization and simulations for a larger time horizon and extended system boundaries.

**Chapter 5** applies a stylized theoretical model framework to investigate the investment behavior of firms as they commit to decarbonizing a production process. The analysis incorporates two distinct risk sources and various carbon pricing regimes, including CCfDs. Firms commit to investments before the uncertainty resolves, but the timing of the carbon price setting depends on the specific carbon pricing regime. Using backward induction, the model solution identifies the subgame-perfect Nash equilibrium. The different pricing policies are then assessed and contrasted with the social optimum. When risks are treated separately, the model yields an analytical solution. However, a numerical solution is employed when applying both types of risk simultaneously. Risk itself is conceptualized as a random variable following a truncated normal distribution. Key assumptions include firms having an exponential utility in profits and a risk-neutral regulator. The model also assumes the absence of shadow costs from public funding. Alleviating some of these assumptions in a different model framework could help to generalize the results. Assuming a regulator with risk aversion or firms that are less risk-averse would likely dampen the beneficial welfare effects of CCfDs. Future research could investigate the consequence of integrating shadow costs of public funds, as it would alter both carbon prices and CCfDs.

Beyond this discussion, the individual chapters describe in detail the methodological approaches used, discuss their limitations, and point out possibilities for further research.

# 2. Network Tariffs under Different Pricing Schemes in a Dynamically Consistent Framework

## 2.1. Introduction

The transition towards a decarbonized energy system requires investments in new electricity consumption technologies, like power-to-gas facilities or electric heating systems. In liberalized electricity systems, investment and operation decisions are private and based on price signals. Therefore, adequately designed prices are of great importance to efficiently coordinate the network and decisions of supply and demand. Increasingly decentralized investments and rising network costs make spatial price signals even more relevant. In many electricity systems, however, prices for consumers do not include spatial signals, and in most cases, they contain several price components that are not necessarily aligned. While the demand-side has traditionally been perceived as price-inelastic, with new demand-side technologies entering the system, consumers can participate more actively in electricity markets. Therefore, misaligned price signals can have an increasingly negative impact on welfare and the system's efficiency. The adequacy of price signals depends on the design of several components, including the spot market pricing scheme and regulatory price components, like network tariffs. In many countries, network tariffs account for a significant part of the consumer price. In addition to the sum of price components that directly affect the consumers' decision-making, the individual price components can interact with each other. These interactions depend on the design of the individual components.

In this paper, we analyze the interactions of price components by combining different spot market pricing schemes and network tariff designs. We derive static and dynamic effects within each regulatory setting and analyze how regulatory changes impact efficiency by ranking the regulatory settings in terms of overall welfare. The analysis particularly accounts for network tariffs' economic efficiency, including their function to recover network costs for the network operator and their ability to ensure a dynamically consistent allocation of demand investments.

We develop a theoretical two-node model, including a spot market and the network tariff setting of a transmission system operator (TSO).[1] The TSO decides on welfare optimal network tariffs that must recover the network costs. She anticipates the dynamic effects of price signals and optimizes network tariffs such that upcoming demand investments are efficiently allocated. Subsequently, the spot market clearing follows, if necessary, accompanied by congestion management measures. We apply the model in four different regulatory settings - the combination of two spot market pricing schemes and two network tariff designs. As pricing schemes, we consider zonal and uniform pricing because they represent two contrasting approaches to incorporate network constraints in the market clearing.[2] As network tariff designs, we consider fixed and volume-based network tariffs. Economic theory on efficient pricing suggests fixed network tariffs as they do not distort market price signals (c.f. Pérez-Arriaga and Smeers, 2003). In contrast, volume-based tariffs increase the per-unit price for consumers. If consumers react to prices, volume-based network tariffs induce a deadweight loss. Ramsey-Boiteux prices minimize this deadweight-loss and constitute the least-distorting volume-based network tariffs (c.f. Wilson, 1993).

The regulatory setting with zonal pricing and fixed network tariffs achieves the highest welfare. Without reducing the static welfare, the TSO can ensure a dynamically consistent allocation of demand investments by restricting the feasible cost allocation between the two nodes. In the regulatory setting with uniform pricing and fixed network tariffs, the TSO also achieves a dynamically consistent allocation of demand investments without reducing the static welfare. However, the cost allocation is further restricted, as the network tariffs are the only possibility for spatial price signals. Additionally, the introduction of uniform pricing leads to inefficiency from congestion management, as we assume a cost-based redispatch mechanism of generators. With volume-based network tariffs, the inefficiency from the congestion management reduces, if the TSO includes a correction term into the network tariff, which imitates zonal prices. Under both pricing schemes, volume-based network tariffs induce a deadweight loss as they increase per-unit prices and, therefore, impact the spot market outcome. In contrast to fixed network tariffs, optimal volume-based network tariffs can lead to an additional loss in static welfare when considering a dynamically consistent allocation of demand investments.

Comparing the four regulatory settings shows that deviating from the regulatory setting of zonal pricing and fixed network tariffs leads to inefficiencies.

[1] In the following, we refer to the transmission network only. However, due to the stylized representation of network constraints, this does not necessarily exclude our model's application in the context of distribution networks.

[2] We use the term zonal pricing as a general approach for spatially differentiated prices within one regulated region. This definition includes all pricing schemes in which the spot market sends locational price signals to the market participants. The concept of zonal pricing preserves the possibility that several nodes of a network constitute a zone, while prices may differ between the zones of one region. Within our two-node model, nodal or zonal prices are equivalent.

Under uniform pricing, additional costs occur due to congestion management, and the use of volume-based network tariffs results in a deadweight loss due to price distortion. If there is only one source of inefficiency, welfare increases by adjusting the respective price component, i.e., changing either to fixed network tariffs or zonal pricing. However, suppose both sources of inefficiency are present. In that case, i.e., the combination of uniform pricing and volume-based network tariffs, an adjustment of only one aspect can have unintended effects on overall welfare. If optimal volume-based network tariffs structurally reduce congestion management costs, switching to fixed network tariffs does not necessarily increase market efficiency. This result is important considering that current electricity systems often use a combination of uniform pricing and mainly volume-based network tariffs. Hence, we demonstrate the importance of addressing the interactions between price components when changing the regulatory setting.

This paper contributes to the broader literature on network cost recovery, focusing on the interactions with different spot market pricing schemes in a dynamic context. Electricity networks constitute a natural monopoly and typically face large, fixed network costs. Thus, competitive pricing at short-run marginal costs does not generate enough revenue to cover total costs (c.f. Joskow, 2007, Pérez-Arriaga et al., 1995). Therefore, cost recovery is necessary independently of the spot market pricing scheme and requires an appropriate network tariff design (c.f. Brunekreeft et al., 2005). Borenstein (2016) comprehensively discusses the aspect of fixed cost recovery in natural monopolies and the economic principles of tariff setting in electricity markets. Furthermore, Batlle et al. (2020) and Schittekatte (2020) conceptually discuss options for residual cost allocation, with a special focus on residential consumers and distributional effects of network tariffs. This strand of literature is expanded by empirical studies on the distributional effects, e.g., by Burger et al. (2020) and Ansarin et al. (2020), as well as numerical simulation models, that analyze the effects of different network tariffs on different consumer groups, e.g., Fridgen et al. (2018) and Richstein and Hosseinioun (2020).

In a dynamic context, the demand-side has received relatively little attention so far, as consumers' investment decisions have long been considered not being influenced by electricity price signals. In their recent work on prosumers, Schittekatte et al. (2018) and Schittekatte and Meeus (2020) analyze the effect of network tariffs on consumers' investment incentives and the installation of residential PV. Gautier et al. (2020) contribute to the discussion on investment incentives by taking the presence of heterogeneous prosumers into account and Castro and Callaway (2020) simulate the impact of different network tariffs on demand's investment decisions in a numerical model. Though, these analyses do not consider the spatial dimension and locational choices. While Ambrosius et al. (2018) do analyze spatial demand investments under different spot market pricing schemes, they do not consider multiple network tariff designs. In comparison, the literature acknowledging the spatial dimension and the impact of network tariffs on location-based price signals is currently limited to the supply side. Tangerås and Wolak (2019) analytically show how locational marginal network tariffs can be designed to incentivize efficient supply-side investments. Bertsch et al. (2016) analyze different pricing schemes in a dynamic numerical framework. They consider the interactions of network tariffs (specifically a g-component) and the pricing scheme. Similarly, Grimm et al. (2019) apply regionally differentiated network tariffs under different pricing schemes for the German electricity market. Ruderer and Zöttl (2018) account for the interaction of congestion management methods and network tariffs by examining the impact of volume- and capacity-based network tariffs on generators' investment decision in an analytical model. The importance of efficient cost recovery mechanisms is also highlighted by Chao and Wilson (2020). In a numerical model they find volume-based Ramsey-Boiteux tariffs to be close to the social optimum.

To the best of our knowledge, the paper at hand is the first, which explicitly considers different network tariff designs and pricing schemes in a consistent dynamic framework to analyze the effect on spatial demand-side decisions. Although each of these topics has been studied extensively from an isolated perspective, integrated approaches are relatively scarce. Borenstein and Bushnell (2018) empirically analyze the interaction of network tariffs and the pricing of externalities in the US. The authors show that if prices are affected by more than one distortion, the effects can level each other out. We contribute to the discussion by developing an analytical framework in which we provide insights into the interaction of the two price components, their potential inefficiencies and the requirements for a dynamically consistent allocation of demand-side investments.

The remainder of this paper is structured as follows: Section 2.2 introduces our model set-up, and Section 2.3 analyzes the optimal network tariffs under different pricing schemes in a dynamic context. Section 2.4 examines the effects of the regulatory settings on overall welfare. Section 2.5 discusses political implications and summarizes concluding remarks.

## 2.2. The model framework

This section introduces the basic model setup to analyze different pricing schemes and network tariff designs in the presence of a congested transmission network. We consider a two-node model with two nodes called *north* and *south* denoted by $i \in \{n, s\}$ with respective generation technologies with constant marginal costs $c_i$. Further, we assume that the generation technology in the north is strictly cheaper, i.e., $c_n < c_s$. Both technologies have an unrestricted generation capacity. Further, we assume perfect competition in both nodes. Thus, producer surplus is equal to zero in all regulatory settings. The aggregated market demand in each node is denoted by $D_i(p_i)$, which is decreasing in price, i.e., ${}^{\partial D_i(p_i)}/_{\partial p_i} < 0 \; \forall \; i$. We assume a positive number of $\omega_i$ identical consumers in each node. The total number of consumers is therefore given by $\Omega = \omega_n + \omega_s$.

Electricity generation $q_i$ in both nodes needs to cover total demand, i.e., $\sum_i q_i = \sum_i D_i(p_i)$. Further, the two nodes are connected by a transmission line, with power flows $l$ and a limited capacity of $\overline{L}$, illustrated in figure 2.1. We focus on congested networks and hence demand exceeds the limited transmission line capacity, i.e., $\overline{L} \leq D_i(p_i)\ \forall\ i$. Since we assume that generation costs are lower in the north, electricity flows from north to south. The transmission system operator (TSO) is responsible for the physical feasibility of the market outcome, which, if necessary, also comprises congestion management.

In our analysis, we consider two pricing schemes - zonal and uniform pricing that differ regarding their congestion management. Under zonal pricing, the spot market clearing simultaneously considers network restrictions, while under uniform pricing, ex-post congestion management of the TSO is necessary. After the spot market clearing, the TSO performs a redispatch of supplied quantities $q_i$ until the transmission constraint $\overline{L}$ is fulfilled.

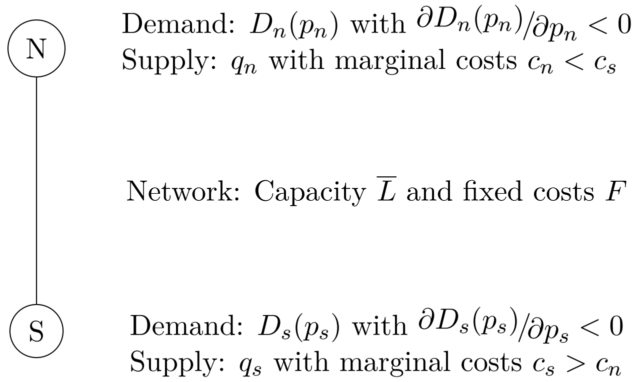



Figure 2.1.: The two-node model.

We assume a redispatch mechanism with incomplete participation. That means, the TSO considers only producers for redispatch, while the demand-side is excluded.[3] This reflects the common practice in many electricity systems and is, in particular, due to the complexity of remunerating the demand for a redispatch measure. With a cost-based redispatch, the TSO compensates generators outside the spot market based on their marginal costs.[4]

Additionally, the operation of the transmission network is associated with fixed costs of $F \in ]0, \infty[$. We assume that the fixed costs are smaller than the consumer surplus given the generation costs in each node, i.e., $F \leq \int_{c_i}^{\infty} D_i(z)dz\ \forall\ i$. This assumption ensures the participation constraint of consumers in all settings. Fixed network costs cannot be attributed to individual network users. Therefore, the principle of cost causality cannot be applied to recover these costs. The

[3]Noteworthy, under the assumption of full participation, uniform pricing with redispatch achieves the welfare optimal result (Bjorndal et al., 2013).

[4]Other congestion management methods are comprehensively discussed in DeVries and Hakvoort (2002), Holmberg and Lazarczyk (2015) and Weibelzahl (2017).

TSO's total network costs $C^{TSO}$ contain the fixed costs $F$ as well as potential congestion rents. Depending on the pricing scheme, congestion rents can be either positive or negative. We introduce the TSO as a benevolent agent who recovers her costs by charging network tariffs. We consider two different network tariff designs: a volume-based tariff $\boldsymbol{\tau} := (\tau_n, \tau_s)$, and a fixed network tariff $\boldsymbol{f} := (f_n, f_s)$. Volume-based network tariffs can be interpreted as an additional demand tax that directly influences the demand decision on the spot market. Fixed network tariffs can be interpreted as an access charge for being connected to the network. These tariffs constitute two extreme cases for network cost recovery. We do not apply general non-linear tariffs, e.g., multi-part tariffs. In both cases, we assume that only consumers pay network tariffs, as is the case in many electricity systems in practice. The TSO can differentiate between consumers in the north and south but cannot distinguish between consumers within one node. Consequently, network tariffs can vary between the two nodes, but not between consumers within a node.

For the network tariff setting, the TSO wants to ensure a dynamically consistent allocation of demand investments. By definition, new consumers choose the location of their investment depending on the prices in each node. We define a pricing schedule $P_i^I$ that includes two price components: the payments at the spot market for each unit demanded and the network tariff payments. The pricing schedule is given by $P_i^I = p_i\overline{D} + f_i$, where $\overline{D}$ is a fixed additional demand for new consumers.[5] If volume-based network tariffs are applied, the per unit price $p_i$ also includes the network tariff $\tau_i$. The TSO aims at achieving a dynamically consistent allocation of demand investments. From a welfare perspective, dynamic consistency is achieved if the new demand investments are in line with the welfare-maximizing result in future periods. As we consider a congested network with lower generation costs in the north, consumers should place new demand investments into the north. The demand invests in the north, if and only if, the pricing schedule is lower in the north compared to the south, i.e., iff $P_n^I \leq P_s^I$, which is:

$$p_n(\boldsymbol{c}, \boldsymbol{\tau}) \cdot \overline{D} + f_n \leq p_s(\boldsymbol{c}, \boldsymbol{\tau}) \cdot \overline{D} + f_s \tag{2.1}$$

The TSO anticipates the rationale of the demand's investment decision and, therefore, accounts for the pricing schedule (2.1) when setting the network tariffs. The structure of this constraint holds in each setting and only the spot market price and the network tariff may change depending on the regulatory setting.[6]

[5] By assuming a price-inelastic demand, we ignore quantity effects, which additionally restrict the optimal solution, but do not change our main results.

[6] We simplify the investment decision by only considering the costs in both nodes and add the investment decision to the pricing problem of the TSO. If the investment decision is modeled endogenously in a sequential setting, i.e., by maximizing the consumer surplus of the invested demand, the rationale slightly differs between the settings, but our main results do not change.

## 2.3. The interactions of network tariffs and pricing schemes considering dynamic consistency

We analyze the interactions between the different combinations of pricing schemes and network tariff designs and their effect on a dynamically consistent allocation of demand investments. The model set-up consists of two steps.

At first, the benevolent TSO introduces a vector of network tariffs for the current time period that can either be fixed ($\boldsymbol{f}$) or volume-based ($\boldsymbol{\tau}$). The TSO has perfect foresight and anticipates the impact of network tariffs on the spot market outcome and possible network congestion while ensuring the dynamic consistency of the pricing schedule.[7]

Second, the spot market clearing takes place, which depends on the pricing schemes. Under zonal pricing, the spot market clears with a cost-minimal dispatch considering the transmission constraint. The solution is equal to the optimal dispatch of a social planner, as we show in A.1. Production is equal to $q_n^* = D_n(p_n) + \overline{L}$ and $q_s^* = D_s(p_s) - \overline{L}$. Prices differ among nodes and reflect marginal costs of generation, with $p_n^* = c_n$ and $p_s^* = c_s$. The spot market clearing under zonal pricing yields a positive congestion rent $(c_s - c_n)\overline{L}$. The TSO anticipates this rent and offsets fixed costs $F$ with it. Under uniform pricing, both nodes belong to the same bidding zone. In contrast to zonal pricing, both nodes trade irrespective of network constraints. Consequently, the generation in the north is dispatched to fully cover the demand in both nodes at marginal costs of $c_n$. The resulting spot market prices are $p_n^* = p_s^* = c_n$.[8] The spot market clearing requires a production of $q_n = D_n(c_n) + D_s(c_n)$, which is technically not feasible as it requires the producer at node $n$ to export more than $\overline{L}$. The TSO is responsible for ensuring the system's physical feasibility by conducting congestion management measures. To do so, the TSO performs a redispatch of suppliers. The TSO instructs the producer at node $n$ to reduce generation to $q_n = D_n(c_n) + \overline{L}$ and instructs the producer at node $s$ to increase generation to $q_s = D_s(c_n) - \overline{L}$. The TSO compensates the producers outside the spot market for redispatching their generation. This leads to additional costs of $(c_s - c_n)(D_s(p_s^*) - \overline{L})$. In the following, we use these spot market results to determine the optimal network tariffs.

### 2.3.1. Fixed network tariffs under zonal pricing

The TSO maximizes welfare by setting the fixed network tariffs under zonal pricing (2.2a). The optimization is subject to the budget constraint (2.2b) to

[7] The assumption regarding the TSO's benevolence is critical for the formulation of the optimization problem. Otherwise, the TSO would only consider her budget and neglect the impact on consumer surplus or dynamic consistency.

[8] With volume-based network tariffs, the per-unit price in each node also includes $\tau_n$ and $\tau_s$, respectively, and hence, in sum $p_i$ may differ between both nodes. However, the spot market price component is the same, regardless of the network tariff design.

ensure full network cost recovery. Due to the positive congestion rent under zonal pricing, the TSO has to recover the following costs $C^{TSO}_{ZP,f} = F - (c_s - c_n)\overline{L}$. Further, the TSO anticipates the impact of network tariffs on the dynamic allocation of demand investments. Therefore, the optimization is additionally restricted by (2.2c).

$$\max_{\boldsymbol{f}} W_{ZP,f}(\boldsymbol{p}^*, \boldsymbol{f}) = \int_{p_n^*=c_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{p_s^*=c_s}^{\infty} D_s(z)\,\mathrm{d}z - F + (c_s - c_n)\overline{L} \tag{2.2a}$$

$$s.t. \quad \sum_i \omega_i f_i - F + (c_s - c_n)\overline{L} = 0 \tag{2.2b}$$

$$c_n\overline{D} + f_n \leq c_s\overline{D} + f_s \tag{2.2c}$$

The fixed network tariffs do not impact the welfare function and the TSO only has to ensure, that the constraints (2.2b) and (2.2c) hold. See A.2 for a proof and the derivation of possible solutions for the optimization problem (2.2a-2.2c). As consumers are homogeneous and fixed costs do not exceed consumer surplus in each node, fixed network tariffs cannot exceed the individual consumer surplus. Hence, the participation constraint holds for each consumer. Thereby, fixed network tariffs do not change the cost-minimal dispatch of supply and demand and thus, do not distort welfare. This is a well-known result from the literature on fixed cost recovery in network industries (e.g. Borenstein, 2016, Joskow, 2007, Wilson, 1993). Within the boundaries of constraints (2.2b) and (2.2c), the TSO can allocate the costs freely among the nodes.[9] Allocating network costs equally among consumers in all nodes would be a practical solution that ensures a dynamically consistent allocation of demand investments. In practice, this approach is often called *horizontal cost allocation*. Such a simple allocation rule would ensure that network tariffs do not distort spatial price signal from the spot market while fully recovering the fixed network costs.

### 2.3.2. Fixed network tariffs under uniform pricing

Under uniform pricing, the optimization problem of the TSO changes to (2.3a-2.3c). First, the spot market prices differ from zonal pricing, and second, the budget constraint of the TSO (2.3b) changes. Since redispatch comes with additional costs for the TSO, she has to recover total costs of $C^{TSO}_{UP,f} = F + (c_s - c_n)(D_s(p_s^*) - \overline{L})$. Again, the TSO ensures the dynamic consistency for the allocation of future demand investments (2.3c). As the per-unit spot price is equal

[9] We ignore income and distribution effects in our model. Considering these effects may change the socially desirable cost allocation, e.g. if additional restrictions are included in the optimization problem. See for example Batlle et al. (2020) for a discussion on this topic and a proposed alternative to fixed network tariffs.

in both nodes, the additional demand quantity $\overline{D}$ cancels out.

$$\begin{aligned} \max_{\boldsymbol{f}} W_{UP,f}(\boldsymbol{p}^*, \boldsymbol{f}) = & \int_{p_n^*=c_n}^{\infty} D_n(z)\,\mathrm{d}z \\ & + \int_{p_s^*=c_n}^{\infty} D_s(z)\,\mathrm{d}z - F - \Big[(c_s - c_n)(D_s(p_s^*) - \overline{L})\Big] \end{aligned} \tag{2.3a}$$

$$s.t. \quad \sum_i \omega_i f_i - F - \Big[(c_s - c_n)(D_s(p_s^*) - \overline{L})\Big] = 0 \tag{2.3b}$$

$$f_n \leq f_s \tag{2.3c}$$

**Proposition 2.3.1.** *With fixed network tariffs and homogeneous consumers, the TSO can ensure dynamic consistency without impacting static welfare by restricting the feasible cost allocation between the two nodes. Under uniform pricing, the cost allocation between the nodes is further restricted compared to zonal pricing.*

Again, the fixed network tariffs do not affect welfare and the TSO only has to ensure that the constraints (2.3b) and (2.3c) are met.[10] However, under uniform pricing, the solution to the optimization problem is more constrained by the dynamic consistency condition compared to the setting under zonal pricing. The boundary on network tariffs changes from $c_n\overline{D} + f_n^* \leq c_s\overline{D} + f_s^*$ under zonal pricing to $f_n^* \leq f_s^*$ under uniform pricing. Thus, to ensure a dynamically consistent allocation, the TSO has to choose network tariffs that compensate for the spot market's missing spatial price signals under uniform pricing.

### 2.3.3. Volume-based network tariffs under zonal pricing

As in section 2.3.1, spot market prices differ between the nodes and reflect the respective marginal costs. However, unlike fixed network tariffs, volume-based network tariffs constitute a levy on consumption and directly influence the demand decision at the spot market. The total price, that consumers pay per unit, is the marginal costs of generation $c_i$ plus the network tariff $\tau_i$, i.e. $p_i = c_i + \tau_i$. The demand-side reduces demanded quantities accordingly.

The TSO maximizes welfare by choosing the optimal vector of volume-based network tariffs (2.4a-2.4c). The optimization is subject to the TSO's break-even constraint (2.4b).[11] The TSO accounts for the positive congestion rent from zonal pricing, and consequently, recovers costs of $C_{ZP,\tau}^{TSO} = F - (c_s - c_n)\overline{L}$.

[10] It is straightforward to see that the solution of this optimization resembles to the solution of the previous chapter, which is depicted in A.2.

[11] Note that the TSO is unbundled. Unlike the case of a classical, vertically integrated natural monopoly, the TSO does not increase the spot market price to recover her fixed cost but introduces a separate network tariff. The difference is that network tariffs are a payment from consumers to the TSO. Therefore, the congestion rent $(c_s - c_n)\overline{L}$ and producer profits are not affected by the network tariffs and remain constant.

Additionally, the optimization is restricted by the dynamic consistency constraint (2.4c). With volume-based network tariffs, the constraint is independent of the fixed additional demand of new consumers ($\overline{D}$) and only depends on the per unit price $p_i(c_i, \tau_i)$.

$$\begin{aligned}\max_{\boldsymbol{\tau}} W_{ZP,\boldsymbol{\tau}}(\boldsymbol{p}^*(\boldsymbol{\tau})) = &\int_{p_n^*=c_n+\tau_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{p_s^*=c_s+\tau_s}^{\infty} D_s(z)\,\mathrm{d}z \\ &+ \sum_i \tau_i D_i(p_i^*) - F + (c_s - c_n)\overline{L}\end{aligned} \tag{2.4a}$$

$$s.t. \quad \sum_i \tau_i D_i(p_i^*) - F + (c_s - c_n)\overline{L} = 0 \quad \longrightarrow \quad \lambda \tag{2.4b}$$

$$c_n + \tau_n \leq c_s + \tau_s \quad \longrightarrow \quad \mu \tag{2.4c}$$

**Proposition 2.3.2.** *If the dynamic consistency constraint is binding, the network tariffs deviate from the optimal static volume-based network tariffs. In this case and under the assumption of constant marginal costs, a dynamically consistent allocation of demand investments lowers static welfare since consumer surplus in the north increases less than consumer surplus in the south decreases.*

To solve the TSO's optimization problem we derive the first-order condition of the Lagrangian ${\partial L}/{\partial \tau_i}$. Rearranging for $\tau_n^*$ and $\tau_s^*$ yields

$$\tau_n^* = \frac{\lambda}{1+\lambda} \cdot \frac{D_n(c_n+\tau_n^*)}{-\partial D_n(c_n+\tau_n^*)/\partial \tau_n^*} - \frac{\mu}{1+\lambda} \cdot \frac{1}{-\partial D_n(c_n+\tau_n^*)/\partial \tau_n^*} \tag{2.5}$$

and

$$\tau_s^* = \frac{\lambda}{1+\lambda} \cdot \frac{D_s(c_s+\tau_s^*)}{-\partial D_s(c_s+\tau_s^*)/\partial \tau_s^*} + \frac{\mu}{1+\lambda} \cdot \frac{1}{-\partial D_s(c_s+\tau_s^*)/\partial \tau_s^*} \tag{2.6}$$

We distinguish between two cases:[12] First, assume that the constraint for dynamic consistency (2.4c) is non-binding and $\mu = 0$. Then, the optimal network tariff in both nodes is equal to:

$$\tau_i^* = \frac{\lambda}{\lambda+1} \cdot \frac{D_i(c_i+\tau_i^*)}{-\partial D_i(c_i+\tau_i^*)/\partial \tau_i^*} \tag{2.7}$$

In this case, the optimal network tariff (2.7) can be interpreted as a modified version of the Ramsey-Boiteux inverse elasticity rule (see A.3.1). A high variation in demand in response to a variation in price leads to lower network tariffs. To solve for the optimal network tariffs, we define the *quasi-elasticity* $\rho_i$, insert it

[12] There exists a third case where $\mu = 0$ and the constraint is binding. This case leads to the same solution as our first case.

into (2.7) and equate for both nodes. We obtain the following relation:

$$\frac{\tau_n^*}{\tau_s^*} = \frac{\rho_s(\tau_s^*)}{\rho_n(\tau_n^*)} \quad \text{with} \quad \rho_i(\tau_i^*) = -\frac{\partial D_i(c_i + \tau_i^*)/\partial \tau_i}{D_i(c_i + \tau_i^*)} \tag{2.8}$$

The relationship between the network tariffs in the two nodes corresponds to the relationship between the quasi-elasticities. By using the relationship from (2.8) and the budget constraint of the TSO (2.4b), we solve for the optimal network tariff in the south:

$$\tau_s^* = \frac{F - (c_s - c_n)\overline{L}}{\frac{\rho_s(\tau_s^*)}{\rho_n(\tau_n^*)} D_n(c_n + \tau_n^*) + D_s(c_s + \tau_s^*)} \tag{2.9}$$

The result can be derived analogously for $\tau_n^*$. Similar to the Ramsey-Boiteux inverse elasticity rule, we see that when the ratio of the quasi-elasticities between the south and the north decreases, i.e., when the price sensitivity of the north increases compared to the south, demand in the south covers a higher share of the residual network costs and vice versa. In this case, the condition for dynamically consistent allocation is already met without any further adjustments to the network tariffs. The optimal static volume-based network tariffs thus provide dynamic consistency by themselves.

Second, assume that (2.4c) is binding and $\mu > 0$. This is the case if the optimal static network tariffs reverse the ratio of price schedules between the two nodes so that the north would become more expensive than the south. This depends on the ratio of the demand functions, particularly the quasi-elasticities, in the two nodes (see (2.8)). We denote the resulting network tariffs with $\hat{\tau}_i$.[13] As $\mu > 0$ it follows from (2.5) and (2.6) that $\hat{\tau}_i$ deviate from $\tau_i^*$. In the north, the optimal volume-based network tariff decreases due to the latter part of (2.5), i.e. $\hat{\tau}_n < \tau_n^*$. The opposite effect occurs in the south. From (2.6) it follows that $\hat{\tau}_s > \tau_s^*$. By setting $\hat{\tau}$ instead of $\tau^*$ the TSO deviates from the optimal static (unconstrained) volume-based network tariffs.

Consequently, this creates a deadweight loss in the current period to benefit the dynamically consistent allocation of future demand investments. While network tariffs rise in the south and, thus, lower consumer surplus there, network tariffs in the north decrease and increase consumer surplus. However, the increase in consumer surplus in the north does not compensate for the decrease in the south. The adjustments are not equal because of the ratio of the two demand functions, which would lead to higher (lower) network tariffs in the north (south) without the constraint for a dynamically consistent allocation of demand investments. For example, consider a situation where the demand function of the north is almost perfectly inelastic, and there is very price-sensitive demand in the south. Without the requirement for dynamic consistency, consumers in the north would

[13] In A.3.2, we solve for the optimal network tariffs for the case that the constraint is binding and derive at what point the constraint restricts the optimal static network tariffs for dynamic consistency.

bear most of the fixed network costs, while network tariffs in the south would be low. If the difference in network tariffs exceeds the difference in marginal generation costs, dynamic consistency is violated. In order to ensure dynamic consistency, the TSO reduces the network tariffs in the north. However, due to the inelastic demand in the north, consumer surplus increases only slightly. Conversely, increasing network tariffs in the south lead to a significant loss of consumer surplus.

### 2.3.4. Volume-based network tariffs under uniform pricing

In a regulatory setting with uniform pricing, the spot market clearing results in $p_i = c_n + \tau_i$. Total prices $p_i$ may differ between the two nodes depending on the network tariffs $\tau_i$.

The TSO maximizes welfare, anticipating the spot market result, her own budget and the dynamic consistency constraint (2.10a-2.10c). Due to uniform pricing, the spot market result is physically infeasible, and the TSO is obligated to redispatch generators. From this, the TSO bears additional costs that sum up to $C^{TSO}_{UP,\tau} = F + (c_s - c_n)(D_s(c_n + \tau^*_s) - \overline{L})$. In contrast to the other regulatory settings, the TSO's network costs depend on the network tariffs, because volume-based network tariffs impact the quantities demanded and they, in turn, impact redispatch costs.

$$\begin{aligned}\max_{\boldsymbol{\tau}} W_{UP,\boldsymbol{\tau}}(\boldsymbol{p}^*(\boldsymbol{\tau})) = &\int_{p^*_n = c_n + \tau_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{p^*_s = c_n + \tau_s}^{\infty} D_s(z)\,\mathrm{d}z \\ &+ \sum_i \tau_i D_i(p^*_i) - F - (c_s - c_n)(D_s(p^*_s) - \overline{L})\end{aligned} \tag{2.10a}$$

$$s.t. \quad \sum_i \tau_i D_i(p^*_i) - F - (c_s - c_n)(D_s(p^*_s) - \overline{L}) = 0 \;\longrightarrow\; \lambda \tag{2.10b}$$

$$\tau^*_n \leq \tau^*_s \quad \longrightarrow \quad \mu \tag{2.10c}$$

The first-order conditions of the Lagrangian $\partial L/\partial \tau_i$ are no longer identical between north and south. The optimal network tariff in the north has the same structure as under zonal pricing, shown in (2.5). For the south, the optimal network tariff slightly changes to:

$$\tau^*_s = \frac{\lambda}{1+\lambda} \cdot \frac{D_s(c_s + \tau^*_s)}{-\frac{\partial D_s(c_s+\tau^*_s)}{\partial \tau^*_s}} + \frac{\mu}{1+\lambda} \cdot \frac{1}{-\frac{\partial D_s(c_s+\tau^*_s)}{\partial \tau^*_s}} - c_n + c_s \tag{2.11}$$

Compared to the structure derived under zonal pricing (2.6), the network tariff in the south consists of an additional component, which functions as a correction-term for redispatch. Under uniform pricing, the optimal volume-based network tariffs mimic zonal prices and partially correct for the inefficiency of the pricing scheme. Plugging equation (2.11) into the demand function of the south $D_s(c_n +$

$\tau_s^*$) yields a similar result as under zonal pricing, i.e. $D_s(c_s + \tau_s)$. However, the result is not equivalent to the setting under zonal pricing, as the values of the network tariffs $\tau_i$ differ.

Under uniform pricing, the ratio between the network tariffs not only depends on the ratio of the quasi-elasticities but also on the generation costs in the respective nodes. We derive the optimal network tariffs in A.3.3 and show the relationship in detail. Like in the setting under zonal pricing, the TSO might adjust the optimal static network tariffs if the dynamic consistency constraint is binding. The rationale is the same as under zonal pricing: Deviating from the optimal static (unconstrained) volume-based network tariffs creates a deadweight loss in the current period to the benefit of the dynamically consistent allocation of future demand investments. However, under uniform pricing, missing dynamic consistency is even more severe, as network tariffs are the only possibility of creating spatial price signals. Investments in the south would amplify the system costs by increasing redispatch and additionally increase the burden from network cost recovery for the consumers in the north.

## 2.4. Welfare implications of the different regulatory settings

In this chapter, we compare the four combinations of network tariffs and pricing schemes in terms of their static welfare. This way, we can show how different regulatory price components affect static efficiency and interact with each other. Based on the results of section 2.3, we further discuss the results for the static welfare in the context of a dynamically consistent allocation of demand investments. From sections 2.3.1- 2.3.4, we derive the optimal static welfare for each regulatory setting:

*Fixed network tariffs and zonal pricing:*

$$W^*_{ZP,f} = \int_{c_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{c_s}^{\infty} D_s(z)\,\mathrm{d}z - F + (c_s - c_n)\overline{L}, \tag{2.12}$$

*Fixed network tariffs and uniform pricing:*

$$W^*_{UP,f} = \int_{c_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{c_n}^{\infty} D_s(z)\,\mathrm{d}z - F - \Big[(c_s - c_n)(D_s(c_n) - \overline{L})\Big] \tag{2.13}$$

*Volume-based network tariffs and zonal pricing:*

$$W^*_{ZP,\tau} = \int_{c_n+\tau_n^{ZP*}}^{\infty} D_n(z)\,\mathrm{d}z + \int_{c_s+\tau_s^{ZP*}}^{\infty} D_s(z)\,\mathrm{d}z \tag{2.14}$$

*Volume-based network tariffs and uniform pricing:*

$$W^*_{UP,\tau} = \int_{c_n+\tau_n^{UP*}}^{\infty} D_n(z)\,\mathrm{d}z + \int_{c_n+\tau_s^{UP*}}^{\infty} D_s(z)\,\mathrm{d}z. \tag{2.15}$$

With volume-based network tariffs, the TSO's costs are indirectly displayed in the lower bounds of the integrals as per definition they are refinanced by the sum over all $\tau_i$-payments. Note that the volume-based network tariffs are not identical under the two pricing schemes.

First, we analyze the isolated effects of changing either the pricing scheme or the network tariff design. Comparing zonal and uniform pricing with the same network tariff design, we show the inherent inefficiency that results from the incomplete redispatch scheme under uniform pricing. With fixed network tariffs, the difference in welfare under zonal and uniform pricing is equal to:

$$\begin{aligned}\Delta W^*_{ZP,f-UP,f} &= (2.12) - (2.13)\\ &= (c_s - c_n)D_s(c_n) - \int_{c_n}^{c_s} D_s(z)\,\mathrm{d}z\\ &= \int_{c_n}^{c_s} D_s(c_n) - D_s(z)\,\mathrm{d}z > 0 \implies W_{ZP,\boldsymbol{f}} > W_{UP,\boldsymbol{f}}\end{aligned} \tag{2.16}$$

The result is always greater than zero as demand decreases in price. It is straightforward to show that the same relation holds with volume-based network tariffs, i.e. $W_{ZP,\boldsymbol{\tau}} > W_{UP,\boldsymbol{\tau}}$. Thus, regardless of the network tariff design, zonal pricing is welfare-superior to uniform pricing. Consumption at the spot market is higher under uniform pricing, as market-participants neglect transmission capacities. The TSO corrects the spot market result ex-post. Due to restricted participation of the supply-side, redispatch induces additional costs. The resulting welfare loss is depicted in the shaded triangle in the south in figure 2.2.

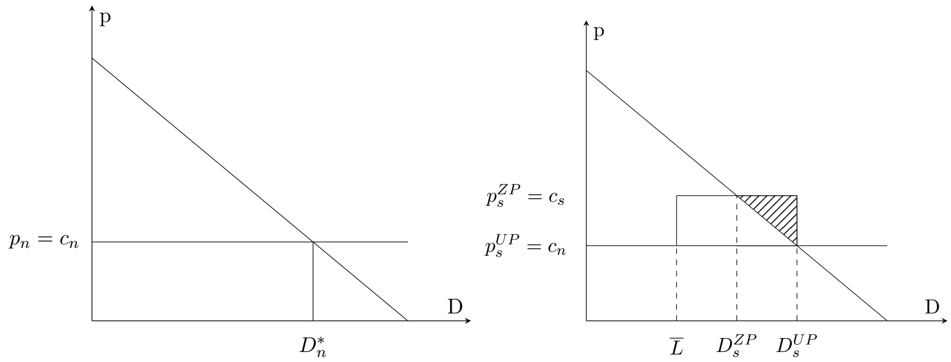



Figure 2.2.: Additional costs from redispatch under uniform pricing compared to zonal pricing; both with fixed network tariffs.

Comparing welfare under zonal pricing with either fixed or volume-based network tariffs, we derive the inefficiency of volume-based network tariffs. Under zonal pricing, the difference in welfare with fixed and volume-based network tariffs yields:

$$
\begin{aligned}
&\Delta W^*_{ZP,f-ZP,\tau} = (2.12) - (2.14)\\
&= \int_{c_n}^{c_n+\tau_n^{ZP*}} D_n(z)\,\mathrm{d}z + \int_{c_s}^{c_s+\tau_s^{ZP*}} D_s(z)\,\mathrm{d}z - F + (c_s - c_n)\overline{L}\\
&= \int_{c_n}^{c_n+\tau_n^{ZP*}} D_n(z)\,\mathrm{d}z + \int_{c_s}^{c_s+\tau_s^{ZP*}} D_s(z)\,\mathrm{d}z - \sum_i \tau_i^{ZP*} D_i(c_i + \tau_i^{ZP*})\\
&= \int_{c_n}^{c_n+\tau_n^{ZP*}} D_n(z) - D_n(c_n + \tau_n^{ZP*})\,\mathrm{d}z + \int_{c_s}^{c_s+\tau_s^{ZP*}} D_s(z) - D_s(c_s + \tau_s^{ZP*})\,\mathrm{d}z\\
&>0 \implies W_{ZP,f} > W_{ZP,\tau}
\end{aligned}
\tag{2.17}
$$

Since $z < c_i+\tau_i$ and demand decreases in price, the welfare difference must always be positive. According to economic theory, fixed network tariffs are welfare-neutral from a static perspective, whereas volume-based network tariffs cause a deadweight-loss. Figure 2.3 depicts the deadweight loss in the static setting, which is in both nodes depicted in shaded triangles.

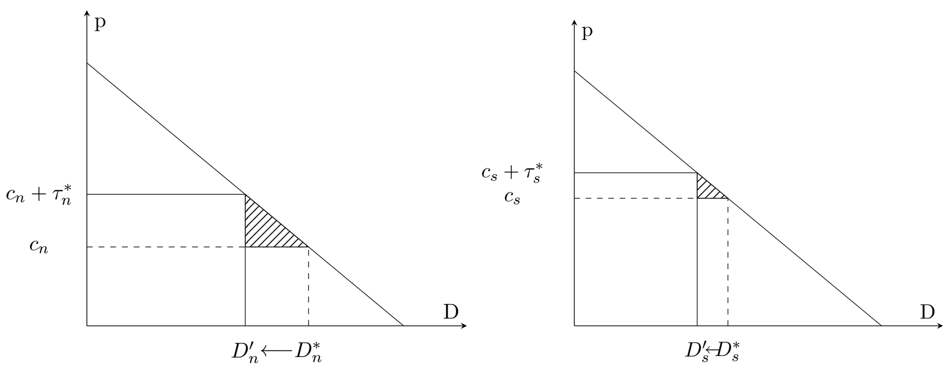



Figure 2.3.: Deadweight loss associated with volume-based network tariffs under zonal pricing.

One could now assume that when applying uniform pricing, the relationship between the network tariffs is identical with the one under zonal pricing, or the inefficient pricing scheme even increases the inefficiency of the network tariff design. However, when both sources of inefficiency are present, it is not so clear-cut, as the following comparison between uniform pricing with fixed tariffs and volume-based network tariffs shows:

$$\begin{aligned}
&\Delta W^*_{UP,f-UP,\tau} = (2.13) - (2.15) \\
&= \int_{c_n}^{c_n+\tau_n^{UP*}} D_n(z)\,\mathrm{d}z + \int_{c_n}^{c_n+\tau_s^{UP*}} D_s(z)\,\mathrm{d}z - F - (c_s - c_n)(D_s(c_n) - \overline{L}) \\
&= \int_{c_n}^{c_n+\tau_n^{UP*}} D_n(z)\,\mathrm{d}z + \int_{c_n}^{c_n+\tau_s^{UP*}} D_s(z)\,\mathrm{d}z - \sum_i \tau_i^{UP*} D_i(c_n + \tau_i^{UP*}) \\
&\quad - (c_s - c_n)(D_s(c_n) - Ds(c_n + \tau_i^{UP*})) \\
&= \int_{c_n}^{c_n+\tau_n^{UP*}} D_n(z) - D_n(c_n + \tau_n^{UP*})\,\mathrm{d}z + \int_{c_n}^{c_n+\tau_s^{UP*}} D_s(z) - D_s(c_n + \tau_s^{UP*})\,\mathrm{d}z \\
&\quad - (c_s - c_n)(D_s(c_n) - D_s(c_n + \tau_s^{UP*}))
\end{aligned} \tag{2.18}$$

The result can be either positive or negative, meaning that the welfare effect is ambiguous. On the one hand, fixed network tariffs do not impact the spot market result, while volume-based network tariffs induce a deadweight loss. On the other hand, equation (2.18) shows that the redispatch costs differ between the two network tariff designs. Since the quantity demanded in the south is lower with volume-based network tariffs, the market outcome requires less redispatch than the setting with fixed network tariffs. However, this is not only due to the general demand reduction associated with the higher prices in both nodes. As shown in equation (2.11), the optimal volume-based network tariff in the south includes a correction term that accounts for the difference in marginal generation costs between both nodes and, therefore, structurally reduces demand in the south. If the welfare-enhancing effect of reducing redispatch costs exceeds the deadweight loss, volume-based network tariffs can increase overall welfare. Whether this is the case depends on the particular demand functions.

**Proposition 2.4.1.** *If multiple market inefficiencies are present through the pricing scheme and network tariff design, it may not be sufficient to offset only one distortion. Uniform pricing with volume-based network tariffs can outperform a regulatory setting of uniform pricing and fixed network tariffs if the redispatch costs outweigh the deadweight loss of volume-based tariffs. Vice versa, the higher the fixed costs of the network, the more likely it is that regulation with fixed network tariffs is welfare superior.*

We analyze the interactions if both the network tariff design and the pricing scheme are varied between the two settings. To do so, we compare the welfare under uniform pricing and fixed network tariffs with the welfare under zonal pricing and volume-based network tariffs:

$$
\begin{aligned}
&\Delta W^*_{UP,f-ZP,\tau} = \; (2.13) - (2.14) \\
&= \int_{c_n}^{c_n+\tau_n^{ZP*}} D_n(z)\,\mathrm{d}z + \int_{c_n}^{c_s+\tau_s^{ZP*}} D_s(z)\,\mathrm{d}z - F - (c_s - c_n)(D_s(c_n) - \overline{L}) \\
&= \int_{c_n}^{c_n+\tau_n^{ZP*}} D_n(z) - D_n(c_n + \tau_n^{ZP*})\,\mathrm{d}z + \int_{c_n}^{c_s+\tau_s^{ZP*}} D_s(z) - D_s(c_s + \tau_s^{ZP*})\,\mathrm{d}z \\
&\quad - (c_s - c_n)D_s(c_n)
\end{aligned}
\tag{2.19}
$$

The result can also be either positive or negative. In this case, the overall effect on welfare depends on whether the deadweight loss from volume-based tariffs, i.e., the inefficiency of the welfare inferior network tariff design, or the redispatch costs under uniform pricing, i.e., the inefficiency of the welfare inferior pricing scheme, predominates.

If the redispatch costs are high enough, they can exceed the deadweight loss from volume-based network tariffs, making zonal pricing with volume-based network tariffs welfare superior. Hence, the higher the inefficiency of redispatch is, the more important the pricing scheme is to manage congestion. Vice versa, if fixed network costs rise, it becomes more likely that the fixed network tariffs become welfare superior as the inefficiency of volume-based network tariffs outweighs the redispatch costs in $W^*_{UP,f}$. Using (2.19), we can show that with rising $F$, the welfare difference between the two network tariff designs increases, i.e. $\partial \Delta W^*_{UP,f-ZP,\tau}/\partial F > 0$. From equation (2.9), we can derive that with increasing fixed network costs $F$, the network tariffs in both nodes increase, too, i.e., $\partial \tau_i^{ZP*}/\partial F > 0 \; \forall i$. It is straightforward to show that $\partial \Delta W^*_{UP,f-ZP,\tau}/\partial \tau_i^{ZP*} > 0$. Therefore, with volume-based network tariffs, the deadweight loss increases as fixed network costs rise. Thus, from a welfare perspective, the higher the fixed network costs $F$ rise, the more advantageous the application of fixed network tariffs becomes.

For the sake of completeness, the difference between $W^*_{ZP,f}$ and $W^*_{UP,\tau}$ can be derived from the results above:

$W^*_{UP,\tau} < W^*_{ZP,\tau} < W^*_{ZP,f}$ and thus, $\Delta W^*_{ZP,f-UP,\tau} > 0$.

Figure 2.4 summarizes the findings.

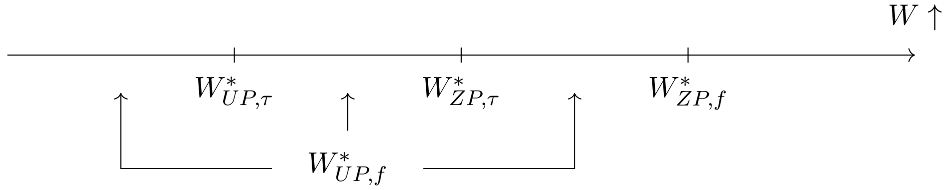



Figure 2.4.: Welfare comparison of the different regulatory settings.

Ranking the regulatory settings in terms of static welfare demonstrates the importance of addressing the interactions between price components. Contrary to the first intuition, there is no clear order regarding the four analyzed settings. Our analysis finds that the distortions of one regulatory element can either amplify or compensate for the distortions of another element. If either the pricing scheme or the network tariff design leads to inefficiencies, it is best addressed by restructuring the respective price component. However, suppose both sources of inefficiency are present. In that case, i.e., the combination of uniform pricing and volume-based network tariffs, an adjustment of only one aspect can have unintended, welfare-adverse effects. As optimal volume-based network tariffs structurally reduce redispatch costs, it is impossible to ensure that switching to fixed network tariffs increases market efficiency. Due to this compensation effect, the two inefficiencies can perform better than a regulatory setting with only one inefficiency in place. This compensation effect is particularly relevant for the static welfare, the higher the costs for redispatch are.

As section 3 shows, the static welfare of the four regulatory settings interacts with the requirements for dynamic consistency. The interaction can be divided into two main effects. The first interaction occurs in regulatory settings with volume-based tariffs. The TSO reduces static welfare in the regulatory settings with volume-based network tariffs if it is necessary to adjust the optimal (static) network tariffs to ensure dynamic consistency. Under zonal pricing, this adjustment only increases the deadweight loss. Under uniform pricing, this adjustment additionally increases the compensation effect. The redispatch costs decrease as the volume-based network tariffs in the south increase to ensure dynamic consistency. This effect partially makes up for the increase in deadweight loss. However, the overall static welfare still decreases due to the adjustment of the volume-based network tariffs. In contrast, the TSO can adjust fixed network tariffs without impacting the static welfare to ensure dynamic consistency. Hence, the welfare-ranking of the regulatory settings changes if the TSO must adjust the volume-based network tariffs to ensure dynamic consistency. It becomes more likely that the regulatory setting with fixed network tariffs and uniform pricing is welfare superior to the regulatory settings with volume-based network tariffs. Second, the importance of dynamically consistent network tariffs increases with the difference in generation costs, regardless of the network tariff design. Under zonal pricing, misaligned demand-side investments, i.e., investments in the south, would lead to higher generation costs in the future and, therefore, lower consumer surplus. Under uniform pricing, costs for redispatch would increase. To prevent congestion from being further exacerbated in the future, investment decisions should be made dynamically consistent. Thus, there is a bi-directional relationship between dynamic consistency of network tariffs and static welfare that policymakers should account for when changing the regulatory setting.

## 2.5. Conclusion

The transformation of the energy system from mainly inelastic consumers towards active market participants challenges the principles of network tariff design. If appropriately designed, network tariffs can serve as a coordination mechanism between the network operator and market participants. Otherwise, network tariffs can distort efficient price signals.

In an analytical model, we examine different regulatory settings, consisting of alternative spot market pricing schemes and network tariff designs, while considering a dynamically consistent allocation of demand investments. In our analysis, we assess the interactions of spot market pricing schemes and network tariff designs. The regulatory setting with zonal pricing and fixed network tariffs yields the highest welfare. A deviation of either the pricing scheme or the network tariff design leads to inefficiency. While under uniform pricing, additional costs occur due to redispatch, the application of volume-based network tariffs leads to a deadweight loss at the spot market. If both sources of inefficiency are present, i.e., the combination of uniform pricing and volume-based network tariffs, an adjustment of one single aspect can have unintended effects on overall welfare. As optimal volume-based network tariffs structurally reduce redispatch costs, it is not possible to ensure that market efficiency increases by switching to fixed network tariffs. Besides the network tariff design, network operators must pay additional attention to the allocation of network costs. It affects spatial price signals and, therefore, the dynamic allocation of demand investments. The restrictions on cost allocation are tighter under uniform pricing, as network tariffs are the only spatial price signal. However, under both pricing schemes, the TSO can ensure a dynamically consistent allocation of demand investments with fixed network tariffs without adversely affecting welfare. In contrast, with volume-based tariffs, the case may arise where the TSO must trade off between static welfare and dynamic consistency. The TSO can adjust the volume-based network tariffs deviating from the optimal static network tariffs to ensure dynamic consistency. By doing so, the TSO reduces static welfare in benefit of a dynamically consistent allocation of demand investments.

In current political debates, pricing schemes and network tariffs are often discussed separately. Our results highlight the relevance of jointly assessing network tariffs and pricing schemes for policymakers and regulating authorities. Our results are important, considering that today's electricity systems often use a combination of uniform pricing and mainly volume-based network tariffs. In such a regulatory setting, it seems advisable to identify the predominating inefficiency instead of partly adjusting the regulatory setting. Especially when a change to zonal pricing and fixed network tariffs seems unlikely, regulators could consider the possibility of using volume-based tariffs in favor of their steering possibilities. Our analysis suggests that an integrated regulatory framework is important to avoid unintended distortions.

Moreover, regulators tend to use simplified rules for cost allocation in practice, which are not aligned with spot market prices and typically do not consider dynamic consistency. Spatial price signals become more important in a system under transition as they impact investment decisions. Therefore, these cost allocation rules have an essential impact on static welfare and dynamic consistency, especially in regulatory settings with uniform pricing.

Future research could include other network tariff designs such as general non-linear tariffs. Those tariffs could improve system efficiency and compensate for the frictions of distorted price components. The analytical model could further be expanded by including concerns on zonal pricing in practice, e.g., market power and illiquid markets. In addition, empirical studies could complement our theoretical findings to distinguish between the ambiguities that we found in our theoretical model and measure the associated welfare loss for the static and dynamic effects.

# 3. How Prices Guide Investment Decisions under Net Purchasing - An Empirical Analysis on the Impact of Network Tariffs on Residential PV

## 3.1. Introduction

Solar photovoltaic (PV) is generally expected to have a substantial share in the future electricity generation mix around the globe (IEA, 2020). In Germany, residential PV systems already count for around 1.2 million installations in 2020 (Bundesnetzagentur, 2021b). These PV systems are typically installed by individual households and, thus, distributed decentrally. To limit network expansion and reduce congestion costs, an efficient coordination of these investments is essential. Recent findings suggest that economic factors are among the main drivers for PV adoption in the residential sector (e.g. Jacksohn et al., 2019). In principle, households can use the self-generated PV electricity to either feed it into the grid or replace electricity consumption from the grid. The profitability of these options depends on the regulatory framework. In Germany, a net purchasing system is in place for residential PV installations, which is also the predominant metering scheme in Europe (Gautier et al., 2018). That is, grid feed-in and grid consumption are metered separately and billed at two different prices. The remuneration of grid feed-in is based on the feed-in tariff, which is the main subsidy for residential PV in Germany, granted under the Renewable Energy Sources Act (EEG.). The value of self-consumption depends on the consumption costs, which households can reduce for each kilowatt-hour (kWh) of grid consumption substituted with self-generated PV electricity.

Higher tariffs for grid consumption increase the consumption costs of the household and raise the incentive for self-consumption and residential PV installations. This relationship is unambiguous under net metering, where grid feed-in and grid consumption are billed at the same price (c.f. Gautier and Jacqmin, 2020). Under net purchasing, the same rationale should apply, although the incentive structure also depends on the remuneration for grid feed-in. In particular, the effect should increase the more profitable self-consumption is compared to the revenue from grid feed-in (c.f. Jägemann et al., 2013).

Additionally, tariffs follow a nonlinear pricing schedule. The investment decision should be incentivized only by the volumetric price rather than the fixed price component or an average price calculated from both. Empirical findings suggest that consumers confuse nonlinear price schedules, which contrasts with the theoretical expectation (Ito, 2014). Such an effect would raise concerns regarding the effect of regulatory changes in electricity price components on residential PV installations. In Germany, for example, reform proposals for the network tariff system plan to shift network costs from predominantly volumetric network tariffs to a more substantial share of fixed network tariffs. Other proposals aim for a change in the EEG-levy that is currently paid exclusively on a volumetric basis. Knowing whether and how consumers respond to the different price components is crucial to assess the consequences of such policy reforms on PV adoption.

We empirically investigate whether and how price signals impact the adoption of residential PV installations in Germany. More specifically, we analyze the impact of network tariffs on PV adoption and exploit the fact that network tariffs are a considerable part of retail tariffs and the decisive driver for their regional variation. The heterogeneity of network tariffs allows us to identify the impact of price signals on a high regional resolution. In contrast, the other components of the retail tariff depend on markets and regulations that are equal across Germany. We use a panel data set of PV installations, network tariffs, and socioeconomic covariates on postcode level covering the years of 2009-2017 and apply a Poisson quasi-maximum likelihood estimator (PQMLE) with fixed effects to capture unobserved heterogeneity across regions and time.

We find evidence that network tariffs significantly impact PV investments across Germany. An increase in network tariffs by one within standard deviation (0.34 eurocent per kWh) is estimated to increase PV installations by 2 %, all else equal. This effect has grown, supporting the hypothesis that the incentive for self-consumption has increased over time. Furthermore, it is indeed the volumetric network tariff that impacts PV adoption rather than the average price. Our results provide valuable insights into the driving forces of residential PV adoption in Germany, which allows evaluating upcoming policy reforms regarding the regional allocation of PV installations and the structure of electricity prices.

The paper is organized as follows. Section 3.2 provides an overview of the empirical literature on residential PV adoption. Section 3.3 outlines the policy framework and the economic rationale for investment in residential PV installations in Germany. Section 3.4 introduces the empirical strategy while section 3.5 presents our panel data set. Our results are shown and discussed in section 3.6 and we discuss our findings and conclude in section 3.7.

## 3.2. Literature review

Our analysis contributes to two streams of the literature: first, the drivers of residential PV expansion, and second, the impact of nonlinear tariff structures on investment decisions in the residential energy sector.

The main drivers for residential PV investments can be classified by socio- and techno-economic factors, behavioral factors, and economic factors.[14] The first and most extensively researched category are socioeconomic factors such as education, per capita income, environmental awareness, and techno-economic factors, such as solar irradiance and specific house characteristics. Schaffer and Brun (2015) conduct a comprehensive analysis on the drivers for adopting residential PV in Germany between 1991 and 2012. They find strong effects for solar irradiance, house density, home-ownership, and per capita income, while the environmental awareness hardly affects PV investments.[15] Subsequent studies, for example, Dharshing (2017), Baginski and Weber (2019), Jacksohn et al. (2019) and Gutsche et al. (2020), generally confirm these findings: environmental awareness has only little explanatory power, while the other socio- and techno-economic factors are important drivers of residential PV adoption in Germany.

Second, behavioral factors, such as myopia, inertia, or peer effects, are also likely to drive PV adoption in the residential sector. For example, regarding peer effects, i.e., the impact of previously installed PV in a surrounding area on the current investment decision of an individual household, findings in the empirical literature are mixed. In their seminal work, Bollinger and Gillingham (2012) examine peer effects on residential PV expansion in the US and find a significant impact. Rode and Weber (2016) conduct a similar analysis for Germany and confirm the impact of imitative adoption behavior. Though Baginski and Weber (2019) also find regional dependencies in their analysis, social imitation does not seem to be the main driver of the regional spillover effects. Similarly, Rode et al. (2020) find that the impact of previously installed PV on current adoption decreases over time and might be mistaken with the regional concentration of craft skills or solar initiatives.

The third category contains literature on the influence of economic factors, i.e., expected costs and revenues of the PV installation.[16] We observe a growing research interest regarding the economic factors due to two simultaneous developments. First, Palm (2020) suggests that in the first stage of the diffusion process, early adopters have fewer concerns for costs or concrete financial benefits. In contrast, in the later stages, the economic factors become more decisive. Hence, the impact of socioeconomic and behavioral factors on PV investments should decrease over time as these factors become less pivotal during the diffusion process of new technologies. Second, in the early years of PV expansion in Germany, a PV installation has been financially attractive mainly due to the feed-in tariffs granted as a subsidy for PV deployment. Ossenbrink (2017), and

[14] Comprehensive reviews on the adoption of building-scale renewable energy systems in European countries can be found in, for example, Heiskanen and Matschoss (2017) and Selvakkumaran and Ahlgren (2019). In this literature review, we mainly focus on analyses for Germany to derive a better understanding of the empirical case for the reader. However, most findings of the literature also apply to other regions.

[15] Balta-Ozkan et al. (2015) find similar factors for the UK.

[16] Intuitively, cost and revenues also depend on techno-economic factors, like irradiance. However, we think of economic factors as monetary metrics.

Germeshausen (2018) analyze the impact of feed-in tariffs in Germany and, in particular, the impact of (changes in ) the policy framework on PV adoption. Jacksohn et al. (2019) analyze the impact of the costs of PV panels and revenues from feed-in tariffs in Germany from 2008 to 2015 on the individual household level. They find that these economic factors mainly drive the investment decisions in PV installations and solar thermal facilities. Also in other countries, economic factors impact households' PV investment decisions. As for the case of feed-in tariffs in Germany, governmental pricing policies play a substantial role for the PV adoption in many countries. Best et al. (2019) quantify the impact of Australia's spatially-differentiated small-scale renewable energy scheme on residential PV investments using postcode-level data. Their results indicate that postcodes receiving a higher subsidy factor have significantly more residential PV investments, after controlling for solar exposure and spatial patterns in the data. Similarly, de Groote et al. (2016) find that local policies have a significant impact on PV adoption in Flanders. Focusing on the residential PV adaption in California, e.g., Hughes and Podolefsky (2015), show a significant regional effect of upfront rebates on PV investments, exploiting variation in rebate rates across electric utilities over time. Similarly, Crago and Chernyakhovskiy (2017) show that rebates have the biggest impact among financial incentives on residential PV adoptions in the Northeast. They further indicate positive impacts of electricity prices.[17] With the increasing attraction of self-consumption, the economic rationale of residential PV installations is further influenced by the costs for electricity consumption and, therefore, not only by the feed-in tariff but also by the retail tariff. Klein and Deissenroth (2017) show that the overall German residential PV expansion is impacted by the anticipation of profitability, including both feed-in and retail tariffs in their analysis. Sahari (2019) analyzes the choice of heating systems in Finland. She finds a significant impact of electricity prices on long-term technology choices. Further and closest to our analysis, Gautier and Jacqmin (2020) analyze the impact of volumetric network tariffs on PV investments under a net metering system in Wallonia. They find a positive and significant effect of network tariffs on PV installations. In a similar vein, de Freitas (2020) analyzes PV investments in Brazil. Both regions currently apply net metering systems, where grid feed-in and self-consumption are both valued at the retail tariff. Therefore, higher retail tariffs should encourage higher PV investments. In a net purchasing system, the incentive is two-fold and depends on the remuneration for grid feed-in, which is determined separately (see section 3.3).

Moreover, we extend the analysis of price signals by examining how the non-linear tariff structure influences investment decisions. In his seminal work, Ito (2014) analyzes the price perception of consumers in US electricity markets. His results suggest that consumers are short-sighted in their response to electricity prices by deciding on their electricity bill of the past rather than current tariffs or

[17] See Ossenbrink (2017), for a comparison of the impact of feed-in tariff designs and their interplay with retail electricity prices between Germany and California.

future expectations. Further, Ito (2014) examines the impact of nonlinear multi-tier tariffs on electricity consumption, and Shaffer (2020) conducts a similar analysis for British Colombia. The authors analyze whether consumers respond to nonlinear tariffs in the way microeconomic theory suggests, i.e., whether they respond to the marginal price rather than the fixed or an average price. Both find that consumers respond to average rather than marginal prices, which contrasts with the theoretical expectation. However, a further analysis by Ito and Zhang (2020) for heating usage in China finds that consumers do indeed respond to the marginal price in the context of a simpler tariff form, i.e., a two-part tariff.

To the best of our knowledge, we are the first to empirically analyze the impact of price signals on PV adoption in a net purchasing system. We use the regional variation in network tariffs in Germany to investigate whether and how prices impact PV investments. We examine whether the incentives for self-consumption have become more relevant in recent years and conduct the first empirical study that analyzes how the price components of a nonlinear tariff impact residential PV adoption.

## 3.3. Residential PV in Germany: policy framework and investment incentives

PV installations enable individual households to generate their own electricity so that they no longer participate in the market only as consumers.[18] To illustrate the economic rationale behind residential PV adoption in Germany, we derive the microeconomic foundation of the investment incentives for an individual household. The regulatory framework in Germany is a net purchasing system. In contrast to a net metering system, where one single price for electricity consumption from the grid (imports) and grid feed-in (exports) exists, these two options are measured separately (c.f. Gautier et al., 2018).

The PV installation offers two options for the household how the self-generated electricity ($q_{PV}$) can be used:

$$q_{PV} = q_{togrid} + q_{self} \tag{3.1}$$

The household can feed the electricity into the grid ($q_{togrid}$) or use it for self-consumption ($q_{self}$), i.e., substitute electricity consumption that is otherwise imported from the grid ($d_{total}$).[19] We structure the economic incentives by ana-

[18] As households with PV installations both produce and consume electricity, the term prosumer has also been established. Prosumers are of general interest in recent literature, seeking to understand their decision-making and how regulatory policies impact them in more detail, (e.g. Gautier et al., 2018).

[19] To fully reflect the potential temporal discrepancy of PV generation and the household's electricity consumption, an (hourly) time index could be introduced (see e.g. Ossenbrink (2017) for a more detailed representation). However, for simplicity and without loss of generality, we refrain from this issue in the following representation.

lyzing the net present value ($NPV$)[20] of the PV installation in equation (3.2):

$$NPV = -C_I + \sum_{t=0}^{T} \frac{R(q_{togrid}) - C(d_{total} - q_{self}) - c_{OM}}{(1+r)^t} \tag{3.2}$$

One-time costs occur due to the initial investment $C_I$. Once the PV system is installed, continuous costs for operation and maintenance $c_{OM}$ incur and the PV installation offers the opportunity to generate revenue by selling electricity to the grid ($R(q_{togrid})$) and to reduce electricity costs by self-consuming electricity from the PV installation ($C(d_{total} - q_{self})$). By assumption, costs and revenues are constant over time, but discounted on a yearly basis $t$ at an interest rate $r$. We briefly describe the institutional and regulatory framework in Germany and discuss the incentives for PV investments over the years.

### 3.3.1. Regulatory framework for residential PV in Germany

The grid feed-in of a residential PV installation is regulated under the EEG, and residential PV owners receive a feed-in tariff, paid for each kilowatt-hour (kWh) of electricity fed into the grid. The feed-in tariff varies depending on the date, size, and type (roof-top or ground-mount) of the installation.

Feed-in tariffs are determined administratively by the government, and the level and the categorization are regularly adjusted for new installations. Residential PV installations with 10 kW or smaller have always been eligible to receive the highest possible feed-in tariff. In contrast, larger installations have been subject to some changes in the definition of their support categories over the years. Adjustments of the level of feed-in tariffs are mainly based on the development of PV investment costs which has led to a declining trend over the past years (see figure 3.1). While the feed-in tariff was about 43 ct/kWh in 2009, this has been reduced to about 12 ct/kWh by 2017. In addition to the feed-in tariff, from 2009 until 2012, the EEG granted an additional remuneration for self-consumption. Although this remuneration was lower than the feed-in tariff, e.g., 25 ct/kWh compared to a feed-in tariff of 43 ct/kWh in 2009, households benefited from self-consumption on top of the savings from reduced electricity consumption costs (Bundesnetzagentur, 2021a).

### 3.3.2. Retail electricity tariffs and the incentive for self-consumption

The value of self-consumption depends on the consumption costs that can be reduced for each kWh of grid consumption substituted with self-generated PV

[20] We focus on the economic rationale in terms of cash flows and do not consider the utility function of the household. One can think of factors that increase the utility beyond the financial aspects, e.g. environmental preferences, and those that have a negative impact, e.g. behavioral biases like inertia or myopia.

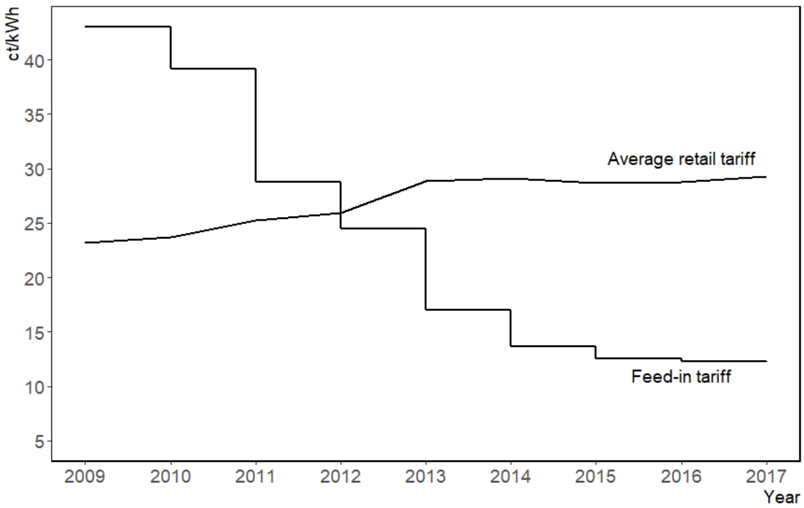



Figure 3.1.: The development of feed-in tariffs for PV installations ¡ 10 kW and average retail tariffs for households in Germany between 2009 and 2017. Own illustration based on data from Bundesnetzagentur (2021a) and BDEW (2021).

electricity. PV owners can profit from self-consumption because the household's electricity bill in Germany mainly depends on the actual consumption. The retail tariff for grid consumption is nonlinear and consists of a volumetric and a fixed price component, i.e., it constitutes a two-part tariff.

The volumetric price per kWh typically predominates, whereas the fixed component, i.e., the basic price for being served and connected to the network, accounts for a smaller proportion of total retail costs. Furthermore, the retail tariff in Germany comprises of three elements: procurement and sales costs of the retailing firm, network tariffs, and administratively determined taxes, charges, and levies. The latter include, for example, the tax on electricity, the EEG-levy, and the concession fee. In 2017, for instance, these three elements split up into 19 % procurement and sales costs, 26 % network tariffs, and 55 % taxes, charges, and levies (BDEW, 2021). Households do not have to pay the volumetric parts of the network tariff and all taxes, charges, and levies for self-consumption.[21] Following the theory on nonlinear pricing, the fixed price component of the retail tariff should not affect the economic rationale to invest in PV installations. These costs always have to be paid unless the household becomes fully independent and, thus, disconnected from the grid. The volumetric tariff describes the opportunity to purchase electricity from the grid and thus, represents the value of self-consumption.

Furthermore, and in contrast to the feed-in tariff that applies equally for all households across Germany, retail prices vary regionally. While wholesale market prices and taxes, charges, and levies are the same across Germany, the network

[21] Though there were changes regarding the EEG-levy for self-consumption in 2012, residential PV installations with 10 kW or less have always been exempted.

tariff is the only cost component that systematically differs on a regional level.[22] In particular for residential consumers connected to the low-voltage network, network tariffs are increasingly diverging.[23] The regional variation of distribution network tariffs in Germany is due to the allocation mechanism, a so-called vertical mechanism, by which network operators allocate the network costs to network users (c.f. Jeddi and Sitzmann, 2019). In Germany, the network costs are refinanced by electricity consumers. The allocation is based on the principle that costs incurred in a particular network area are borne by consumers connected to the respective network. Network operators calculate the network tariffs on an annual basis, based on their individual, regulated revenue cap. In practice, this regulatory procedure means that network costs of the current year are decoupled from this year's network tariffs and rather passed on to the network tariffs in later years.

### 3.3.3. The economic rationale for investments in PV installations

The profitability of a PV investment hinges on the the value of self-consumption, the feed-in tariff and the interaction of both options. On the one hand, substituting electricity from the grid reduces electricity costs. On the other hand, each kWh used for self-consumption cannot be fed into the grid, i.e., the PV owner does not receive the feed-in tariff. Therefore, it is not only the absolute level of prices and tariffs compared to the PV installation costs that is decisive, but also the relation of the feed-in tariff to the retail electricity price. We apply the regulatory setting in Germany to equation (3.2). The expected revenue consists of the subsidization of grid feed-in via feed-in tariffs ($p^{fit}$), self-consumption via a reduction of electricity consumption costs valued at the volumetric tariff ($p^{retail}$), plus, if applicable, the additional subsidy for self-consumption ($p^{self}$):

$$NPV = -C_I + \sum_{t=0}^{T} \frac{q_{togrid} \cdot p^{fit} - [(d_{total} - q_{self}) \cdot p^{retail} + q_{self} \cdot p^{self} - c_{OM}]}{(1+r)^t} \tag{3.3}$$

Equation (3.3) shows that as soon as the volumetric retail tariff ($p^{retail}$) rises above the feed-in tariff ($p^{fit}$), self-consumption becomes financially more profitable compared to grid feed-in.

The feed-in tariff has been continuously decreasing to accommodate the declining costs of PV installations and technological developments. Contrarily, the average retail tariff across Germany has been increasing in most years. Both developments are depicted in figure 3.1 for the period between 2009 and 2017. Since 2012, the average retail tariff is higher than the feed-in tariff by a constantly in-

[22] The concession fee can also vary depending on the network area. However, the magnitude is legally fixed, so that the differences are minor compared to the variation in network tariffs.
[23] See e.g. Hinz et al. (2018) and Schlesewsky and Winter (2018) for further investigations.

creasing margin. Therefore, we expect the investment incentives for residential PV adoption to be increasingly affected by the incentive for self-consumption rather than the feed-in tariff. If this holds, the impact of price signals should have become more relevant since 2012. The abolition of the explicit subsidy for self-consumption in 2012 should have further strengthened the influence of the implicit incentive of the retail tariff.

However, one should keep in mind that self-consumption is attractive only if the household can use the electricity when the sun shines or if a storage opportunity exists. Installation numbers of batteries in households only recently begin to increase as storage is still relatively costly (Figgener et al., 2021). If storage opportunities become economically attractive, the incentive for self-consumption might increase in the upcoming years. Thus, it could become interesting to distinguish between PV systems with and without battery storage.[24]

In principle, the economic incentives of PV adoption apply equally to all households. The feed-in tariff does not vary regionally across Germany, and thus, all else equal, it should have a similar impact on the investment decision. In contrast, network tariffs of the distribution grid vary throughout Germany and over time. Therefore, the implicit investment incentive from self-consumption can differ between regions. As summarized in section 3.3.2, network tariffs are the only price component, which varies substantially between regions, and, therefore, are the main driver for regional retail price variation in Germany. Our empirical strategy takes advantage of this heterogeneity to investigate the impact of price signals on PV investments in Germany.

## 3.4. Empirical strategy

Our objective is to identify whether network tariffs influence investments in PV installations. Therefore, we set up our analysis on postcode-specific panel data for Germany and exploit the regional variance of network tariffs across Germany. Our dependent variable, the number of new PV installations ($Y_{i,t}$) per postcode ($i$) and year ($t$), is a count variable, i.e., it follows a non-negative distribution and can only take on integer values. Given the characteristic of the dependent variable and the panel data structure, we employ a Poisson quasi-maximum likelihood estimator with multiple fixed effects (PQMLE) (c.f. Wooldridge, 2010). The consistency of the estimator neither requires that our dependent variable follows a Poisson distribution nor any additional assumptions concerning the distribution of our dependent variable. As part of the estimation procedure, we calculate robust standard errors. By clustering the standard errors at a regional level, we accommodate for arbitrary correlation across clusters. The choice of

[24]Due to the low number of installed batteries and data availability, we refrain from including batteries in this analysis. Predictive simulations for the development of combined PV and storage systems in Germany can be found, for example, in Kaschub et al. (2016), Fett et al. (2021) and Günther et al. (2021).

the PQMLE approach as our preferred estimation method is in line with recent research by Gautier and Jacqmin (2020) and de Freitas (2020), who apply it in a similar setting.

The formulation of our preferred estimation model is as follows:

$$Y_{i,t} = exp(\beta \cdot tariff_{i,t-1} + \gamma \cdot X_{i,t} + \phi_t + \mu_i + \theta_i \cdot t) \cdot \epsilon_{i,t} \tag{3.4}$$

, where $tariff_{i,t-1}$ is our primary explanatory variable, $X_{i,t}$ is a vector of postcode-specific covariates, $\phi_t$ are year-specific fixed effects, $\mu_i$ are postcode-specific fixed effects and $\theta_i$ are postcode-specific time trends. $\epsilon_{i,t}$ is an error term.

In our preferred model specification, we lag our primary explanatory variable by one year. Although fully rational households should form an expectation about future electricity costs, in practice, it may be reasonable to assume that households are rather short-sighted and base their expectation on the currently observed electricity costs (c.f. de Groote and Verboven, 2019, Ito, 2014). In Germany, households pay their electricity bill annually and ex-post, which results in a time lag of one year between the temporal validity of the network tariff and the cost realization. In addition, some time passes between the investment decision and the actual PV installation, e.g., due to administrative reasons. Therefore, we assume that households are more likely to respond to the previous year's tariff than the current one and use the network tariff lagged by one year as our explanatory variable.[25] We check the robustness of our assumption against the current network tariff $tariff_{i,t}$ in Section 3.6 and for tariffs further in the past, i.e., $tariff_{i,t-2}$ and $tariff_{i,t-3}$, in B.2.

An advantageous effect of using the time lag is that it helps us to alleviate the strict exogeneity assumption of our primary explanatory variable. The endogeneity concerns arise because, in recent years, network tariffs increase mainly due to network expansion costs which in turn are due to the integration of renewable energy sources, including residential PV installations (c.f. Just and Wetzel, 2020). However, PV adoption in the current year does not affect the network tariffs of the previous year. Therefore, based on our choice of lagged network tariffs as our explanatory variable and because network tariffs reflect historical network costs, we suggest that reverse causality is not a concern in our setting.

We further include a vector of covariates to control for observable heterogeneity of postcode areas. This vector contains the average income and age of the population, the share of detached and semi-detached houses in the building stock, and the number of residential buildings.

[25] Our assumption is supported, for example, by an empirical analysis regarding electricity consumption behavior by Bushnell and Mansur (2005), who find that households respond more strongly to recent past electricity bills than to new retail tariff price information, even when the new tariff has already been announced. Also, Gautier and Jacqmin (2020) find the assumption of using a lagged network tariff to be justified in their analysis on the effect of network tariffs on PV installations under a net metering scheme in Wallonia.

The fixed effects approach takes advantage of the panel data structure of our data and allows us to control for unobserved heterogeneity. By applying multiple fixed effects, we can isolate and identify the impact of our primary explanatory variable on the dependent variable based on the within-postcode variance in our data. A random effects model would not be consistent as we expect a correlation between the individual effects and the independent variables.[26] By including year-specific fixed effects, we control for overall developments over time. Examples are declining prices for solar modules, overall trends in electricity demand[27] or national policy changes, in particular changes in feed-in tariffs. Another aspect covered by these effects is the development of retail price components that do not vary across Germany, such as the EEG-levy or wholesale electricity prices. Postcode-specific fixed effects account for factors that regionally differ between postcode areas but are constant over time, e.g., socioeconomic aspects and solar irradiance.[28] Postcode-specific time trends control for any linear postcode-specific development over time that is not addressed by the nationwide year-specific fixed effects. Examples of such trends include local demographic change or local economic growth.

In addition to the PQMLE, other commonly used models in count data applications are, for example, negative binomial regression models or OLS models with a logarithmized dependent variable. We include these models as robustness checks for our main findings.

To analyze the effect of the nonlinear pricing schedule, we apply the encompassing approach by Davidson and MacKinnon (1993), which can be used to identify a preferable model specification for non-nested models. We specify the encompassing model as an augmented model of (3.4) and include both alternative explanatory variables, i.e., the volumetric tariff ($\mathit{tariff}_{i,t-1}$) and the average tariff ($\varnothing\text{-}\mathit{tariff}_{i,t-1}$):

$$Y_{i,t} = exp(\beta \cdot \mathit{tariff}_{i,t-1} + \delta \cdot \varnothing\text{-}\mathit{tariff}_{i,t-1} + \gamma \cdot X_{i,t} + \phi_t + \mu_i + \theta_i \cdot t) \cdot \epsilon_{i,t} \quad (3.5)$$

We want to test our hypothesis that the volumetric tariff impacts PV investments rather than the average tariff. Hence, we expect that as long as the model accounts for the volumetric tariff, the coefficient of the average tariff $\delta$ is statis-

[26] A Hausman test rejects the null hypothesis that there is no significant correlation at the significance level of 1 %, which supports the choice of a fixed effects approach.

[27] In Germany, the overall electricity demand has decreased over the past years, which is covered by the year-specific fixed effects. If spatial heterogeneity in demand exists, this is covered by the postcode-specific fixed effects. We do not expect substantial variation in both dimensions, as we see no indication that energy efficiency gains should vary significantly across regions over time.

[28] Generally, solar irradiance is a decisive variable influencing residential PV investments. However, we assume that households do not account for the (relatively small) solar irradiance variation over time. Instead, we expect that households consider it as a spatial component, such as whether one lives in a generally sunnier region. Therefore, we do not include solar irradiance as a covariate in our model, as it is reflected in the postcode-specific fixed effects.

tically insignificant, i.e., not influencing the number of PV installations, and we can check this hypothesis with a standard F-test (c.f. Greene, 2003).

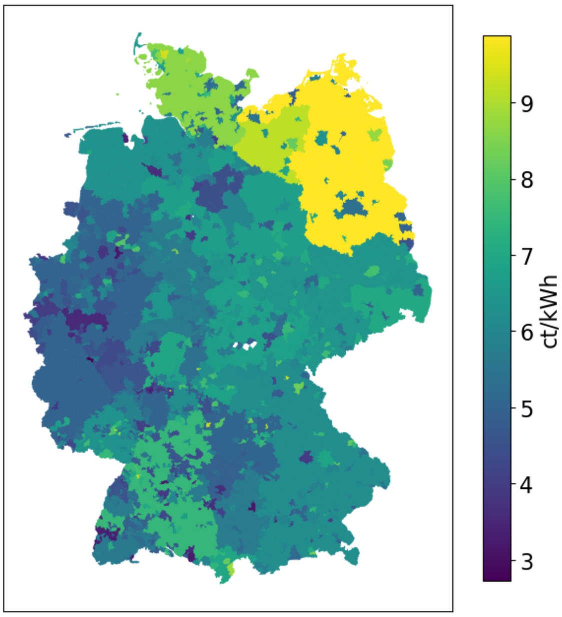
## 3.5. Data

For our analysis, we use a unique panel data set at the German postcode level. The panel data set covers 8,148 postcodes (PLZ) for 2009-2017, a total of 72,672 observations. For our dependent variable we rely on data from the Marktstammdatenregister (MaStR) (Bundesnetzagentur, 2021b). For each unit, the MaStR documents the energy carrier, the installed capacity, the postcode, the installation date, and various additional information. In this paper, we focus on PV installations with a size up to 10 kW as this is the typical size installed on residential buildings. Our data consists of 708,555 PV installations commissioned between 2009 and 2017. By aggregating the number of new PV installations per year and postcode, we receive our dependent variable ($\#$ *of PV*).

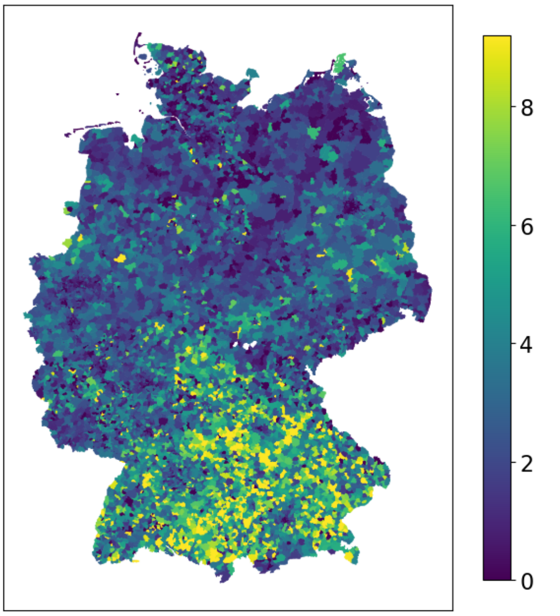
Furthermore, we use detailed data on annual network tariffs on postcode level from ene't, a German data provider for the electricity industry (ene't, 2021). The data contains information on the annual fixed component of network tariffs (*fixed_tariff*, in Euro/year) and the volumetric component (*tariff*, in ct/kWh). For our investigation of price perception, we use both components to calculate an average tariff (*∅-tariff* in ct/kWh) by assuming a reference load profile of 3,500 kWh annual consumption. Figure 3.2 illustrates the regional distribution of the volumetric network tariff and the number of PV installations per 1000 residential buildings for the year 2017. The maps show regional heterogeneity for both variables. The volumetric tariffs are highest in north-east and south-west Germany, driven by the high wind penetration, especially in the north. PV installations per 1000 buildings concentrate in the southern regions, which is in line with the general expectations, as these regions show the highest solar irradiance. Note that the fixed effects of our estimation approach capture this persistent difference between regions. The spatial heterogeneity of the variables differs over time, shown in further illustrations of the temporal variation of our data in B.1.

To analyze whether network tariffs had a greater impact on the number of PV installations after 2012, we define two binary dummy variables: One that takes on the value 1 for all years before 2012 ($d_{<2012}$), and one that takes on the value 1 otherwise ($d_{\geq 2012}$).

We further control for the heterogeneity of postcode areas by including socioeconomic drivers of PV expansion that have been identified in the literature described in section 3.2. We use yearly and postcode-specific data for these socioeconomic covariates from RWI-GEO-GRID, a data set from the Leibniz Institute for Economic Research (RWI) (RWI and Microm, 2020). First, we consider the average purchasing power of households per capita (*income*, in Euro/year).




(a)




(b)

Figure 3.2.: Regional resolution of (a) the volumetric network tariff and (b) # of PV per 1000 residential buildings, both for the year 2017.

Table 3.1.: Descriptive statistics, 2009-2017 (N = 73,329)

| Variable | Mean | Median | SD | Min | Max | Source |
|---|---|---|---|---|---|---|
| *Dependent variable* | | | | | | |
| # of PV | 9.66 | 6 | 11.57 | 0 | 184 | MaStR |
| *Independent variables* | | | | | | |
| tariff (ct/kWh) | 5.29 | 5.08 | 1.04 | 2.38 | 9.90 | ene't |
| fixed_tariff (Euro/year) | 21.56 | 18.00 | 17.72 | 0 | 95.00 | ene't |
| ∅-tariff (ct/kWh) | 5.90 | 5.65 | 1.24 | 2.67 | 11.55 | ene't |
| income (log of) | 9.95 | 9.95 | 0.19 | 9.30 | 11.01 | RWI |
| housetype (% of 1- and 2-family homes) | 58.32 | 63.64 | 20.69 | 0.30 | 100 | RWI |
| age | 43.74 | 43.58 | 2.35 | 35.11 | 58.48 | RWI |
| buildings (log of) | 7.40 | 7.46 | 0.92 | 0.69 | 9.80 | RWI |

We expect a positive impact of the purchasing power of households on PV expansion as the investment costs of the installation are more likely to be afforded by more affluent people. The variable *age* denotes the average age of inhabitants in a specific postcode area. One would assume that a younger population is more aware of the possibility to invest in PV, thus leading to a negative influence of average age on our dependent variable. For the number of residential buildings (*buildings*), which is closely correlated with the number of inhabitants, we would expect a positive effect on our dependent variable as more buildings in a postcode mean more opportunities for PV investments. Further, we include the share of detached and semi-detached houses in the building stock (*housetype*, in %). Detached and semi-detached houses are well suited for residential PV installations, for example, due to the unity of electricity consumer and investor. Therefore, we would expect a positive impact of the housetype on our dependent variable. Another factor that could have an influence on PV investments but is not included in our analysis is environmental awareness. Election results, i.e. the proportion of green voters, are usually taken into account as a measure of environmental awareness. There is no continuous annual data for this, so the approach conflicts with the panel-based fixed-effects approach of our model. Moreover, the existing literature shows that environmental awareness has little to no effect on PV investment (see Chapter 3.2).

## 3.6. Results

We estimate the impact of network tariffs on residential PV installations in Germany within our preferred model specification, described in section 3.4. Further, we analyze whether the incentives for self-consumption have become more relevant in recent years compared to the early years of PV adoption and how the nonlinear pricing schedule affects PV adoption. Using additional model specifications, we also check the robustness of our results.

We present our main results regarding the impact of network tariffs on PV adoption in table 3.2. Regression (1) shows our preferred model specification (c.f. equation 3.4), which estimates the impact of lagged network tariffs on the number of new PV installations, controlling for socioeconomic covariates. Our estimation suggests that network tariffs have a positive and significant impact on the number of PV installations. All else equal, an increase of one within standard deviation (0.34 eurocent per kWh) in network tariffs is estimated to increase the number of PV installations by 2 %.[29] The magnitude of this effect is in line with the findings of Gautier and Jacqmin (2020) for PV investments in Wallonia. The results further confirm the findings of Frondel et al. (2019), who show that households in Germany are aware of yearly price variations and change their electricity consumption respectively. Furthermore, the impact of the other covariates in our model is not statistically different from zero. The fixed effects absorb their impact due to their relatively low within-variance, which is depicted in B.3.

We further examine whether the incentives for self-consumption have become more relevant in recent years compared to the early years of PV adoption. Therefore, we analyze how the change in the economics of PV investments from 2012 onward has affected the impact of network tariffs on PV installations in Germany (c.f. section 3.3). We include an interaction term between our binary dummy variables ($d_{<2012}$ and $d_{\geq 2012}$) and the network tariff in regression (2). This estimation allows us to compare the effect of network tariffs before and after 2012. The results suggest that network tariffs did not significantly impact PV adoption before 2012, while they do afterward. We estimate that, since 2012, an increase in network tariffs of one standard deviation (0.34 eurocent per kWh) increases PV installations by 2.4 %. A Chow test confirms the difference between the estimates of the two time-subsets, revealing significance at the 1 % level. Hence, we can confirm our hypothesis that self-consumption has gained importance since 2012 when rising retail tariffs started to exceed declining feed-in tariffs.

We further examine how the different price components of nonlinear tariffs impact PV installations. We make use of the volumetric and the fixed component of network tariffs and test the theoretical expectation that PV adoption should only be affected by the volumetric tariffs. In a first step, we estimate the impact of average instead of the volumetric tariffs in regression (3). This

[29] Within standard deviation refers to the variation of the network tariffs that is not accounted for by the applied fixed effects. The model results show an increase by 5.8 % for one cent per kWh increase in network tariffs. However, we cannot make reliable statements about the effect of a shift of that magnitude, because the within standard deviation of network tariffs in the model is significantly lower than one cent per kWh. We include a more detailed discussion in B.3.

Table 3.2.: Main results

| Model: | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable: | # of PV | # of PV | # of PV | # of PV |
| $\text{tariff}_{t-1}$ | 0.0578*** | | | 0.0914*** |
| | (0.0061) | | | (0.0208) |
| $\text{d}_{<2012} \times \text{tariff}_{t-1}$ | | 0.0112 | | |
| | | (0.0083) | | |
| $\text{d}_{\geq 2012} \times \text{tariff}_{t-1}$ | | 0.0707*** | | |
| | | (0.0064) | | |
| $\varnothing\text{-tariff}_{t-1}$ | | | 0.0577*** | -0.0386* |
| | | | (0.0066) | (0.0224) |
| income (log of) | -0.0334 | 0.0230 | -0.0374 | -0.0332 |
| | (0.1497) | (0.1488) | (0.1502) | (0.1495) |
| housetype | 0.0041 | 0.0050 | 0.0037 | 0.0042 |
| | (0.0042) | (0.0042) | (0.0042) | (0.0042) |
| age | 0.0168 | 0.0184 | 0.0160 | 0.0171 |
| | (0.0136) | (0.0136) | (0.0137) | (0.0136) |
| buildings (log of) | -0.1225 | -0.1363 | -0.0988 | -0.1287 |
| | (0.1688) | (0.1688) | (0.1687) | (0.1689) |
| *Fit statistics* | | | | |
| observations | 64,531 | 64,531 | 64,531 | 64,531 |
| AIC | 330,230 | 330,094 | 330,271 | 330,225 |
| BIC | 476,772 | 476,644 | 476,812 | 476,776 |
| Log-Likelihood | -148,967 | -148,898 | -148,987 | -148,963 |

*Robust standard errors clustered at the postcode level.*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

estimation yields similar results compared to our preferred model specification with the volumetric tariffs in regression (1). In a second step, we jointly test the two alternatives in the encompassing model (c.f. equation 3.5). In regression (4), we include both the volumetric ($\textit{tariff}_{t-1}$) and the average tariff ($\varnothing\textit{-tariff}_{t-1}$). The coefficient of the volumetric tariff is still positive and statistically significant, while the average tariff does not have a statistically significant impact on the number of PV installations. Thus, the encompassing test confirms the theoretical expectation that volumetric tariffs drive PV investments. The results indicate that consumers differentiate between the price components of the two-part tariff, which contributes to the empirical evidence on consumers' perception of nonlinear pricing. Consumers may understand the taxonomy of the two-part tariff and base their investment decision on the volumetric rather than an average tariff. However, given the aggregate nature of our data, this finding should be complemented by further analysis of microeconomic data.

In table 3.3, we provide several robustness checks regarding our model specification and our estimation strategy. In regression (5), we check our assumption that PV adoption is impacted by the lagged network tariff rather than the contemporary one by using the contemporary tariff ($tariff_t$) as our explanatory variable instead of the lagged network tariff ($tariff_{t-1}$). The results indicate a positive effect of the current network tariff on PV adoption. However, the coefficient is smaller compared to the impact of the lagged network tariff in regression (1). Moreover, in regression (5), the values of the two information criteria, AIC and BIC, increase while the value of the log-likelihood decreases compared to regression (1), implying that the explanatory power of our preferred model specification is higher. This finding supports our assumption that households respond to their electricity bill rather than current tariffs and, thus, may have a rather short-sighted perception of prices.[30]

We aggregate our data to the next higher regional level (NUTS-3) in regression (6) to check whether our results remain valid at a higher regional aggregation. The estimation suggests that, even under a higher regional aggregation, network tariffs positively and significantly impact PV investments, supporting the results derived from postcode-level data.[31] In regression (7), we estimate our preferred model specification without the postcode-specific time trends. We observe that the positive and significant impact of network tariffs persists. Further, as expected, income has a significantly positive and age a significantly negative impact on the number of new PV installations. Hence, in our preferred model specification, the postcode-specific time trends do indeed capture the assumed postcode-specific demographic change and local economic growth.

To further check the robustness of our results, we apply alternative estimation strategies to determine the impact of network tariffs on the number of PV installations. First, regression (8) assumes a linear relationship, using an OLS regression. To accommodate for the non-negative nature of our count data, we take the log of the dependent variable to which we add one unit due to the presence of zero outcomes. Second, we estimate a negative binomial regression (9). Negative binomial regressions make stronger assumptions regarding the distribution of the dependent variable, which do not fully hold for our data. However, the results can provide a robustness check. Overall, both results confirm the finding of our preferred model specification, that higher network tariffs lead to more PV installations.

Finally, we perform another robustness check of our hypothesis by replacing the dependent variable with a sample of PV systems that should not be affected by network tariffs. Regression (10) shows the results of such a placebo test. The dependent variable is defined as the number of PV installations larger than 300 kW. PV systems with this size can be assumed to be commercial systems, i.e., installed on non-residential buildings or ground-mounted. Al-

[30] An additional robustness check on tariffs further in the past can be found in B.2.

[31] In B.2 we further analyze whether the impact of network tariffs may differ between regions and include a regression on state-specific effects of network tariffs on PV investments.

Table 3.3.: Robustness checks

| Model: Dependent Variable: | (5) # of PV | (6) # of PV | (7) # of PV | (8) log(# of PV+1) | (9) # of PV | (10) # of PV >300 kW |
|---|---|---|---|---|---|---|
| $\text{tariff}_t$ | 0.0351*** | | | | | |
| | (0.0056) | | | | | |
| $\text{tariff}_{t-1}$ | | 0.0725*** | 0.0540*** | 0.0478*** | 0.0550*** | -0.0468 |
| | | (0.0153) | (0.0047) | (0.0056) | (0.0045) | (0.0520) |
| income | -0.1770 | -1.320** | 0.6786*** | -0.0810 | 0.7198*** | 0.6676 |
| (log of) | (0.1468) | (0.5806) | (0.1241) | (0.1462) | (0.1140) | (1.2350) |
| housetype | 0.0152*** | 0.0286** | 0.0017 | 0.0051 | 0.0027 | -0.0690 * |
| | (0.0038) | (0.0144) | (0.0030) | (0.0036) | (0.0028) | (0.0342) |
| age | -0.0043 | 0.0547 | -0.0997*** | 0.0153 | -0.1025*** | 0.2476* |
| | (0.0131) | (0.0571) | (0.0076) | (0.0116) | (0.0070) | (0.1202) |
| buildings | -0.1371 | -0.5982 | 0.1874 | 0.0796 | 0.2362* | -0.8075 |
| (log of) | (0.1543) | (0.5511) | (0.1379) | (0.1386) | (0.1285) | (1.3720) |
| *Fixed effects* | | | | | | |
| PLZ | Yes+slope | | Yes | Yes+slope | Yes | Yes+slope |
| year | Yes | Yes | Yes | Yes | Yes | Yes |
| NUTS-3 | | Yes+slope | | | | |
| *Distribution* | PQMLE | PQMLE | PQMLE | OLS | Neg.Bin. | PQMLE |
| *Fit statistics* | | | | | | |
| observations | 72,672 | 3,192 | 64,531 | 65,179 | 64,531 | 27,595 |
| AIC | 375,142 | 32,949 | 338,674 | 91,389 | 330,167 | 42,126 |
| BIC | 523,758 | 37,864 | 411,999 | 239,563 | 403,492 | 98,980 |
| Log-Likelihood | -171,406 | -15,664 | -161,257 | -29,384 | -157,003 | -14,151 |

*Robust standard errors clustered at the regional level.*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

though non-residential network users are also required to pay network tariffs, self-consumption should generally not be the driving factor for PV investments in these cases. Rather, investment decisions should be motivated by potential revenues from the sale of electricity. Therefore, we expect network tariffs not to affect investment decisions for PV installations larger than 300 kW. The regression results confirm this hypothesis, as they do not show a significant impact of network tariffs on PV installations larger than 300 kW.

## 3.7. Conclusion

Within a net purchasing system, investment incentives for residential PV arise from feed-in tariffs and the value of self-consumption. With the latter becoming the dominant economic driver, network tariffs, which constitute a substantial part of the consumption costs, are expected to gain importance. By exploiting the regional heterogeneity of network tariffs, we investigate whether network tariffs encourage to invest in PV systems using a unique panel data set at the German postcode level over the period 2009-2017. We further evaluate how the nonlinear tariff structure impacts residential PV adoption.

We use a Poisson quasi-maximum likelihood estimator with conditional fixed effects and provide additional robustness checks for various distributional assumptions and the regional aggregation level. All else equal, an increase in network tariffs by one standard deviation (0.34 eurocent per kWh) is estimated to increase PV installations by 2 %. Thus, our results indicate that network tariffs impact PV adoption across Germany. We find evidence that the impact of network tariffs has increased over time, supporting our expectation that the economic incentives for self-consumption have become more important in recent years. Furthermore, our analysis of the different price components indicates that the volumetric network tariff drives PV adoption rather than the average price.

For policymakers, our results provide essential insights for upcoming reforms of electricity price components. Our results suggest that households do react to price signals and that prices effectively guide investments. The current incentive for self-consumption is a side effect of the retail tariff design in Germany. Due to taxes, levies and the network tariff design, retail tariffs contain various price components that are not necessarily aligned and, thus, may distort the investment decision of the household in a way that is economically inefficient. If the retail tariff is higher than economically efficient, the incentives for PV investments are distorted. For instance, a feedback effect, as discussed in Jägemann et al. (2013), arises when rising retail tariffs lead to rising residential PV expansion and rising PV expansion, in turn, leads to increasing retail tariffs. Therefore, from an economic point of view, it is essential to create price signals in the least distorting way. In Germany, reform proposals are currently considered for the network tariff system and include a shift from predominantly volumetric network tariffs to a more substantial fixed network tariff. Other proposals aim for a change in the EEG-levy that is currently paid exclusively on a volumetric basis. Consequently, these reforms influence not only household consumption behavior but also investment incentives for PV installations.

The regional variation of price signals may explain at least part of the present heterogeneity of PV installations in Germany. However, as we use fixed effects to control for unobserved heterogeneity between regions, our analysis is limited in this regard. Further analyses could examine the impact of economic factors on the regional heterogeneity across Germany in more detail. Furthermore, declining costs for storage technologies, such as batteries, will further strengthen the case for self-consumption in the residential sector. Therefore, future empirical research could investigate the incentives that drive households to invest in combined PV and storage systems. In a similar vein and in the light of currently increasing adoption rates of electric vehicles and electric heating systems in the residential sector, future empirical analyses could shed light on the impact of price signals on these technologies. Finally, our analysis focuses on the influence of price signals on the initial decision to invest in a PV installation. Another promising field would be to supplement our results with empirical studies on consumption profiles to provide insights into the short-term price sensitivity of households with PV installations.

# 4. Grid Connection Sizing of Hybrid PV-Battery Systems: Navigating Market Volatility and Infrastructure Constraints

## 4.1. Introduction

The rapid integration of wind and solar power has become central for decarbonizing energy systems globally. However, the inherent intermittency and regional distribution of these renewable energy sources (RES) can create challenges in power systems. Energy storage technologies play a pivotal role in addressing these challenges. While long-term storage, such as hydrogen, addresses seasonal imbalances, battery energy storage systems (BESS) are well suited for providing short-term flexibility, which is essential in power systems with high shares of intermittent RES (Ruhnau and Qvist, 2022).

BESS can offer temporal and spatial flexibility to the power system (Czock et al., 2023). By storing electricity, they shift supply and demand over time, helping to reduce power price volatility. In Europe, price volatility has surged in recent years due to rising and fluctuating commodity prices and a growing share of wind and solar generation. Spatial flexibility is needed to integrate intermittent renewable generation on all voltage levels as curtailment rates increase and grid connection processes become an emerging bottleneck for the energy transition.

The time required to secure a grid connection has increased over the last decade, and grid connection costs have risen substantially (Gorman et al., 2025, IEA, 2023, Wind Europe, 2024). In Germany, legislators decided to limit the grid injection of new residential PV installations to 60 percent of their installed capacity, effectively reducing the available grid connection capacity. Given the increasing competition for scarce grid connection capacity, co-locating BESS with renewable generation — so-called hybrid systems — offers cost-saving opportunities, as they enable a more effective grid access utilization (Chinaris et al., 2025, Schleifer et al., 2023).[32] A co-location also saves costs in planning and construction, reduces energy losses, and enhances the energy value of renewable production (Gorman et al., 2020).

Despite their critical role in the energy transition, battery investments remain in their early stages in many countries. Beyond profitability concerns, regulatory

[32]The term hybrid BESS system defines assets that combine solar or wind assets and a BESS while maintaining locational and operational linkages, as suggested by Murphy et al. (2021).

uncertainties and energy market risks are significant barriers to investments in BESS (Côté and Salm, 2022, Jayaraj et al., 2024). Therefore, many European countries introduced support schemes to enable storage investments in "standalone" and "hybrid" configurations (Paolacci et al., 2024). In Germany, the government has introduced the so-called "EEG innovation tender" to incentivize investments of up to 8 GW of hybrid BESS capacity by 2029. The support scheme pays a market premium on every MWh fed into the grid. This subsidy is tied to grid connection restrictions, as the BESS can only charge from the renewable generation asset, not the grid. Similar requirements exist internationally. For instance, the federal Investment Tax Credit for solar generation assets in the U.S. has historically limited grid charging of battery storage when paired with renewable generation (Kim et al., 2024).

In theory, efficiently designed grid connection rationing or grid connection charges can steer socially optimal market entry decisions for new intermittent renewable energy sources (Newbery and Biggar, 2024, Simshauser and Newbery, 2024). However, the impact of grid connection restrictions on contribution margins of hybrid PV-BESS systems has not yet been quantified. We also lack an understanding of the impact of these restrictions on the related risk of contribution margins, which are crucial for BESS investments. Moreover, the interaction between grid connection sizing and a market premium payment, such as in the German EEG innovation tender scheme, is unclear. To contribute to addressing these gaps, this paper asks: *How do grid connection restrictions and market premium payments affect contribution margins and revenue risks of hybrid PV-BESS systems?*

The analysis is based on a techno-economic mixed-integer linear programming (MIP) model applied to a German case study, simulating the optimal dispatch of a hybrid PV-BESS system against multiple stochastically derived, exogenous price samples. By systematically varying the grid connection configuration, the analysis derives the change in contribution margins resulting from incremental constraints on grid access. This framework enables investors to identify the optimal grid withdrawal and injection capacities by comparing the risk-return profiles of grid cost-adjusted contribution margins. The findings show that hybrid PV-BESS systems exhibit strong diversification effects, significantly reducing contribution margin risk compared to standalone PV or BESS assets. In the absence of regulatory requirements, investors would not reduce the grid withdrawal capacity, as charging restrictions reduce contribution margins significantly and increase associated risks by lowering the diversification of PV and BESS assets. In contrast, grid injection capacities of hybrid PV-BESS systems can be significantly reduced without impacting margins, as high grid connection utilization levels typically coincide with low power prices. A market premium alters the price signals faced by investors. It incentivizes higher grid injection capacities as power generation during low-price periods becomes more valuable. As the market premium varies with the market value of RES, the diversification benefit of combining PV and storage is reduced. It effectively mutes the negative correlation between PV revenues and BESS arbitrage. The findings are robust for different asset configurations and benchmark years. Policymakers and network operators may need to reconsider support schemes for hybrid PV-BESS systems. Current grid connection restrictions focus on the wrong side of the grid - instead of grid withdrawal restrictions, grid injection could be limited at lower costs. Additionally, market premia could inadvertently incentivize project developers to increase grid connection capacities and raise their financing costs. Subsidy payments from the EEG innovation tender could have been reduced by 50% in 2024 with a more efficient policy design while reaching the same contribution margins.

The structure of this paper is as follows. Section 4.2 reviews the relevant literature. Section 4.3 outlines the model framework and describes the numerical assumptions employed in the case study. The results are presented in Section 4.4, followed by a discussion of their implications in Section 4.5. Section 4.6 concludes the paper.

## 4.2. Literature review

Several studies have analyzed the value of BESS from a system-oriented and microeconomic perspective. This review focuses on the relevant microeconomic literature on utility-scale storage systems, which takes the perspective of an investor to understand how market developments or regulatory elements impact storage value and the operational dispatch.[33]

The value of standalone storage systems for investors has been investigated intensively. Mercier et al. (2023) analyze the value of storage arbitrage on day-ahead markets across Europe. They find that storage value has increased between 2000 and 2021 and that an additional storage duration beyond four hours has a low marginal benefit. Many studies show that the storage value increases when an asset participates in multiple markets. However, the focus most commonly lies on operational strategies for the participation in day-ahead and ancillary service markets, e.g., aFRR or mFRR markets (e.g., Hu et al., 2022, Merten et al., 2020, Mohamed et al., 2023, Nitsch et al., 2021). Despite their increasing role in storage business cases, intraday markets are less often included in analyses (some examples are Collath et al., 2023, Kraft et al., 2023). Recently, hybrid system configurations coupling intermittent RES and BESS have gained increasing attention. Significant focus has been put on the value of different asset configurations under different price profiles (Schleifer et al., 2022). Keles and Dehler-Holland (2022) investigate the profitability of hybrid PV-BESS systems in Germany and evaluate different storage durations. The analysis reveals that the most profitable storage configuration has a duration of two hours. Similarly,

[33] Insights from system-level analyses are presented and referenced in Section 4.5. Zhang et al. (2022) provide a comprehensive literature review of hybrid PV-BESS systems with a strong focus on residential applications.

Schreiber et al. (2022) formulate a techno-economic dispatch model for hybrid PV-BESS systems with an application to Germany. To the best of the author's knowledge, they are the only study with an application to the German EEG innovation tender scheme. However, they do not investigate the impact of the respective regulatory features, nor include intraday markets in the analysis.

Another strand of literature analyzes the interaction of hybrid storage systems with the grid. Gorman et al. (2022) analyze the value of hybrid storage systems considering locational prices in the U.S. They show a locational value of storage, which does not necessarily align with the value of the renewable resource in hybrid systems. Similarly, Kim et al. (2024) examine the value of hybrid PV-BESS asset configurations in congested regions in the U.S. They find that the value of hybrid BESS systems varies significantly depending on the renewable share in the regional market. Motivated by the U.S. Investment Tax Credit scheme, both studies analyze binary charging restrictions. The grid connection dimensioning of utility-scale hybrid storage applications has received little attention, as most analyses on the interaction between batteries and grid connection have been limited to residential applications (e.g., Cuenca et al., 2023). Chinaris et al. (2025) are one of the few studies analyzing the impact of utility-scale hybrid storage applications on the utilization of the grid infrastructure. They highlight that grid connection utilization increases when batteries are included in hybrid setups, but exclusively focus on grid injection. None of the studies mentioned above includes multiple markets or investigates varying grid connection capacities and their impact on the investment risk.

Most research that includes elements of uncertainty in its analysis focuses on developing optimal trading strategies to maximize revenue.[34] Literature on the investment risk perspective is scarce, especially for hybrid PV-BESS systems (Hsi and Shieh, 2024). The survey by Côté and Salm (2022) shows that this research gap is especially severe, as investors reveal a strong aversion towards energy market risk. Yu and Foggo (2017) investigate the stochastic valuation of storage from an investor's perspective but do not consider the combination with renewable assets. Some papers analyze the option value and diversification effect of batteries coupled with PV assets, but only focus on residential applications (Andreolli et al., 2022, Ma et al., 2022, Parra and Patel, 2019). Sinsel et al. (2019) are among the few studies that analyze the diversification effect of utility-scale batteries and renewable energy sources from an investor perspective. The paper applies the Modern Portfolio Theory (MPT) and compares a technological (wind, solar, and storage) with a geographical (different generation profiles) diversification.[35] They find that technological diversification reduces risk more

[34]See Yang et al. (2022) for a review of operational BESS energy management modeling approaches in renewable energy systems.

[35]See deLlano Paz et al. (2017) for a review of applications of MPT in the field of energy planning and electricity production. Recent examples of MPT applications focusing mainly on wind and solar complementarity can be found in Castro et al. (2022), Li et al. (2024), and Prol et al. (2024).

effectively than geographical diversification. The paper does not analyze hybrid PV-BESS systems but focuses on general portfolio compositions.

Previous research has proposed using feed-in tariffs to promote energy storage (Krajačić et al., 2011). Feed-in tariffs are widely applied to PV systems coupled with BESS, primarily in residential applications (see Bayod-Rújula et al. (2017) for a review). Therefore, most literature focuses on residential PV-BESS systems when analyzing the impact of feed-in tariffs (e.g., Hassan et al., 2017, Parra and Patel, 2016). To the best of the author's knowledge, feed-in tariffs or market premium schemes for utility-scale hybrid PV-BESS systems and their impact on risk and grid connection have not been analyzed.

Existing research has separately addressed BESS valuation, grid connection challenges, or risk assessment. However, a critical gap remains in understanding their confluence for utility-scale hybrid PV-BESS projects from an investor's standpoint. Specifically, literature is scarce that systematically quantifies how varying grid connection capacities for withdrawal and injection interact with contribution margins, associated risks, and the influence of policy instruments like market premia. Therefore, the main contributions of this study are as follows: First, the paper develops and applies a methodology to quantify the weather-related contribution margin risk for hybrid PV-BESS systems participating in day-ahead and intraday markets. Second, this study provides a systematic microeconomic analysis of how different grid connection configurations affect the contribution margins and risk profiles of these hybrid systems. This is particularly important as most literature on the grid connection of hybrid systems has focused primarily on grid injection or residential applications and has neglected their interactions with risk. Third, this paper offers novel insights into the role of market premium payments, such as those in the German EEG innovation tender scheme, in shaping the economics and risks of utility-scale hybrid PV-BESS systems. The paper analyzes explicitly how a market premium influences the grid connection sizing and the inherent diversification benefits of hybrid assets. Finally, by integrating these elements — grid connection sizing (injection and withdrawal), detailed risk assessment from an investor perspective, and the impact of market premium payments — this paper is the first to comprehensively analyze the interplay of these critical factors for utility-scale hybrid PV-BESS systems, with direct implications for policy design, such as the EEG innovation tender scheme.

## 4.3. Methodology

To answer the research question, this study applies a model framework similar to Schlund and Theile (2022) (see Figure 4.1). A techno-economic MIP problem is formulated to jointly optimize a hybrid PV-BESS system and estimate its optimal dispatch and contribution margins.[36] The dispatch is optimized for exogenous PV generation profiles and corresponding electricity prices.

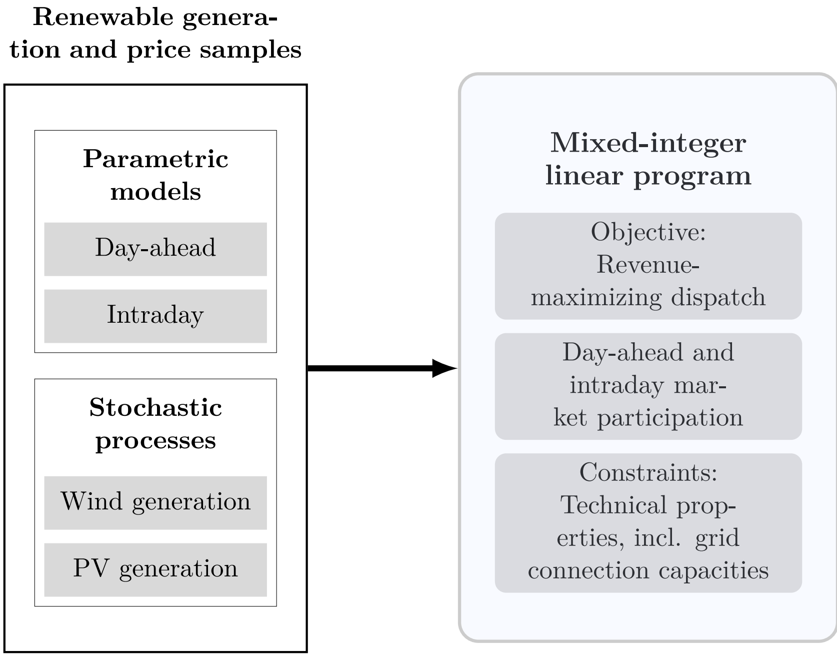



Figure 4.1.: Model framework for the analysis (Own illustration based on Schlund and Theile, 2022).

In contrast to other valuations of hybrid PV-BESS systems, the model considers day-ahead and intraday markets. Other sources of revenue, like ancillary service markets, are not included in the analysis, as previous studies have shown their limited importance for BESS revenues (Keles and Dehler-Holland, 2022). The dispatch is optimized for different asset configurations with varying grid withdrawal and injection constraints to derive the change in contribution margins from incremental grid connection constraints and enable investors to identify cost-optimal grid connection capacities. Additionally, the cases differ depending on whether they receive market premia payments. Exogenous generation and price patterns are derived from stochastic models for renewable energy feed-in and related forecast errors. Two parametric models for day-ahead and intraday markets capture the relationship between wind and solar generation and electricity prices based on the benchmark year 2024. Therefore, the analysis accounts for the interdependency of renewable energy generation and electricity prices, which is crucial for evaluating RES, given the concurrent operation of the plant under evaluation and all other renewable assets selling electricity simultaneously. The model focuses on weather-induced uncertainties, which are an important driver

[36] As the primary analysis focuses on BESS coupled with a PV asset, this section refers to hybrid PV-BESS systems. Still, the methodology also allows for the analysis of hybrid Wind-BESS systems.

for the value of renewable assets and storage (Mathews et al., 2023).[37] The stochastic nature of the analysis allows for the assessment of related risks and distributions of contribution margins by examining the arithmetic mean values and coefficients of variation (CoV). The CoV, also known as the relative standard deviation, measures the spread of a data set by relating the standard deviation to the mean of the distribution.

### 4.3.1. Mixed-integer linear program for hybrid BESS operation

To assess the hybrid PV-BESS system, a techno-economic dispatch model is formulated as a MIP problem. The model is formulated similarly to Mercier et al. (2023) or Schreiber et al. (2022) with adjustments to account for the market participation in intraday and day-ahead markets, the variation of grid access configurations, and market premium payments. The optimization considers the viewpoint of a price-taking power producer managing a renewable generation asset (e.g., solar power generation) coupled with a BESS, aiming to maximize profit. The power producer has access to the day-ahead and the intraday electricity markets. The model is solved for a full year at a quarter-hourly resolution, employing a rolling horizon approach in which the asset is optimized on a daily basis. This approach is especially suited for storage systems with storage durations of up to four hours. The model assumes that the operator has perfect foresight for the next day, given that day-ahead electricity prices and renewable production can be accurately forecasted (Ziel et al., 2015). Section 4.5 discusses this assumption and its impact on the findings of this paper.

The techno-economic dispatch model maximizes the total gross margin $\pi$ from arbitrage and power sales over all simulated periods $t \in T$ (4.1).

$$\max \pi = \sum_{t}^{T} R_t - C_t \tag{4.1}$$

The revenue $R_t$ in (4.2) represents the income from spot market sales of the battery $q^-_{m,t}$, and the PV asset $q^{FeedIn}_t$. The battery can sell the stored electricity on the different markets $m \in M$. In this paper, these markets represent the intraday $p^-_{ID,t}$ and day-ahead market $p^-_{DA,t}$. The electricity from the PV asset is sold at a price $p^{PV}_t$. Note that, depending on the investigated case, a market premium $p^{MP}_t$ is added to the respective market prices. Therefore, the prices for charging $p^+_{m,t}$ and discharging $p^-_{m,t}$ might differ between cases.

$$R_t = \sum_{m}^{M} p^-_{m,t} q^-_{m,t} + p^{PV}_t q^{FeedIn}_t \quad \forall t \in T \tag{4.2}$$

[37] Other sources of risk, such as fuel prices, affect the contribution margins of BESS. These factors are partially addressed in the robustness test for the benchmark year 2019, presented in Section 4.4.5. However, a comprehensive analysis of other risk sources is beyond the scope of this paper.

The cost of charging the battery $C_t$ from the grid depends on the market:

$$C_t = \sum_{m}^{M} p^+_{m,t} q^+_{m,t} + c_{cycle} * N^{cycle}_t \quad \forall t \in T \tag{4.3}$$

Additionally, the cost function includes the penalty term $c_{cycle} * N^{cycle}_t$, which accounts for battery degradation based on the total number of cycles (Grimaldi et al., 2025). One equivalent full cycle is defined as the amount of energy throughput (charge or discharge) equivalent to one complete charge-discharge cycle at the battery's maximum energy capacity $\overline{SOC}$ (4.4). The costs for one cycle are based on the cycle-based degradation and replacement costs of the energy storage. Note that this (virtual) penalty term is not considered when displaying the total contribution margin.

$$N^{cycle}_t = \frac{(\sum_m^M q^+_{m,t} + q^{+,PV}_t) * \eta^{BESS} + \sum_m^M q^-_{m,t}/\eta^{BESS}}{2 * \overline{SOC}} \tag{4.4}$$

The model includes several constraints to ensure the system operates within its physical and operational limits. The energy balance constraint (4.5) ensures that the total renewable energy production $q^{PV}_t$ equals the power sold $q^{FeedIn}_t$, charged $q^{+,PV}_t$, or curtailed $q^{curt}_t$ at any given time.

$$q^{FeedIn}_t + q^{+,PV}_t + q^{curt}_t = q^{PV}_t \quad \forall t \in T \tag{4.5}$$

The state of charge ($SOC_t$) is based on the charging and discharging activities, summarized as $\Delta^{SOC}_t$. For the initial time step ($t = 0$), the $SOC_t$ is set based on the current charging and discharging, i.e., the battery starts empty. For subsequent time steps ($t > 0$), the SOC equals the previous SOC plus the net effect of charging and discharging.

$$SOC_t = \begin{cases} \Delta^{SOC}_t & t = 0 \\ SOC_{t-1} + \Delta^{SOC}_t & \forall t > 0 \end{cases} \tag{4.6}$$

The net effect of charging and discharging ($\Delta^{SOC}_t$) accounts for the battery's efficiency ($\eta^{BESS}$) and is defined as

$$\Delta^{SOC}_t = (\sum_m^M q^+_{m,t} + q^{+,PV}_t) * \eta^{BESS} - (\sum_m^M q^-_{m,t})/\eta^{BESS} \quad \forall t \in T \tag{4.7}$$

Several capacity constraints ensure that charging and discharging activities remain within their respective limits. The battery's state of charge cannot exceed its maximum energy capacity. The battery import capacity constraint ensures that the total power used for charging from all sources (day-ahead market, intraday market, and renewable energy system) does not exceed the maximum charging power capacity ($\overline{q^{BESS}}$). Similarly, the battery export capacity constraint ensures that the total power discharged to the day-ahead and intraday markets does not exceed the maximum discharging power capacity.

$$0 \leq SOC_t \leq \overline{SOC} \quad \forall t \in T \tag{4.8}$$

$$0 \leq \sum_{m}^{M} q_{m,t}^{+} + q_t^{+,PV} \leq \overline{q^{BESS}} \quad \forall t \in T \tag{4.9}$$

$$0 \leq \sum_{m}^{M} q_{m,t}^{-} \leq \overline{q^{BESS}} \quad \forall t \in T \tag{4.10}$$

The grid connection capacity constraints ensure that the total power injected into or withdrawn from the grid does not exceed the grid connection's maximum capacity in the respective direction ($\overline{q^{+,grid}}$, $\overline{q^{-,grid}}$). For the analysis of different grid connection configurations, the respective maximum capacities vary. In the base case, the grid withdrawal capacity equals the BESS capacity, and the grid injection capacity is assumed to equal the cumulative nameplate capacity of the hybrid PV-BESS system.

$$\sum_{m}^{M} q_{m,t}^{-} + q_t^{FeedIn} \leq \overline{q^{-,grid}} \quad \forall t \in T \tag{4.11}$$

$$\sum_{m}^{M} q_{m,t}^{+} \leq \overline{q^{+,grid}} \quad \forall t \in T \tag{4.12}$$

Two conditional (Big-M) constraints (4.13)-(4.14) ensure the battery cannot charge and discharge simultaneously using a binary variable $I_t^{+}$. Therefore, the model includes an arbitrarily high scalar $M$. If the binary variable is 1, charging is possible, while discharging is not, and vice versa. To correctly bound the integer constraints, the artificial scalar $M$ is set to be above $\overline{q^{BESS}}$, while it is kept small enough to ensure computational efficiency.

$$\sum_{m}^{M} q_{m,t}^{+} + q_t^{+,PV} \leq I_t^{+} * M \quad \forall t \in T \tag{4.13}$$

$$\sum_{m}^{M} q_{m,t}^{-} \leq (1 - I_t^{+}) * M \quad \forall t \in T \tag{4.14}$$

Finally, all variables except for the binary variables are non-negative.

$$0 \leq q_{m,t}^{-}, q_{m,t}^{+}, SOC_t, q_t^{FeedIn}, q_t^{+,PV}, q_t^{curt} \quad \forall t, m \in T, M \tag{4.15}$$

In some cases, the hybrid PV-BESS system receives a market premium, which is calculated according to the German EEG innovation tender regulation (Verordnung zu den Innovationsausschreibungen, InnAusV) and the Renewable Energies Act (Erneuerbaren Energien Gesetz, EEG). Therefore, the market premium is calculated yearly, as the difference between a strike price ($\overline{p}$) and the average market value of the system-wide PV generation ($p^{PV}$). The payment of market premia is only applicable if the day-ahead market price in an hour is greater than zero.[38]

$$p_t^{MP} = \begin{cases} \overline{p} - p^{PV} & \text{if} \quad p_{DA,t} > 0 \\ 0 & \text{else} \end{cases} \quad \forall t \in T \tag{4.16}$$

In cases where grid charging is possible and the hybrid PV-BESS system receives a market premium, it is ensured that the subsidy is only paid for electricity production from the renewable generation asset. In these cases, a new variable $q_{m,t}^{-,PV}$ is introduced, which is compensated with a market premium in addition to the respective market price. The constraint (4.17) restricts $q_{m,t}^{-,PV}$ such that the market premium is only paid for electricity production from the renewable generation asset.

$$\sum_t^T \sum_m^M q_{m,t}^{-,PV} \leq \sum_t^T q_t^{+,PV} \tag{4.17}$$

### 4.3.2. Synthetic renewable generation and electricity price time series

The price patterns for the techno-economic optimization are derived from two parametric models that predict day-ahead and intraday electricity market prices based on stochastic samples of renewable electricity generation forecasts and their corresponding forecast errors.

To model the renewable electricity generation samples, this paper follows the approach of Wagner (2014) and Keles and Dehler-Holland (2022). This approach models wind and solar generation as their respective capacity factors ($CF_t^{tech}$ where $tech \in \{PV, Wind\}$) rather than the underlying wind speed and solar radiation. The capacity factors are logit-transformed to normalize the time series.

The core idea for the solar generation sampling is to capture the primary stochasticity in the daily maximum solar generation while treating the intraday quarter-hourly profile as deterministic. For each day $d \in D$, the maximum normalized value is identified.

$$\overline{CF}_d^{PV} = logit(\max_{t \in d}(CF_t^{PV})) \tag{4.18}$$

[38] Details can be found in §9 InnAusV, and §23a Appendix 1 (2) EEG.

This daily maximum series is deseasonalized to handle yearly variations by subtracting a trigonometric function of the form:

$$\eta_d^{PV} = a_1 \cos(2\pi a_2 d + a_3) + a_4 \sin(2\pi a_5 d + a_6) + a_7 \tag{4.19}$$

An AR(2) process is fitted to the deseasonalized series ($\overline{\hat{CF}}_d^{PV}$) to capture the temporal autocorrelation:

$$\overline{\hat{CF}}_d^{PV} = \gamma_0 + \gamma_1 \overline{\hat{CF}}_{d-1}^{PV} + \gamma_2 \overline{\hat{CF}}_{d-2}^{PV} + \epsilon_d \tag{4.20}$$

The wind generation sampling is constructed similarly to the solar generation process. However, the process is based on the complete quarter-hourly time series instead of the daily maximum. In line with the solar sample generation process, the logit-transformed capacity factors for wind are deseasonalized with the help of a trigonometric function. As proposed by Wagner (2014), an AR(3) model is fitted to the residual time series. The stochastic wind and solar capacity factor simulation is performed by running the respective auto-regressive models forward, using randomly drawn residuals based on the fitted distribution. The simulated series are then re-transformed by adding the seasonal component and reverting the initial transformation (logit-transformation and reverting the daily profile in the case of PV). Finally, the resulting wind and solar capacity factor samples are multiplied by the benchmark year's overall available wind capacity to obtain the final simulated production series. C.1 presents a statistical analysis of the simulated wind and solar generation forecast series.

The deviation of the actual generation from the renewable generation forecasts, i.e., the forecast errors of wind and solar generation, is modeled according to Wang et al. (2018). A Gaussian Mixture Model based on conditional distributions replicates the dependency of the distribution of forecast errors on the forecast levels. Note that while these models do not incorporate autocorrelation features, the underlying process of the forecast values exhibits autocorrelation characteristics.

Two parametric models capture the relationship between wind and solar generation and electricity prices. Following Schlund and Theile (2022), the first parametric model establishes a link between day-ahead electricity prices $p_t^{DA}$ (the dependent variable) and the forecasted residual load $q_t^{res}$ (the independent variable). Equation (4.21) presents the corresponding model formulation. Employing a third-degree polynomial captures the non-linear relationship between day-ahead prices and residual load. The functional relationship is not merely a reflection of the merit order; it also implicitly incorporates demand-side price elasticity and accounts for scarcity (Elberg and Hagspiel, 2015). The model is estimated monthly to consider the seasonal effects of renewable generation, demand, and fuel prices.

$$p_t^{DA} = \alpha_0 + \alpha_1 q_t^{res} + \alpha_2 (q_t^{res})^2 + \alpha_3 (q_t^{res})^3 + \epsilon_t \tag{4.21}$$

The second parametric model explores the relationship between intraday prices $p_t^{ID}$, which serve as the dependent variable, and the day-ahead prices $p_t^{DA}$, along with forecast errors from PV ($FE_t^{PV}$) and wind generation ($FE_t^{Wind}$), which are the independent variables outlined in equation (4.22). The forecast errors reflect deviations between actual and predicted outputs for wind and solar generation, while all other influencing factors are held constant. To account for the non-linear relationship and varying impacts of forecast errors on intraday prices, a second-degree polynomial model is employed that differentiates between the forecast errors of PV and wind generation (Kulakov and Ziel, 2021). This functional relationship implicitly incorporates several influencing factors on intraday prices, including scarcity and ramp-up constraints (Pape et al., 2016).

$$p_t^{ID} = \beta_0 + \beta_1 p_t^{DA} + \beta_2 FE_t^{PV} + \beta_3 (FE_t^{PV})^2 + \beta_4 FE_t^{Wind} + \beta_5 (FE_t^{Wind})^2 + \epsilon_t \tag{4.22}$$

The parametric models capture the functional relation between renewable generation, forecast errors, and electricity market prices. Using stochastic wind and solar generation forecast and realization profiles, synthetic electricity price time series are constructed based on these parametric models.

### 4.3.3. Case study design and data

The models are calibrated with historical data from the German electricity market and with technical parameters for the hybrid PV-BESS system. The power system data covers the period from 2015 to 2024. Data on forecasted and realized values for electricity generation and demand are obtained from the German government's data publication platform (BNetzA, 2025b).[39] All data is in quarter-hourly resolution and MWh. Electricity prices, including day-ahead and intraday market prices, are sourced from EPEX Spot. As the German intraday market is continuous, prices vary until settlement. In line with the proposals of Kulakov and Ziel (2021), the model uses the volume-weighted average price of all intraday trades for each quarter-hour period. The parametric models for the electricity prices are fitted to the benchmark year 2024, thereby avoiding distortions arising from the atypical market dynamics in 2020 and 2022. No significant regulatory change affected the intraday and day-ahead market in the benchmark year. The wind and solar generation samples used to derive the corresponding electricity prices are based on the full temporal span of the dataset. The simulation is run in quarter-hourly resolution over a one-year horizon, using 100 samples presented in Section 4.4.1.

[39] The realized and forecasted generation data are post-grid stability measures, i.e., re-dispatch. As TSOs' actions influence both parameters, the bias is expected to be negligible.

The parameterization of the hybrid PV-BESS system is informed by existing literature and aligns with the German innovation tender regulation. The assumed parameters represent a typical battery; in practice, the technical and economic characteristics may be more complex and differ based on various factors, such as the cable lengths and the inverter type. The hybrid PV-BESS system is assumed to be AC-coupled and to have a PV-to-BESS ratio of 3:1, which is the standard configuration required under the EEG innovation tender scheme (Figgener et al., 2022). The PV system's generation profile perfectly correlates with the overall PV generation in the market. In other words, the model does not differentiate between the site-specific production and the overall production in Germany. Section 4.5 discusses the impact of this assumption. The storage duration of the BESS is two hours, which is the required and usual size for hybrid PV-BESS systems in the EEG innovation tender scheme and has been found to be the optimal system configuration (Figgener et al., 2022, Keles and Dehler-Holland, 2022). The round-trip efficiency is assumed to be 85%. Data on degradation for the parametrization of the cycle penalty term is sourced from Grimaldi et al. (2025). In the base case, the hybrid PV-BESS system neither faces grid connection constraints nor receives a market premium. This case serves as a benchmark for comparison with other configurations. Subsequently, the grid connection configurations are changed, and a market premium is introduced. The simulation includes various (partially) asymmetric grid connection capacities, all of which comply with the grid code requirements in Germany. Note that while the physical grid connection capacity might be symmetric, the commercial grid connection depends on the grid connection agreement with the network operator.[40] To compare the profitability of the different grid connection configurations, this paper considers grid connection charges. In Germany, these charges vary by region and voltage level. They are currently debated among regulators and the industry (see C.4 for an in-depth discussion of German connection charges). The analysis assumes a grid connection charge of 152 EUR/kW, corresponding to an annualized cost of 15 EUR/kW. This value reflects the average high-voltage connection charge applied by major German DSOs and aligns with recent proposals from the Federal Network Agency (Bundesnetzagentur, BNetzA). In Germany, connection charges apply only to grid withdrawal, and no cost figures are available for grid injection capacity (ACER, 2023). Therefore, investors have limited incentives to choose grid connection capacities below the installed nameplate capacity.[41] As an approximation, this analysis assumes the grid connection costs for injection capacity to be similar to connection charges for grid withdrawal, aligning with the principle of symmetric network tariff design

[40] The technical requirements for connecting batteries to the German power grid are outlined in standards such as VDE-AR-N 4110 and VDE-AR-N 4120. IRENA (2022) provides an overview of international grid codes.

[41] Note that some incentives may result from savings due to inverter capacity reduction. In Germany, utility-scale PV systems usually have a DC-to-AC ratio between 1.1 and 1.3, meaning the PV array's DC capacity is 10% to 30% higher than the inverter's AC capacity. However, these considerations are not in the scope of this paper, as they are highly project-specific (Cossu et al., 2021).

(Morell et al., 2021, Morell-Dameto et al., 2023). Table 4.1 presents all input parameters, along with the cost parameters used for calculating annuities.

Table 4.1.: Input parameters for the hybrid PV-BESS system (own assumptions based on Keles and Dehler-Holland (2022) and Fraunhofer ISE (2024)).

| Parameter | Unit | PV system | BESS |
|---|---|---|---|
| Capacity | [MW] | 3 | 1 |
| Storage duration | [h] | - | 2 |
| Storage round-trip efficiency | [%] | - | 85 |
| Cycle penalty | [EUR/cycle] | - | 19.5 |
| Economic lifetime | [a] | 30 | 15 |
| CAPEX | [EUR/kW] | 550 | 720 |
| Fixed OPEX | [EUR/kW/a] | 13 | 20 |
| Interest rate | [% p.a.] | 5.3 | 10 |
| Grid withdrawal capacity | [MW] | [0, 0.25, 0.5, 0.75, 1] | |
| Grid injection capacity | [MW] | [0.25, 0.5, 0.75, 1, 1.5, 2, 3] | |

## 4.4. Results

This section presents the results of the techno-economic dispatch model for the case study. The analysis isolates the impact of key features of hybrid PV-BESS systems, such as grid connection restrictions and market premium payments, by examining them separately. First, the section introduces the renewable generation samples and corresponding electricity prices. Then, it presents the base case results, assuming no grid restrictions (neither for withdrawal nor injection) and no market premium payments. This base case illustrates the distribution of contribution margins, their interdependencies, and the risk diversification potential of PV and BESS assets. Subsequently, the impact of grid withdrawal and injection limits on the techno-economic dispatch and associated margins is analyzed. Next, the effect of market premia is examined. Finally, sensitivity analyses and robustness tests are conducted, considering a co-location with wind and a different benchmark year (2019).

### 4.4.1. Electricity market price samples

Following the methodology outlined in Section 4.3.2, the analysis is based on 100 samples of quarter-hourly renewable generation profiles and corresponding day-ahead and intraday market prices spanning over one year. The model outcomes for the renewable electricity generation samples and the regression analysis of the parametric price models are provided in C.1 and C.2. This section focuses specifically on the simulated price samples. Table 4.2 presents descriptive statistics comparing 2024 prices with the simulated time series.

Table 4.2.: Price statistics of actual prices and samples in EUR/MWh.

| | Day-ahead Actual (2024) | Sample mean | Intraday Actual (2024) | Sample mean |
|---|---|---|---|---|
| Mean | 79 | 75 | 81 | 79 |
| Std. | 53 | 50 | 84 | 53 |
| Min. | -135 | -301 | -868 | -349 |
| 5% | 0 | -3 | -5 | -8 |
| 50% | 80 | 79 | 80 | 81 |
| 95% | 143 | 144 | 151 | 153 |
| Max. | 936 | 389 | 2902 | 435 |
| Spread | 111 | 93 | 228 | 130 |

It is worth noting that wind speeds and solar radiation levels in Germany in 2024 were close to their long-term average over the past decade (Bär and Kaspar, 2025). The sample space effectively replicates historical weather variability and produces realistic price patterns. The samples' mean price levels align well with observed market prices. While the model adequately replicates the volatility observed in the day-ahead market, it underestimates intraday market volatility, primarily due to limitations in capturing extreme price fluctuations in the distributional tails. Nonetheless, the generated samples provide a robust and meaningful range for the analysis.

Figure 4.2 displays the range of price duration curves and average hourly profiles of the day-ahead price samples, illustrating the weather-driven price dispersion. Price variability is most pronounced during periods of high and low residual load, resulting in greater dispersion at both ends of the price duration curve. Conversely, moderate residual load conditions yield smaller price differentials. The visualizations also confirm the negative correlation between renewable generation and electricity prices, underscoring the merit-order effect.

This effect becomes even more evident in the average daily price profile. Price dispersion peaks at noon, coinciding with the PV generation maximum. During these hours, uncertainty from both PV and wind generation compounds, whereas only wind generation contributes to price variability at night. Consequently, the relative price variance is highest during periods of PV production. This time-variable price variance influences the potential for arbitrage and associated risk mitigation.

### 4.4.2. Base case

In the base case, the hybrid PV-BESS system faces no grid connection restrictions and receives no market premium payments. This configuration serves as a benchmark for the comparison with other asset configurations and cases with market

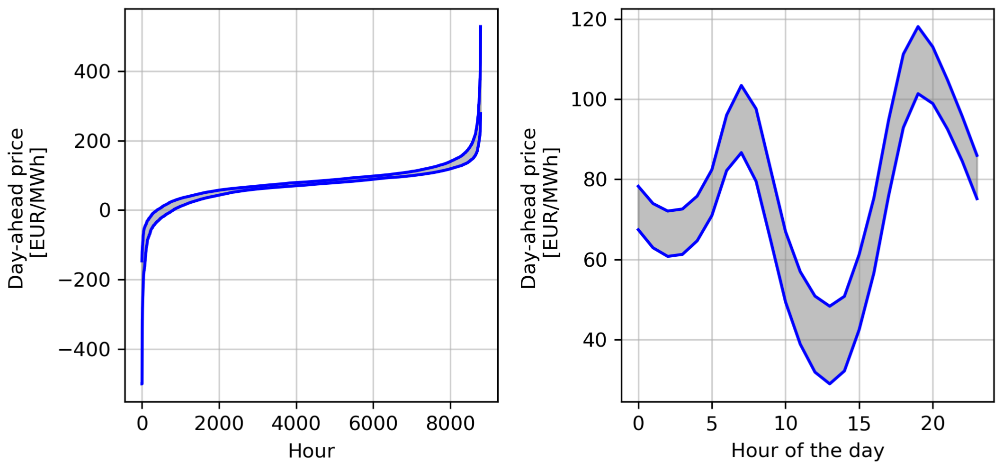



Figure 4.2.: Price duration curve (left) and average hourly profile (right) of day-ahead price samples. The upper and lower limits of the samples are shown.

premium payments. The primary evaluation metrics are the mean contribution margins and the corresponding CoV. To highlight the individual contributions of each asset to the overall margin of the hybrid system, the analysis separates the margins of the BESS and the PV asset, where applicable. All energy flows between the two assets are valued at the opportunity costs of selling the electricity to the grid.[42]

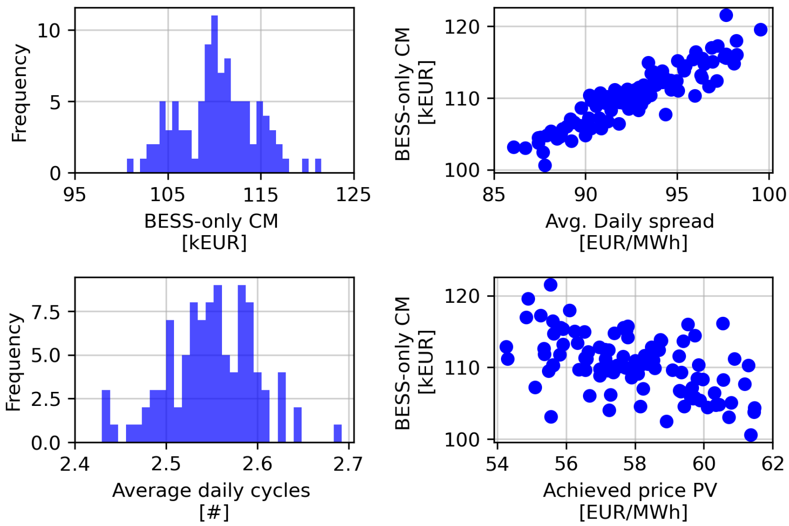



Figure 4.3.: Distribution of margins and cycles in the base case, and relevant correlations.

Figure 4.3 illustrates the distribution and correlations of BESS margins in the base case. The average BESS margin is 110 kEUR, with a standard deviation of

[42]In times of negative prices, it is assumed that the PV asset would otherwise be curtailed.

4 kEUR.[43] The daily cycles are distributed around 2.5 cycles per day. Typically, the BESS charges at night (when demand is low) and at noon (when solar production peaks), while it discharges during the morning and evening peaks (cf. Fig 4.2). The BESS margins correlate strongly with the average daily spread, defined as the difference between the highest and lowest prices within a day. Thus, the daily spread is a reliable proxy for BESS margins when no operational constraints exist. Furthermore, the BESS margins negatively correlate with the PV asset's achieved price. In other words, the BESS margins increase when PV margins decrease and vice versa. During periods of high PV production, electricity prices tend to drop, causing PV margins to fall if the price reduction outweighs the production increase. Simultaneously, the BESS can charge at lower prices, resulting in higher margins. This negative correlation creates a strong diversification effect for hybrid PV-BESS systems, significantly reducing their risk compared to the individual assets. Table 4.3 presents the respective contribution margins and their CoV. The contribution margin of the hybrid PV-BESS system has a CoV that is roughly 40 % lower than the average contribution margin variance of the individual assets.

Table 4.3.: Contribution margin statistics for the respective assets in the base case.

| | Unit | Hybrid PV-BESS | PV-only | BESS-only |
|---|---|---|---|---|
| Mean | [kEUR] | 225.84 | 115.47 | 110.37 |
| Std. | [kEUR] | 5.02 | 4.66 | 4.04 |
| Min. | [kEUR] | 211.55 | 102.29 | 100.61 |
| Max. | [kEUR] | 238.17 | 125.28 | 121.54 |
| CoV | [%] | 2.22 | 4.04 | 3.66 |

It is important to note that a physical co-location of the assets is not a prerequisite for risk diversification. However, co-location may still be advantageous due to project cost savings in planning and constructing hybrid systems. C.3 offers an excursion on how investors could consider the negative correlation of PV and BESS margins when choosing the optimal PV-to-BESS ratio based on Modern Portfolio Theory.

### 4.4.3. Impact of grid connection restrictions

This section presents the change in contribution margins and risks of hybrid PV-BESS systems under different grid connection configurations. For this assessment, the maximum grid injection and withdrawal capacities are varied in equations (4.11) and (4.12), respectively. The analysis considers 35 distinct grid connection configurations derived from the capacities listed in Table 4.1, while holding the nominal capacities of the PV (3 MW) and the BESS (1 MW / 2

[43] BESS margins are commonly stated in relative terms. Since the BESS capacity is set to 1 MW, 110 kEUR translates to 110 EUR/kW.

MWh) asset constant. Figure 4.4 illustrates the *grid restriction-induced contribution margin change* (upper panels) alongside changes in contribution margin variance (lower panels).

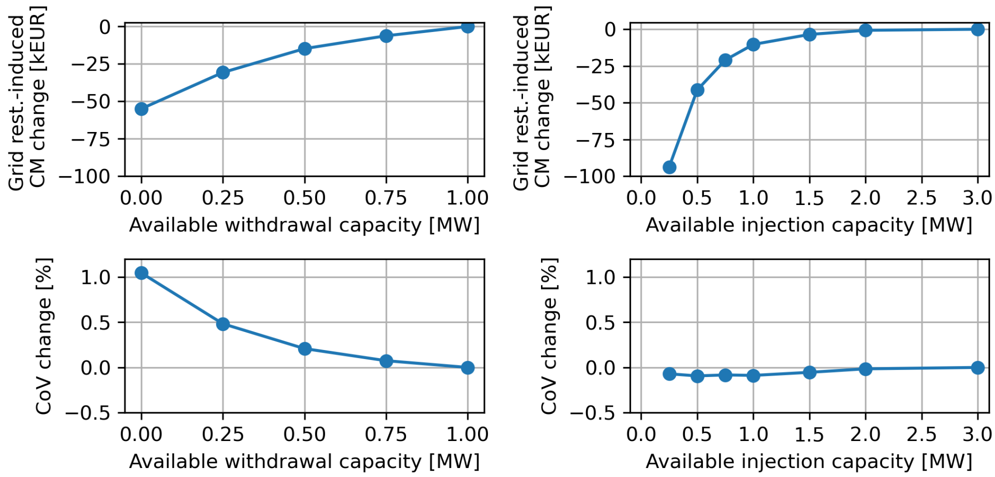



Figure 4.4.: Grid restriction-induced contribution margin change and related changes in contribution margin variance.

Restricting the BESS from charging from the grid significantly impacts its contribution margin. Figure 4.4 (upper left panel) demonstrates a substantial and non-linear reduction in the mean contribution margin of the hybrid system as withdrawal capacity decreases. A complete prohibition on grid charging (0 MW withdrawal capacity) reduces the system's average annual contribution margin by approximately 55 kEUR, representing a 25% decrease in the total hybrid system margin and a 50% reduction relative to the standalone BESS margin in the unconstrained base case. The primary economic driver for this loss is the inability to engage in price arbitrage between low-price periods (e.g., overnight) and high-price periods (e.g., the morning peak), significantly reducing the frequency and profitability of BESS cycling. Furthermore, withdrawal restrictions prevent the BESS from charging at negative prices. The effect of partial charging restrictions on revenue is non-linear, as they create an asymmetry in the storage duration. For example, with a grid withdrawal restriction of 50%, a two-hour BESS needs four hours to fully charge the storage while maintaining a two-hour duration for discharging. However, the marginal loss rises as the BESS requires longer charging periods (e.g., eight hours for a 25% grid withdrawal reduction), resulting in higher average charging prices. These findings align with Mercier et al. (2023), who report low marginal benefits from extending storage duration beyond four to six hours. Besides reducing absolute contribution margins, the charging restriction also exacerbates their variance (lower left panel of Figure 4.4). Reducing the grid withdrawal capacity increases the contribution margin's CoV, which rises by nearly one percentage point under a full charging restriction. This heightened risk exposure stems from the diminished operational flexibility of the BESS, which weakens the negative correlation between PV generation revenue and BESS arbitrage margins. Two main factors explain this effect. First, unrestricted hybrid PV-BESS systems can exploit negative prices by curtailing PV output and charging the BESS from the grid, effectively getting paid to store electricity. Under withdrawal restrictions, the BESS must absorb otherwise curtailed PV production, losing the chance to benefit from negative prices. Second, limited grid charging reduces the BESS's ability to monetize low PV capture prices. Without grid access, the BESS can only charge from concurrent PV production, while grid-connected systems can charge at full capacity whenever it is most profitable. Consequently, charging restrictions reduce total contribution margins and increase their risk.

In contrast to grid withdrawal constraints, limiting the grid injection capacity has a markedly smaller effect on the hybrid system's economics, especially for capacities above the BESS's nameplate capacity. Figure 4.4 (upper right panel) reveals that the asset's mean contribution margin remains largely unaffected even with significant reductions in the grid injection capacity. For instance, restricting the injection capacity to 1 MW – one-fourth of the system's combined nameplate capacity – results in a contribution margin loss of only about five percent compared to the unconstrained case. The underlying economic reason is that curtailment of electricity feed-in predominantly occurs during periods of peak PV generation, which frequently coincides with low, or even negative, wholesale electricity prices due to the merit-order effect. Consequently, the opportunity cost of curtailed energy is low. The CoV of contribution margins is virtually unaffected by injection capacity restrictions (Figure 4.4, lower right panel). In the unconstrained case, the BESS typically charges during these high-PV, low-price periods anyway, meaning moderate curtailment does not substantially alter the system's overall dispatch pattern or risk structure.

Determining the optimal grid connection requires investors to balance the absolute contribution margin (net of grid connection costs) and the associated risks.[44] Figure 4.5 illustrates the mean-variance relationship of the *grid cost-adjusted contribution margins* across all investigated grid connection configurations. These margins represent the respective contribution margins net of grid connection costs, calculated using the annuitized grid connection charges (cf. Section 4.3.3). Figure 4.5 highlights the dominant configurations, i.e., the set of configurations that offer the highest expected grid cost-adjusted contribution margin for a given level of risk (standard deviation).

For most grid injection capacities, the highest margins are achieved when the grid withdrawal capacity equals the BESS capacity, effectively eliminating charging restrictions. This is indicated by the diamond markers representing the highest values per color on the y-axis. Reducing the grid withdrawal capacity significantly lowers the contribution margin and increases the risk (shifting points down and to the right), rendering such configurations sub-optimal from a

[44] Due to the microeconomic nature of this analysis, "optimality" is assessed from the investor's perspective. Potential implications for system-level efficiency and optimality are addressed in Section 4.5.

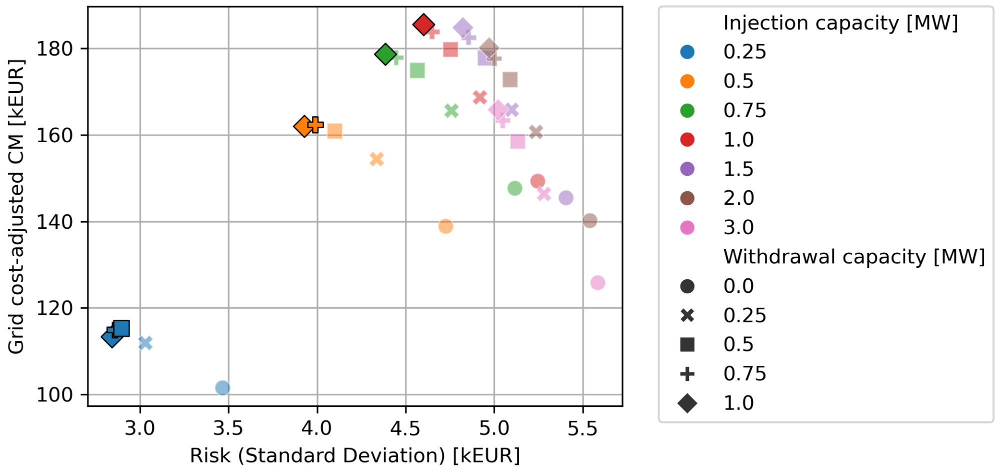



Figure 4.5.: Mean-Variance relation of grid cost-adjusted contribution margins for the different asset configurations. Colors: Various injection capacities; Shapes: Various withdrawal capacities.

risk-adjusted perspective. Conversely, limiting injection becomes attractive once investors consider connection costs. Increasing injection capacity up to the BESS capacity (1 MW) raises grid cost-adjusted contribution margins, as the marginal benefit of avoiding lost revenue outweighs the marginal cost of providing that capacity. Specifically, an injection capacity of 1 MW – one-fourth of the hybrid system's total nominal capacity – yields the highest grid cost-adjusted contribution margin across all asset configurations. Investors would select the optimal grid connection capacities from the set of dominant configurations based on their individual risk preferences. Following the approach of Sinsel et al. (2019), this paper assumes that investors choose the configuration based on the highest Conditional Value at Risk (CVaR) at the 10% quantile.[45] Under the assumed cost structure, combining unrestricted withdrawal (1 MW) with restricted injection (1 MW) yields the highest CVaR, confirming its optimality for risk-averse investors.

Notably, the sensitivity analysis in C.5 demonstrates that while the precise optimal grid connection capacities depend on the level of the grid connection charges, unrestricted or minimally restricted withdrawal capacity remains the most profitable option across a plausible range of costs. In contrast, substantial injection capacity reductions are consistently favored. The results robustly indicate an asymmetry: Restricting grid injection is more cost-effective and carries lower risk implications than restricting grid withdrawal for hybrid PV-BESS systems.

[45] The findings would not differ when using either the CVaR of the worst 5% quantile or the maximum ratio between the average CM and its standard deviation as a selection criterion for the optimal configuration.

### 4.4.4. Impact of market premia

Feed-in tariffs, such as a market premium, are a widely implemented policy instrument to support renewable electricity generation. The German EEG innovation tender scheme applies a market premium payment to hybrid PV-BESS systems. This section examines the impact of market premia on contribution margins and financial risks of hybrid PV-BESS systems and assesses their effect on optimal grid connection sizing. As outlined in Section 4.3, the market premium is determined according to the EEG innovation tender regulation. The subsidy represents a yearly fixed feed-in tariff calculated as the difference between a predefined strike price and the market value of the system-wide PV generation in Germany. This study assumes a strike price of 85 EUR/MWh, consistent with recent EEG innovation tender results. For reference, the average market value of PV generation in Germany in 2024 was 46 EUR/MWh.[46] The market value for solar PV generation is derived from the respective renewable generation and price samples. Furthermore, following current German regulations, market premium payments for hybrid PV-BESS systems are only granted when day-ahead market prices are non-negative. Notably, this exception does not apply to the majority of PV assets operating in Germany.

Table 4.4 (second column) presents the contribution margin statistics of hybrid PV-BESS systems with market premium payments but without grid connection constraints. The market premium increases the total contribution margin of the hybrid PV-BESS system, as the strike price exceeds the average market value of PV generation. This increase primarily results from the higher effective price (market price + market premium) for PV production. The average market premium in the sample space is 44 EUR/MWh, around 75% of the asset-specific market value of PV production (58 EUR/MWh).[47] The contribution margin of the BESS also rises, albeit to a small extent. The BESS benefits from market premium payments on electricity generation that would otherwise be curtailed.

Market premia aim to mitigate the risk of renewable assets' contribution margins by reducing market value exposure. When market values decline, the market premium compensates with higher payments, and vice versa, thereby stabilizing revenue streams. As shown in Table 4.4, introducing a market premium reduces the variance of PV contribution margins by one percentage point relative to the base case. However, the overall contribution margin variance of the hybrid PV-BESS system increases. The reasons for this effect are twofold: First, the market premium increases the contribution margin variance of the BESS, as it can discharge some energy (the energy that was previously charged from the PV asset) at a higher price. Therefore, the BESS benefits twice from low market values, as

[46] Data on average market values can be found in German TSOs (2025). Previous auction results of the EEG innovation tender are listed in BNetzA (2025a).

[47] Note that the market value of the asset under investigation includes curtailment at negative prices, as incentivized by the EEG innovation tender regulation. In contrast, the majority of Germany's system-wide PV production has limited incentives to curtail during periods of negative prices, leading to a lower system-wide market value.

Table 4.4.: Contribution margins for hybrid battery systems under different scenarios.

| | | Base case | Market premium | Wind co-location | Base Case (2019) | Market premium (2019) |
|---|---|---|---|---|---|---|
| Hybrid | Mean [kEUR] | 225.84 | 316.70 | 446.43 | 113.47 | 245.46 |
| | Std [kEUR] | 5.02 | 10.14 | 13.24 | 2.58 | 8.14 |
| | CoV [%] | 2.22 | 3.20 | 2.96 | 2.27 | 3.32 |
| RES-only | Mean [kEUR] | 115.47 | 202.71 | 336.13 | 89.60 | 220.44 |
| | Std | 4.66 | 6.14 | 12.76 | 2.08 | 6.83 |
| | CoV [%] | 4.04 | 3.03 | 3.80 | 2.32 | 3.10 |
| BESS-only | Mean [kEUR] | 110.37 | 113.99 | 110.30 | 23.87 | 25.03 |
| | Std [kEUR] | 4.04 | 4.82 | 4.04 | 1.62 | 1.88 |
| | CoV [%] | 3.66 | 4.22 | 3.66 | 6.81 | 7.52 |

it can charge at lower prices and discharge at higher prices, leading to a greater variance. Second, market premia weaken the diversification effect between PV and BESS margins in the hybrid system. Since the market premia already hedge the PV asset's market value exposure, the correlation between PV and BESS margins declines. A key factor contributing to this outcome is the structure of the German EEG regulation, which bases the market premium on the system-wide market value of PV generation rather than the asset-specific market value. This misalignment weakens the risk-mitigating function of the market premium, as subsidy payments diverge from the actual dispatch of assets. As a result, instead of lowering the financial risk as intended, the market premium amplifies the contribution margin exposure for hybrid systems. This effect contrasts with the stabilizing influence of market premia on margins for standalone renewable generation assets.

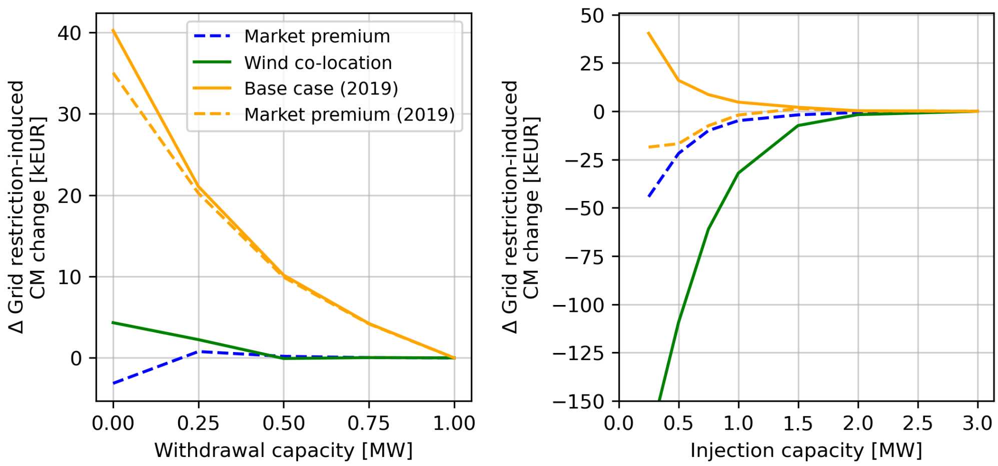



Figure 4.6.: Difference in the grid restriction-induced contribution margin change relative to the base case for different scenarios (represented by the different lines).

Besides their impact on risk and absolute contribution margins, market premia interact with grid connection constraints. Figure 4.6 illustrates how different scenarios, including the case with market premium payments, influence the grid restriction-induced contribution margin change, relative to the base case shown in Figure 4.4. A positive difference ($\Delta > 0$) indicates a lower grid restriction-induced contribution margin change than in the base case, i.e., losses from grid restrictions are less severe, and vice versa. The left panel of Figure 4.6 reveals that receiving a market premium has little effect on the grid restriction-induced contribution margin change. The small difference suggests that grid withdrawal constraints reduce contribution margins similarly, regardless of whether market premium payments are received. The BESS operates comparably in both cases, as its behavior remains unaffected by the subsidy payment. By contrast, grid injection capacity constraints respond differently. Market premia increase the grid restriction-induced contribution margin loss (right panel). Ceteris paribus, investors are likely to opt for larger grid connection capacities when market premia are available. Based on the CVaR, investors would favor a system design with the same withdrawal capacity as in the base case (1 MW) but a higher injection capacity of 1.5 MW. The extent of this effect depends on the available grid injection capacity – the difference in contribution margin change increases with lower grid connection capacities. When grid connection capacity is scarce and associated costs are high, market premia may incentivize greater grid connection capacities than in cases with lower connection costs. This effect is even more pronounced for standalone renewable assets. C.6 presents the grid restriction-induced contribution margin change of standalone PV and wind assets for cases with and without market premium payments. The analysis shows that wind assets face higher contribution margin changes than PV assets. Furthermore, PV is more sensitive to market premium payments than wind.

### 4.4.5. Impact of different asset configurations and robustness tests

The contribution margins of hybrid PV-BESS systems are sensitive to the asset configuration and electricity price dynamics, particularly under grid connection constraints. To illustrate these dependencies, this section extends the analysis to hybrid Wind-BESS systems, offering a comparative perspective relative to PV co-located systems. Furthermore, C.7 explores how varying PV-to-BESS capacity ratios and extended storage durations change the impact of charging restrictions. Finally, this section concludes with a robustness test using an alternative benchmark year to support the paper's main findings.

#### 4.4.5.1. Wind co-location

While BESS assets are most commonly co-located with PV assets, integration with wind generation is also feasible. This section examines the implications of substituting PV with wind in hybrid configurations and evaluates the impact on contribution margins. Table 4.4 (central column) presents the contribution margin statistics of a hybrid Wind-BESS system without grid connection constraints or market premium payments. In this configuration, BESS profitability remains invariant to the co-located renewable source, as the optimal storage dispatch is (almost) independent of the generation profile. However, wind assets achieve substantially higher contribution margins than PV, driven by their superior capacity and value factors.[48] The contribution margin's CoV is greater for hybrid Wind-BESS systems due to a weaker correlation between the respective technologies, implying that PV-BESS configurations offer stronger diversification benefits.

The nature of the co-located renewable asset also influences the grid restriction-induced contribution margin change, thereby altering the optimal grid configuration for investors (see Figure 4.6). The contribution margin loss induced by grid injection restrictions is significantly higher for hybrid Wind-BESS systems (indicated by the negative values in the right panel), reflecting the higher value factor and reduced price cannibalization associated with wind generation. Wind's higher and more consistent capacity factors (cf. Table C.1 and C.2) exacerbate losses under limited grid injection capacity. Conversely, the contribution margin change induced by grid withdrawal constraints is slightly lower than in hybrid PV-BESS systems. The wind asset's steadier generation profile enables a higher utilization rate of the BESS, leading to higher revenues, particularly in cases where complete charging restrictions are in place. These asymmetries imply that investors would choose a different grid connection configuration when co-locating a battery with wind instead of PV. Under current German grid connection charges, a hybrid Wind-BESS configuration with a 1.5 MW injection and a 1 MW withdrawal capacity yields the highest CVaR. Compared to PV co-located systems, Wind-BESS configurations require greater injection capacity. The core result remains robust despite the distinct grid configuration under wind co-location: Investors would favor restricting grid injection capacity over limiting withdrawal.

#### 4.4.5.2. A different underlying benchmark year for price patterns

The contribution margins of hybrid PV-BESS systems are sensitive to the underlying electricity price pattern. Consequently, the grid restriction-induced contribution margin changes vary with the price levels and the price volatility. This section conducts a sensitivity analysis using an alternative benchmark year for the sample generation process to assess the robustness of this paper's main findings. Specifically, the parametric models (4.21) and (4.22) are recalibrated using data from 2019 instead of 2024. Table 4.5 compares the key characteristics of the resulting price samples. In 2019, fuel prices and installed solar capacity were lower than in 2024, resulting in a price structure characterized by a lower average level and reduced volatility, which is reflected in substantially lower day-ahead price spreads. Despite these changes, the average achieved price for solar gener-

[48]Note that wind assets also have significantly higher CAPEX than PV assets.

ation in 2019 was only 20% lower than in 2024 due to a higher solar value factor driven by lower PV penetration. It is important to note that the average grid connection charge in 2019 was also around 40% lower. Previous studies have shown that distributed generation from renewable energy sources is a significant cost driver for network operators (Just and Wetzel, 2020). These dynamics underscore the dual role of renewable electricity generation in shaping both market outcomes and grid economics. On the one hand, increased renewable penetration raises price volatility and, in turn, enhances storage arbitrage potential. On the other hand, higher shares of distributed generation impose additional costs on the grid, raising connection charges and network tariffs.

Table 4.5.: Metrics for the average price samples for the benchmark years 2024 and 2019.

| | Unit | 2024 | 2019 |
|---|---|---|---|
| Day-ahead price | EUR/MWh | 74.83 | 38.02 |
| Day-ahead spread | EUR/MWh | 92.70 | 24.50 |
| Intraday spread | EUR/MWh | 129.28 | 39.46 |
| (System-wide) Achieved price PV | EUR/MWh | 40.97 | 32.90 |
| (System-wide) Value factor PV | % | 55 | 87 |
| (Annualized) Grid connection charge | EUR/kW | 15 | 9 |

The hybrid PV-BESS system's contribution margin in Table 4.4 reflects the differences in PV market value and the less favorable conditions for arbitrage in 2019, leading to a substantial decline in absolute contribution margins. These findings are consistent with earlier results by Keles and Dehler-Holland (2022), who report a lack of profitability for hybrid PV-BESS systems under 2019 market conditions.[49] Given the variation in absolute contribution margins, the grid restriction-induced contribution margin change differs between the benchmark years (see Figure 4.6). Lower price levels and a reduced number of negative prices in 2019 diminish the losses from charging restrictions (left panel), making withdrawal constraints potentially more favorable. The contribution margin loss induced by grid injection restrictions is also sensitive to the underlying benchmark year but diverges notably only at smaller injection capacities. This resemblance indicates that substantial reductions in grid injection capacity remain feasible even under different price environments. Including a market premium payment alters this finding. Given that the market premium was higher under the lower price conditions in 2019, the effective price is similar for the two benchmark years. Therefore, the grid restriction-induced contribution margin change shifts to a similar level as for the case with market premium payments in 2024. The results suggest that the effect of market premia on grid connection configurations becomes more pronounced in low-price environments with reduced market values for renewable generation. In such cases, investors are increasingly incentivized to opt for greater grid connections than in cases without market premium

[49] In fact, the contribution margins reported by Keles and Dehler-Holland (2022) closely align with the 2019 base case in this study.

payments. Based on these results and the grid connection charges of 2019, investors would opt for a grid connection configuration with a withdrawal capacity of 0.75 MW and an injection capacity of 1 MW in the absence of a market premium. With a market premium, they would increase the injection capacity to 1.5 MW, while maintaining the same withdrawal capacity. This suggests that, irrespective of the benchmark year, investors tend to limit grid injection more than grid withdrawal. Therefore, regardless of the benchmark year, investors would restrict grid injection to a greater extent than grid withdrawal.

## 4.5. Discussion

This study presents an economic framework for determining how grid connection restrictions impact contribution margins of hybrid PV-BESS projects in the presence of risk from variable renewable generation. The analysis provides practical insights into balancing infrastructure costs and risk exposure by quantifying grid cost-adjusted contribution margins and assessing the role of market premia. The results show that the grid injection capacity can be substantially reduced without impacting contribution margins or risk exposure. Conversely, restricting grid withdrawal capacity inflicts significant losses and worsens the risk profile. This asymmetry arises because peak grid injections typically coincide with periods of low prices, while grid withdrawal enables storage to capitalize on price spreads during off-peak hours. The analysis reveals that market premia, such as those in Germany's EEG innovation tender scheme, change the incentives for investors: By increasing the value of generation during low-price periods, the market premium raises the losses from grid injection restrictions, making greater grid injection capacities more profitable. Moreover, the market premium design reduces the diversification benefit of combining PV and BESS, as it mutes the negative correlation between PV revenues and BESS arbitrage that typically stabilizes hybrid asset returns. This effect undermines one of the central advantages of hybrid BESS systems – risk mitigation.

### 4.5.1. Implications for the EEG innovation tender scheme

This paper presents a detailed quantitative analysis of two central features of the German EEG innovation tender scheme: the mandatory grid withdrawal constraints (i.e., BESS can only charge from the co-located RES) and the payment of a market premium. The findings suggest that the restriction of grid charging imposes a significant economic penalty on hybrid PV-BESS projects; in 2024 market conditions, this is estimated to be around 50% of the potential standalone BESS contribution margin. Consequently, without these charging restrictions, projects could achieve their target profitability with substantially lower subsidy payments. Extrapolating this indicative saving to the targeted 8 GW of hybrid capacity under the scheme (assuming a similar PV-to-BESS ratio and market conditions) could translate to potential national savings of around 108 mEUR per year. As subsidies are granted for 20 years, the total savings could be up to 2.2 billion EUR (around 61 % of the total subsidies given under this scheme).[50] It is crucial to acknowledge that these figures are illustrative and sensitive to the specific benchmark year and market dynamics; for instance, the 2019 sensitivity showed smaller, though still significant, impacts. Nevertheless, with the continued expansion of RES and a corresponding increase in the frequency and depth of negative prices, the economic burden of such charging restrictions is more likely to escalate than to diminish in the near term. Furthermore, the combination of charging restrictions and the specific design of the market premium not only affects the profitability of hybrid PV-BESS systems but also exacerbates their weather-induced revenue risk. This amplified risk profile could inadvertently increase project financing costs, thereby paradoxically increasing the perceived need for subsidies. While market premia aim to de-risk investments, their effectiveness is diminished when they simultaneously increase exposure to other risk factors or counteract natural hedging mechanisms inherent in hybrid systems. It should be noted that the market premium also mitigates other risks, such as those from a lower absolute price level or regulatory interventions. Should long-term assessments confirm a persistent financing gap necessitating public support, alternative support mechanisms — perhaps decoupled from the per-MWh production, such as availability payments or targeted CAPEX subsidies — might offer more cost-effective means for promoting investment than the current market premium structures. Examples of such policy instruments are the PERTE scheme in Spain and the Cap-and-Floor scheme in the UK (Paolacci et al., 2024). Therefore, German policymakers are encouraged to reconsider the current design of the EEG innovation tender scheme, particularly the efficacy and economic impact of mandatory charging restrictions and the structure of the market premium.

### 4.5.2. Potential system implications

Beyond the specific context of the German EEG innovation tender, the microeconomic insights derived from this study offer broader implications for system-level planning and regulatory design. The results of the microeconomic optimization should align with the system-optimal outcome if price signals (from the market and the grid) are efficient and the price-taker assumption holds (i.e., the dispatch of individual hybrid PV-BESS assets does not significantly alter market prices or grid costs). In particular, the selection of grid connection capacity reflects a trade-off between the grid access costs and the temporal market value of storage and renewable generation.

[50] While the absolute subsidy savings mainly depend on the impact of charging restrictions, their relative share of the total subsidy payments is highly reliant on the market value of PV.

Regulatory charging restrictions for hybrid PV-BESS systems are likely welfare-detrimental, as they diverge from the microeconomic optimal grid connection configuration. These restrictions prevent storage from fully utilizing its temporal system value to the electricity market, which increases with the level of RES penetration, as it mitigates the merit-order and cannibalization effects (López Prol and Schill, 2021). This role as an economic buffer will become critical as negative prices become more frequent and structural in systems with high shares of wind and solar. However, where peak-related grid costs exceed the market value of generation, enforcing or incentivizing grid injection limitations may enhance welfare. In fact, this paper's findings show that for a wide range of grid connection costs, the optimal grid connection capacity (in both directions) is largely determined by the size of the battery. Implementing efficient grid connection charges for grid injection and withdrawal capacity will be critical for aligning private investment decisions with system-level welfare. These charges should reflect the marginal costs of providing a grid connection to new projects. Alternatively, efficiently designed grid access rationing may achieve similar allocative outcomes (Newbery and Biggar, 2024). Recent policy proposals in Germany, such as regional grid connection charges and capacity-based injection restrictions, are consistent with the findings of this paper. Nevertheless, there remains a need to assess whether a unified policy instrument for all market participants, relying solely on price signals or capacity restrictions, can more effectively coordinate decentralized investment decisions.

Previous system-level analyses have shown that the co-location of storage with PV generation can offer spatial flexibility to the power system (Czock et al., 2023, Manocha et al., 2025). In addition to mitigating local and transmission-level congestion, storage investments reduce price risk and offer a diversification value to risk-averse system planners (Diaz et al., 2019, Möbius et al., 2023). These findings imply a strategic co-location value of storage systems for system planners. This paper confirms that hybrid PV-BESS systems can significantly reduce injection capacity with minimal private economic losses, implying a potential for cost-effective grid relief. Moreover, hybrid PV-BESS systems demonstrate greater risk diversification and more favorable cost profiles for curtailing grid injection than Wind-BESS configurations. These features suggest that co-location incentives — particularly those favoring PV — could enhance system efficiency by reducing congestion management costs and the overall system risk. A policy that explicitly links battery deployment to solar generation sites may thus deliver system-wide benefits. Such approaches would align with the suggestions of Czock et al. (2023).

Given the current scale of BESS deployment in Germany, the price-taker assumption for hybrid PV-BESS systems remains valid. However, as BESS deployment scales, system-level interactions will become increasingly relevant. Additionally, a rigorous application of grid connection pricing for injection and withdrawal capacities across all market participants and asset types would alter price signals and likely reduce negative prices driven by excess generation from

RES. In such cases, grid connection restrictions would also influence grid congestion and overall system dynamics. Future research should employ system-wide equilibrium models to capture these feedback loops and grid impacts.

### 4.5.3. Assessment of model assumptions

Several model assumptions merit further reflection. Recent changes in the European electricity market design, particularly the anticipated shift to 15-minute resolution in the day-ahead market coupling, further amplify the need for flexibility and responsiveness in asset dispatch. Finer market granularity enhances the ability of storage assets to capture short-term price fluctuations. However, interactions with intraday markets are likely, and current price patterns resulting from restricted market participation are expected to change (Knaut and Paschmann, 2019). Future modeling should explicitly incorporate 15-minute day-ahead market granularity to refine the revenue impact. Moreover, the modeling framework assumes that the hybrid PV-BESS system's generation profile aligns perfectly with the system-level PV output. However, fleet-wide capacity factors tend to be more stable than capacity factors of individual assets. This difference arises from geographic diversification and smoothing effects from aggregation. Consequently, project-specific exposure to curtailment risks, negative prices, and forecast errors may be subject to bias. Therefore, fleet-level analysis may understate the impact of grid connection restrictions on renewable assets' contribution margins. However, as BESS can mitigate localized peaks more effectively than system-wide averages suggest, the effect on hybrid PV-BESS systems remains unclear. Future work should differentiate between fleet-level and project-specific generation profiles. The assumption of perfect foresight in the dispatch model likely overestimates the revenue potential of BESS, particularly in intraday markets, which are subject to greater uncertainty than day-ahead markets. According to the paper by Keles and Dehler-Holland (2022), imperfect foresight reduces monthly returns by approximately 20%. Although this assumption applies to all analyzed cases, it may benefit those cases without grid connection restrictions more, given the higher degrees of freedom in trading. On the other hand, excluding ancillary service markets, such as aFRR and mFRR, from the modeling framework might underestimate potential value streams that are more accessible with unrestricted grid connections. Therefore, grid connection constraints below BESSs' nameplate capacity may limit the participation of hybrid PV-BESS systems in these markets.

## 4.6. Conclusion

Integrating large shares of renewable electricity generation, like wind and solar, requires energy storage to manage intermittency and ensure system stability efficiently. Hybrid battery projects, which are co-located with renewable generation, offer a promising option to reduce grid congestion by optimizing grid usage. However, investment decisions in storage are sensitive to revenue risks, especially in volatile power markets.

This paper evaluates the contribution margins of hybrid PV-BESS systems under different grid connection configurations and support schemes. The analysis reveals that hybrid PV-BESS configurations yield significant diversification effects, thereby reducing contribution margin variance compared to standalone assets. Hybrid systems hedge against weather-induced price volatility and fluctuating renewable generation. The results demonstrate that restricting grid withdrawal capacity (charging from the grid) significantly reduces contribution margins and increases risk exposure. In contrast, grid injection capacity can be substantially limited, resulting in only minor losses. This asymmetry arises because peak grid injection often coincides with periods of low prices, while withdrawal restrictions eliminate valuable arbitrage opportunities during off-peak hours. Moreover, the analysis reveals that market premia incentivize larger grid connections by increasing the value of generation during low-price periods. In contrast to the subsidy's intention, a market premium increases the contribution margin variance of hybrid PV-BESS systems by weakening the diversification and the correlation of PV and BESS margins.

The study finds that the grid connection design for hybrid PV-BESS systems depends strongly on grid connection costs and policy design. Current charging restrictions and market premium structures in the German EEG innovation tender scheme could misalign private incentives with system efficiency. Policymakers and regulators should reconsider the structure of hybrid PV-BESS support schemes. Efficient grid connection charges, which account for both injection and withdrawal, combined with production-independent subsidies, could better align investor behavior with system-level efficiency.

# 5. Complementing carbon prices with Carbon Contracts for Difference in the presence of risk

## 5.1. Introduction

The decarbonization of the industrial sector requires substantial investments throughout the next decade (IEA, 2021). These investments are typically irreversible decisions that firms have to take in the presence of risk. The risk of an investment's profitability in a decarbonizing world mainly stems from two sources:

First, the profitability of investments in low-carbon or emission-free technologies depends on carbon prices. These technologies are only competitive with conventional technologies if the carbon price throughout the asset's economic life reaches a certain level. However, carbon prices may feature risk. One reason is that the expected carbon damage may change as new scientific evidence on climate change emerges.[51] Another reason is the potentially changing public valuation of carbon damage, shown by court rulings on climate policy in 2021 in Germany (Bundesverfassungsgericht, 2021, Economist, 2021). Both circumstances create a *damage risk*. Firms facing irreversible investments are exposed to such a damage risk as the regulator may adjust the carbon price according to these changes. In fact, Chiappinelli et al. (2021) report that four out of five firms state that the lack of effective and predictable carbon pricing mechanisms is a major barrier to low-carbon investments. López Rodríguez et al. (2017) or Dorsey (2019) provide further empirical analysis that firms reduce their investments due to environmental regulation-related risks.

Second, there is a *variable cost risk*. Variable costs of low-carbon technologies are not fully known, as adopting innovative production processes may involve novel input factors. The markets for some of these input factors are highly immature, the most prominent example being green hydrogen. The production costs of hydrogen might vary depending, e.g., on the costs of electricity or transport (Brändle et al., 2021). Additionally, there is an active and ongoing market ramp-up involving multiple stakeholders to facilitate technological learning

[51] For instance, the Sixth Assessment Report of the Intergovernmental Panel on Climate Change concludes that the climate system is warming faster than previously estimated (IPCC, 2021). Furthermore, OECD (2021) highlight the risks to predict the environmental damage due to the complex climate dynamics.

(Schlund et al., 2021). Hence, the market for hydrogen is still at the beginning of organising itself (IEA, 2019).

Firms' possibilities to hedge against these risks are limited or prohibitively costly.[52] For instance, in the European Emission Trading System (EU ETS), the availability of futures contracts with a maturity longer than three years is low (Newbery et al., 2019).[53] Similarly, there are limited hedging possibilities against variable cost risk from novel input factors traded on immature markets (OEIS, 2021). The described risks and the missing hedging possibilities deter firms from investing, which, in turn, poses a challenge to decarbonization.

To nevertheless facilitate and incentivize large-scale investments in the presence of such risks, the European Commission's Hydrogen Strategy and the reform proposal for a *Fit for 55* package, suggest Carbon Contracts for Differences (CCfDs) as a support scheme for firms in the industry sector (European Commission, 2021a). CCfDs are contracts between the government and a firm that pay out the difference between a guaranteed price, the so-called *strike price*, and the actual carbon price, per tonne of emission reduction delivered by the firm through a low-carbon project. The contracts can be interpreted as a short position in a forward on emission permits. Therefore, CCfDs are effectively a hedging instrument to reduce the firms' risk when making investment decisions. Besides their hedging properties, CCfDs may contain a subsidy for decarbonization investments.[54] Such subsidies may be justified by, e.g., positive externalities. In this paper, we do not consider such externalities, and, hence, CCfDs mainly serve as hedging instrument in our setup. So far, there is only a limited understanding of how regulators should design such instruments and under which circumstances the introduction of CCfDs is welfare-enhancing.

In this paper, we analyze how different sources of risk affect the efficiency of CCfDs and when these contracts are preferable to other policies, like committing to a carbon price early on or a flexible carbon pricing regime. We develop an analytical model in which a regulator sequentially interacts with a continuum of risk-averse firms. These firms can either supply the market with a conventional technology, which causes carbon emissions subject to carbon pricing, or invest in an emission-free technology. The valuation of environmental damage from carbon emissions and the variable costs of the emission-free technology may be subject to risk. The firms are heterogeneous regarding their investment costs when adopting the emission-free technology. Firms invest if they increase their expected utility by adopting the emission-free technology. The regulator maximises social welfare by choosing one out of three carbon pricing regimes: 1) setting a carbon price

[52] If markets were complete, a perfect hedge of all relevant factors determining an investment's profitability would always be possible (Arrow and Debreu, 1954). Thereby, the profitability of abatement investments would not be volatile, and investments would be made as long as they are profitable in expectation without the impact of risk.

[53] There are several reasons why forward markets for emission allowances are incomplete (e.g. Tietjen et al., 2020, for a survey).

[54] This is the case for the German and EU Hydrogen Strategy, as well as 'Fit for 55' package.

flexibly after the actual damage or costs are revealed (*Regulatory Flexibility*), 2) committing to a carbon price early (*Commitment*)[55], and 3) a hybrid policy regime containing a CCfD and flexible carbon pricing (*CCfD*). We compare these three carbon pricing regimes against the social optimum.

We find that under perfect foresight, i.e. in the absence of risk, all carbon pricing regimes result in the social optimum. In all regimes, the carbon price equals the marginal environmental damage of production. The marginal firm investing in the emission-free technology balances the marginal costs and the marginal benefit of abatement. This finding arises from two effects: First, because the regulator has perfect foresight, she can set the optimal carbon price level at any time. Second, firms do not face a risk in profits. Any risk would hamper firms' willingness to invest if they are risk averse.

We then assess the effect of risk and risk aversion on the performance of the three carbon pricing regimes. In a first setup, we assume that production of the emission-free technology is always socially optimal given the actual damage and variable costs. In these cases, offering a CCfD results in the social optimum irrespective of the source of risk. The regulator can incentivize socially optimal investments via the CCfD and adjust the carbon price according to the actual damage valuation. In contrast, both *Regulatory Flexibility* and *Commitment* fall short of reaching the social optimum. Which of the two regimes is welfare-superior depends on the source of risk. In case of damage risk, the welfare ranking is ambiguous and depends on the level of the firms' risk aversion (with high risk aversion favouring *Commitment*) and the elasticity of demand (with high elasticity favouring *Regulatory Flexibility*). In contrast, committing to a carbon price is welfare-superior to *Regulatory Flexibility* in settings with variable cost risk, as the regulator can incentivize additional investments under *Commitment*.

Lastly, we assess the effects of emission-free production that is potentially welfare reducing given the actual damage and variable costs. In this case, we find that offering a CCfD does not reach the social optimum. If the regulator offers a CCfD, the firms' production decision does not depend on the actual carbon price. Thereby, the regulator safeguards emission-free production even if it is socially not optimal ex-post. The same holds for *Commitment*. In contrast, under *Regulatory Flexibility*, the firm faces a carbon price equal to the social costs of carbon, such that it does not distort the production decision. Depending on the level of risk aversion and the probability of ex-post socially not optimal production, either *Regulatory Flexibility* or offering a CCfD is welfare superior.

Our paper contributes to two broad streams of literature in the context of irreversible investments in low-carbon technologies in the presence of risk.

The first literature stream focuses on policy options when firms face irreversible decisions. Baldursson and Von der Fehr (2004) analyze policy outcomes

[55] Literature suggests that regulators may have an incentive to deviate from announced carbon prices ex-post, implying regulators may not be able to credibly commit (e.g. Helm et al., 2003).

in a model in which firms choose between an irreversible long-term investment in abatement under risk and a short-term abatement option after the risk resolves. In the presence of risk aversion, the authors show that committing to a carbon tax ex-ante outperforms flexible carbon prices stemming from tradable permits because the latter increase the firms' risk exposure. Jakob and Brunner (2014) show that regulators can combine the advantages of flexibility and commitment by not committing to a specific climate policy level but a transparent adjustment strategy in response to climate damage shocks. In reality the regulator may need to address not only the optimal level of an irreversible investment decision but also the optimal consumption level. Höffler (2014) points out that regulators should address each target with a separate instrument. Therefore, a hybrid policy, i.e. the combination of two policies may be necessary. Offering a CCfD in addition to carbon prices constitutes a hybrid policy in the sense that the CCfD targets the firms' investment decisions while the complementary carbon price targets the optimal consumption level. Closely linked to our paper, Christiansen and Smith (2015) extend the analysis of Baldursson and Von der Fehr (2004) to hybrid policy instruments. The authors analyze a sequential setting in which firms initially have to decide on an investment in a low-carbon technology under risk and subsequently adjust output after the risk resolves. If a carbon tax commitment is the only instrument, the regulator sets the tax higher than the expected damage to incentivize more appropriate investments.[56] Supplementing the carbon tax with a state-contingent investment subsidy increases welfare as it allows for incentivizing investment without setting a carbon tax that is too high. In a similar vein, Datta and Somanathan (2016) analyze a carbon tax and a permit system and examine the role of research and development (R&D) subsidies. They conclude that using only one instrument cannot be welfare-optimal if the regulator aims to address two targets - the internalisation of external effects from R&D and carbon damage. This is in line with our finding that a hybrid policy, in our case a CCfD, can improve welfare in a setting with an irreversible investment decision.

The second literature stream examines the role of hedging instruments for incentivising investments in low-carbon technologies under risk. Within this literature stream, the introduction of hedging instruments are found to increase investments in the presence of risk aversion. Borch (1962), who analyzes reinsurance markets, demonstrates that players are willing to share risks according to their level of risk aversion by trading reinsurance covers which act as hedging instruments. This finding is supported by Willems and Morbee (2010), who examine investments in energy markets. The authors find that the availability of hedging opportunities increases investments of risk-averse firms and welfare. Habermacher and Lehmann (2020) analyze the interaction between a regulator

[56]This result resembles the insights from the real options literature where risk, combined with investment irreversibility, gives rise to an option value of waiting, e.g., Dixit et al. (1994). Chao and Wilson (1993) find an option value for emission allowances. Purchases of emission allowances provide flexibility to react to risk in a way that irreversible investments do not. The price of emission allowances may therefore exceed the marginal cost of abatement.

aiming to maximise welfare and firms facing an investment decision in low-carbon technologies. Similar to our paper, the authors assess carbon damage and variable costs risk. They find that the introduction of stage-contingent payments which partly hedge the risks of the regulator and the firm improve welfare compared to committing to carbon price or setting it flexibly. Those findings are in line with our result that a CCfD as an instrument for firms to hedge their risk leads to more investment and may increase welfare. Furthermore, hedging instruments may improve welfare even in the absence of risk aversion. An early example is Laffont and Tirole (1996), who show that the introduction of options solves the problems arising from strategic behaviour between the regulator and a firm.[57] If the regulator faces incomplete information, Unold and Requate (2001) show that offering options in addition to permits is welfare-enhancing. In contrast to this stream of literature, Quiggin et al. (1993) find that hedging instruments may also be welfare-deterring, as they may foster undesired behaviour. This result resembles our findings in the case of potentially ex-post welfare-reducing production in Chapter 5.4.

CCfDs combine the effects of a hybrid policy and a hedging instrument. They recently gained attention from academic literature. Richstein (2017) focuses on the optimal combination of CCfDs and investment subsidies to lower policy costs and support investment decisions under risk and risk aversion. However, the study does not include the regulator's decision on the carbon price regime. To the best of our knowledge, Chiappinelli and Neuhoff (2020) provide the only study that explicitly analyzes CCfDs in the context of multiple carbon pricing regimes. The authors model firms which face an irreversible investment decision and behave strategically, which influences the regulator's decision on the carbon price. In this setup, higher investments in abatement technologies lead to lower carbon prices so that firms strategically under-invest to induce higher carbon prices. Offering CCfDs can alleviate such a hold-up problem. We build on the model developed in Chiappinelli and Neuhoff (2020) but change the focus of analysis. We analyze a setup with a large number of small firms in a competitive market. Chiappinelli and Neuhoff (2020) show how CCfDs can alleviate the hold-up problem that results from regulation and, hence, mitigate regulatory risk. In contrast, we focus on the impact of CCfD in an environment of risks that are outside the control of regulator and firms, i.e., damage and variable cost risk. We also present the first paper in this literature stream to point out that CCfDs can cause a lock-in in technologies that are ex post not socially optimal.

## 5.2. Carbon pricing regimes in the absence of risk

This section introduces the model setup to analyse the effects of CCfDs. In the model, we assess the interactions between a regulator and firms in the absence of

[57] This type of expropriation game constitutes a type of climate policy risk but mainly includes strategic behaviour.

risk. The regulator can apply three carbon pricing regimes to reduce emissions while firms face an irreversible investment decision to abate emissions during production.

### 5.2.1. Model framework in the absence of risk

We model the market for a homogeneous good $G$ in which three types of agents participate - namely, consumers, firms, and a regulator. Consumers have an elastic demand $Q(p_G)$ for the good at a market price $p_G$. Demand decreases in the good's price, i.e., $Q'(p_G) < 0$.

A continuum of firms supplies the good in a competitive market. Each firm produces one unit. Initially, all firms produce the good with a conventional technology. Using the conventional technology to produce one unit of $G$ induces constant marginal production costs ($c_0 \geq 0$) that are identical among all firms. The production process emits one unit of carbon emission. The emission causes constant marginal environmental damage $d$, which lowers the overall welfare, and is subject to a carbon price ($p \geq 0$). The resulting total marginal costs of the conventional technology equal $c_c = c_0 + p$.[58]

Firms can invest in an emission-free technology to produce G at carbon costs of zero. Investing implies that firms adopt new production processes within their existing production sites. As a result, the production capacity of the firms remains unaffected by an investment.[59] The investment decision is irreversible and induces investment costs as well as higher marginal production costs. We assume firms face heterogeneous investment costs, similar to the approach in Harstad (2012) or Requate and Unold (2003).[60] This heterogeneity may stem from several sources, e.g., because firms can adopt different technologies, have different access to resources, or have different R&D capacities. In our model, firms are ranked from low to high investment costs, such that they can be placed within an interval ranging from $[0, \chi_{max}]$.[61] We assume the firm-specific investment costs to be the product of the firm-specific position on the interval $\chi$ and a positive investment cost parameter $c_i$ that is identical among firms. Hence, the investment costs of the firm positioned at $\chi$ equal $C_i(\chi) = \chi c_i$. Firms invest if they increase their profit by adopting the emission-free technology. Otherwise, they produce conventionally. We identify the firm which is indifferent between the two technologies by $\overline{\chi}$. As $C_i'(\chi) > 0$, all firms with $\chi \leq \overline{\chi}$ invest. In other words, $\overline{\chi}$ refers to the marginal firm investing in the emission-free technology. The position of a

[58] We discuss the implication of assuming constant marginal damage in Chapter 5.5.

[59] This does not exclude market entry of new firms; however, we do not model entry or exit decisions explicitly, as adopting new processes in established installations is likely less costly then investing in new installations.

[60] Empirical evidence shows that firms differ with respect to their costs of investing in pollution abatement Blundell et al. (2020).

[61] $\chi_{max}$ represents the production capacity of all firms and is assumed to exceed the demand $Q(p_G)$ for all possible values of $p_G$.

firm on the interval $\chi$ not only defines the firm-specific investment costs but also corresponds to the cumulative production capacity of all firms facing investment costs lower than the respective firm. In consequence, $\overline{\chi}$ defines the emission-free production capacity. In the following, we refer to $\overline{\chi}$ interchangeably either as the emission-free production capacity or as the marginal firm.

Emission-free production has additional marginal production costs $c_v$. This technology may, for instance, require more expensive input factors compared to the conventional technology. Hence, the total marginal production costs of firms using the emission-free technology equal $c_f = c_0 + c_v$. In Chapter 5.2 and 5.3, we assume the marginal production costs of the emission-free technology to be lower than the carbon price (i.e., $c_v < p$). We alleviate the assumption in Chapter 5.4. Additionally, we adopt the normalisation $c_0 = 0$. Considering investment and production costs, the profit of investing in the emission-free technology equals $\pi(\chi) = p_G - (c_0 + c_v + c_i\chi)$.

The regulator aims at maximising the welfare resulting from the market for $G$. For this, the regulator can choose among the three different carbon pricing regimes. Firstly, she can opt for *Regulatory Flexibility* (short: *Flex*), in which she sets the carbon price flexibly after the investment decisions of the firms took place. Secondly, she can make a *Commitment* (short: *Com*) and commit to a carbon price before the investment takes place. The third option *CCfD* is a hybrid policy of offering CCfDs to the firms before the investments take place and setting the carbon price afterwards. The CCfD sets a strike price $p_s$ that safeguards firms against carbon price volatility. If the carbon price, which realises after the investments, is lower than the strike price, the regulator pays the difference $(p_s - p)$ to the firm. If the carbon price is higher than the strike price, firms have to pay the difference to the regulator.

Before introducing the sequence of actions, we discuss the model approach and its main assumptions. First, a price-elastic demand, a competitive market structure, and the provision of homogeneous goods resemble many industries for which CCfDs are proposed, e.g., steel and chemicals (e.g. European Commission, 2021b, Fernandez, 2018, OECD, 2002). Second, these industries likely face a discrete, irreversible investment decision to decarbonise the production in combination with increased marginal production costs of the low-carbon technology. Currently, a switch of production processes from the coal- and coke-based blast furnace to hydrogen-based direct reduction is seen as the most promising way to decarbonise the primary steel sector (e.g. IEA, 2021). This switch in the production process induces a shift in input factors from coal to more expensive hydrogen (Vogl et al., 2018). Hence, our model captures many characteristics of industries, for which policymakers propose the use of CCfDs.

The agents in our model can take actions in four stages, namely the Early Policy stage $t_1$, the Investment stage $t_2$, the Late Policy stage $t_3$, and the Market Clearing stage $t_4$. Figure 5.1 depicts these stages. The sequence of actions differs between the carbon pricing regimes that we analyse in this paper. We subsequently discuss the agents' actions during the various stages of the game. As we derive the sub-game perfect Nash equilibrium by backward induction, we begin by presenting the last stage of the game.

| | **Firms** | **Regulator** | | | **Social Planner** |
|---|---|---|---|---|---|
| | | *Com* | *Flex* | *CCfD* | *Opt* |
| Early Policy ($t_1$) | | Sets $p$ | | Sets $p_s$ | |
| Investment ($t_2$) | Invest up to $\overline{\chi}$ | | | | Sets $\overline{\chi}$ |
| Late Policy ($t_3$) | | | Sets $p$ | Sets $p$ | Sets $p$ |
| Market Clearing ($t_4$) | $p_G^* = p$ and $Q(p_G^*) = Q(p)$ | | | | |
| $T$ | | | | | |

Figure 5.1.: Sequence of actions in the different carbon pricing regimes.

**Market Clearing stage:** In $t_4$, the market clearing takes place. Firms produce the good with the respective technologies and serve the demand. In this stage, the carbon price $p$ and the resulting emission-free production capacity $\overline{\chi}$ are already determined.

**Late Policy stage:** In $t_3$, the regulator sets the carbon price under *Regulatory Flexibility* and *CCfD*, given the previously determined production capacity of the emission-free technology.

**Investment stage:** In $t_2$, the firms decide whether to invest in the emission-free technology or not. Firms with $\chi \leq \overline{\chi}$ invest as they increase their profit by adopting the emission-free technology, while the others ($\chi > \overline{\chi}$) maintain the conventional technology.

**Early Policy stage:** In $t_1$, the regulator can take actions in two of the three carbon pricing regimes. Under *Commitment*, she announces and commits to a carbon price for the subsequent stages. Under *CCfD*, the regulator offers firms CCfDs and determines the strike price.

In contrast to the other stages, the market clearing in $t_4$ is independent of the carbon pricing regime, such that we present the result upfront. We assume the investment costs to be sufficiently high compared to the demand, such that investments in the emission-free capacity cannot supply the overall demand, i.e., $\overline{\chi} < Q(p_G)$. This assumption implies that the demand for the good is partially served by firms that invested in the emission-free technology and by firms producing conventionally.[62] As demand exceeds the emission-free production capacity and marginal production costs of the emission-free technology are lower than of the conventional technology, the latter sets the market price. Due to the normalisation of $c_0 = 0$, the market price is defined by $p_G = p$ and the demand is equal to $Q(p_G) = Q(p)$, i.e., the carbon price fully determines the product price. Figure 5.2 illustrates the market clearing.

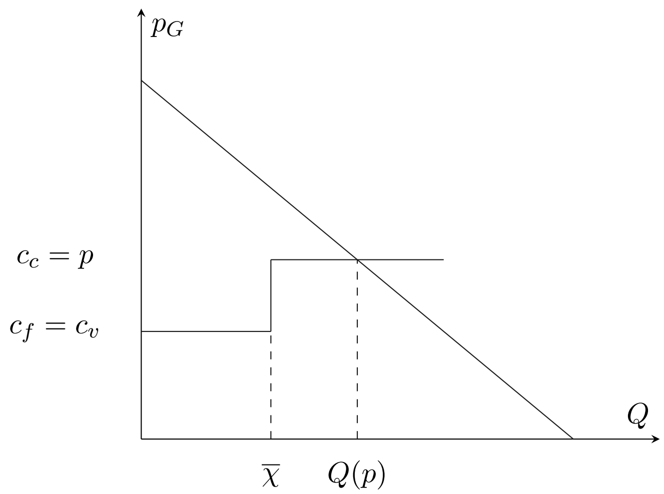



Figure 5.2.: Market clearing.

Firms producing the good with the conventional technology do not generate profits as marginal revenue equals marginal costs, which are constant. The marginal profit of production of the firms investing in the emission-free technology equals $p - c_v$. Together, the assumptions $\chi < Q(p_G)$ and $c_v < p$ ensure that some firms will invest in the emission-free technology. The first assumption addresses the fixed investment costs and the second the variable costs of the emission-free technology. These assumptions also ensure that some firms continue producing conventionally. Chapter 5.5 discusses why CCfDs can only be beneficial in this setting.

To evaluate the carbon pricing regimes, we compare the respective outcomes to the social optimum (short: *Opt*). In this hypothetical benchmark, a social planner sets the socially optimal investment in $t_2$ and the carbon price level in $t_3$. The social planner's objective is, identical to the regulator, to maximise social welfare stemming from the market for the product $G$. Social welfare comprises four elements: 1) net consumer surplus (CS), 2) producer surplus, 3) environmental damage, and 4) policy costs/revenues from carbon pricing and the CCfD.

[62]We discuss this assumption in Chapter 5.5, as it is crucial for the outcome of the market clearing and the resulting incentives to invest in the emission-free technology.

The producer surplus is defined as the margin between marginal revenue and marginal costs. It differs before and after the irreversible investment. Before the investment, i.e., in $t_1$ and $t_2$, the marginal costs comprise investment and marginal production costs. After the investment, i.e., in $t_3$ and $t_4$, the investment costs are sunk, such that the marginal costs only comprise the marginal production costs. Equation 5.1 displays the welfare before the investment takes place. The welfare representation after the investment takes place does not contain the investment costs $\int_0^{\overline{\chi}}(c_i z)dz$.

$$\mathcal{W}^{Flex/Com/Opt} = \underbrace{\int_p^\infty Q(z)dz}_{\substack{\text{consumer}\\\text{surplus}}} + \underbrace{\int_0^{\overline{\chi}}(p - c_v - c_i z)dz}_{\text{producer surplus}} - \underbrace{d[Q(p) - \overline{\chi}]}_{\substack{\text{environmental}\\\text{damage}}} + \underbrace{p[Q(p) - \overline{\chi})]}_{\substack{\text{revenues from}\\\text{carbon pricing}}}$$

$$\mathcal{W}^{CCfD} = \underbrace{\int_p^\infty Q(z)dz}_{\substack{\text{consumer}\\\text{surplus}}} + \underbrace{\int_0^{\overline{\chi}}(p_s - c_v - c_i z)dz}_{\text{producer surplus}} - \underbrace{d[Q(p) - \overline{\chi}]}_{\substack{\text{environmental}\\\text{damage}}} + \underbrace{p[Q(p) - \overline{\chi})]}_{\substack{\text{revenues from}\\\text{carbon pricing}}} - \underbrace{(p_s - p)\overline{\chi}}_{\substack{\text{CCfD}\\\text{payment}}} \tag{5.1}$$

Payments arising from the CCfD do not affect the overall welfare as they only shift payments between firms and the regulator.[63] Hence, we can simplify welfare with and without CCfDs before investment to:

$$\mathcal{W} = \int_p^\infty Q(z)dz + (p - d)Q(p) + \int_0^{\overline{\chi}}(d - c_v - c_i z)dz \tag{5.2}$$

This simplified representation illustrates that welfare can be grouped into two elements. On the one hand, welfare is defined by consumption, the associated environmental damage, and the carbon pricing revenue. On the other hand, welfare stems from the level of emission-free production capacity $\overline{\chi}$ and the related costs and benefits from abatement.

### 5.2.2. Policy ranking in the absence of risk

In the following, we derive the optimal emission-free production capacity $\overline{\chi}$ and the optimal carbon price $p$ in the absence of risks (i.e., under perfect foresight) under the assumption of a social planner. The solution serves as a hypothetical benchmark for the three carbon pricing regimes. To solve the optimisation of

[63] Note that we do not assume shadow costs of public funds. We discuss this assumption in Chapter 5.5.

the social planner, we derive the first-order conditions of the welfare function:

$$\begin{aligned}
\max_{\overline{\chi},p} \mathcal{W} &= \int_p^\infty Q(z)dz + (p-d)Q(p) + \int_0^{\overline{\chi}} (d - c_v - c_i z)dz \\
\frac{\partial \mathcal{W}}{\partial \overline{\chi}} &= (d - c_v - c_i \overline{\chi}) \longrightarrow \overline{\chi}^{Opt} = \frac{d - c_v}{c_i} \\
\frac{\partial \mathcal{W}}{\partial p} &= -Q(p) + Q(p) + Q'(p)(p-d) \longrightarrow p^{Opt} = d
\end{aligned} \tag{5.3}$$

The social planner chooses the emission-free production capacity such that the abatement costs (i.e., the investment and production costs) of the marginal firm ($\overline{\chi}^{Opt}$) equal the damage avoided by the investment in and the utilisation of the emission-free technology. The optimal carbon price ($p^{Opt}$) equals the marginal damage, i.e., the Pigouvian tax level (Pigou, 1920), as the marginal unit of the good is produced with the conventional technology, associated with an environmental damage of $d$. With this carbon price, the social planner inhibits all consumption with a lower benefit than damage to society.

We provide the optimal solutions under the different carbon pricing regimes in Supplementary Material D.1. We find that

**Proposition 5.2.1.** *In the absence of risk, all carbon pricing regimes reach the social optimum. In all regimes, the carbon price is equal to the marginal environmental damage of production, i.e., $p = d$. The marginal firm using the emission-free technology balances the marginal investment costs and the respective marginal benefit of abatement, i.e., $\overline{\chi} = {}^{(d - c_v)}/_{c_i}$.*

In the absence of risk, i.e., under perfect foresight, the optimisation rationales in $t_1$ (before investing) and $t_3$ (after investing) regarding balancing the damage from carbon emission and the costs of abatement are identical. Therefore, it does not make a difference if the regulator commits to a carbon price before the firms invest or sets the carbon price flexibly afterward. Under all regimes, Pigouvian taxation is optimal. Hence, offering a CCfD in $t_1$ does not improve social welfare.

This result regarding the welfare ranking of carbon pricing regimes and, notably, CCfDs differs from Chiappinelli and Neuhoff (2020). In their model, firms also face an irreversible investment decision but behave strategically and influence the regulator's decision on the carbon price. Thereby, firms under-invest to induce higher carbon prices, leading to a hold-up problem. In this setting, CCfDs can alleviate the investment-hampering effect of flexible carbon prices and increase welfare. In contrast, firms do not have market power in our model and cannot affect the regulator's carbon pricing decision. Hence, it does not make a difference if the firms invest before or after the regulator sets the carbon price under perfect foresight.

*Proof.* We provide the proof of Proposition 5.2.1 in Supplementary Material D.1.
■

## 5.3. Carbon pricing regimes in the presence of risk

In this chapter, we analyse the impact of damage and variable cost risk on the welfare ranking of the carbon pricing regimes in the presence of risk aversion.

### 5.3.1. Model framework in the presence of risk and socially optimal production

We integrate risk into the model by redefining the marginal environmental damage and the variable production costs of the emission-free technology from the model introduced in section 5.2.1 as random variables $D$ and $C_v$. Both random variables realise after the firms invest in abatement ($t_2$), but before the late policy stage ($t_3$) and the market clearing ($t_4$). We denote the realisation of $D$ and $C_v$ by $\hat{d}$ and $\hat{c_v}$. In this chapter, we assume the production with the emission-free technology to be socially optimal under all circumstances, i.e., the environmental damage is always larger than the variable costs of abatement $P(D > C_v) = 1$. For this assumption to hold, we define the random variables to follow a truncated normal distribution, i.e., $D \sim TN(\mu_D, \sigma_D^2, \underline{\theta_D}, \overline{\theta_D})$ and $C_v \sim TN(\mu_{C_v}, \sigma_{C_v}^2, \underline{\theta_{C_v}}, \overline{\theta_{C_v}})$ with $\underline{\theta_D} > \overline{\theta_{C_v}}$, where $\mu$ denotes the mean value, $\sigma^2$ the variance and $\underline{\theta}$ and $\overline{\theta}$ the lower and upper limit of the distribution, respectively. Hence, the lowest possible damage is larger than the highest possible realisation of variable costs.[64] As in Chapter 5.2.1, we assume $\chi < Q(p(d))$, such that for all $\hat{d} \in D$ the total demand in the market exceeds the emission-free production capacity.

[64] We assess a setting in which the social costs of damage are potentially smaller than the variable costs of abatement, i.e., $P(D > C_v) < 1$, in Chapter 5.4 by assuming an non-truncated normal distribution.

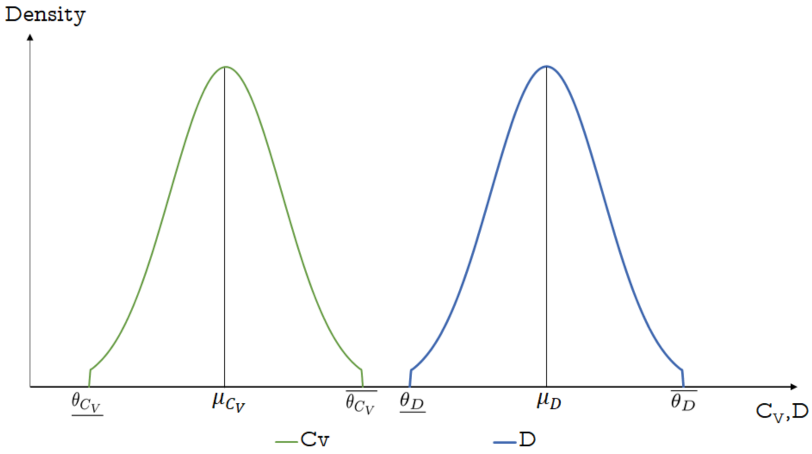



Figure 5.3.: Density of $D$ and $C_v$ following a truncated normal distribution with $P(C_v > D) = 0$.

We assume that firms are risk averse, facing a utility that is exponential in profits. Whether or not risk aversion is a real-world phenomenon for firms and how it manifests in actions is debated within the broad literature of economics and the context of energy and environmental economics (Meunier, 2013). Diamond (1978) argues that even if markets were incomplete, firms should act as if they were risk neutral, and shareholders could hedge their risks at the capital markets. However, there are several reasons why firms may act aversely to risk (see e.g. Banal-Estañol and Ottaviani (2006) for a review). These reasons include non-diversified owners, liquidity constraints, costly financial distress, and nonlinear tax systems. Additionally, and independently of the owners' risk aversion, the delegation of control to a risk-averse manager paid based on the firm's performance may cause the firm to behave in a risk-averse manner.

How the firms' risk aversion can be modelled depends on the distributional assumptions of the underlying risks. Markowitz (1952) show that for non-truncated normally distributed profits, the mean-variance utility could express firms' optimisation rationale. However, this simplification is not appropriate for our model in which the distribution of firms' profits is truncated due to distributional assumptions on damage and variable cost risk. Norgaard and Killeen (1980) show that the optimisation rationale of an agent facing an exponential utility and truncated normally distributed profits can be approximated by a mean-standard deviation decision rule containing a risk aversion parameter $\lambda$.[65] We apply this approximation by using a mean-standard deviation utility in our model. Firms invest in the emission-free technology if their expected utility is positive. The expected utility of the marginal firm investing in the emission-free technology is

[65] In the context of energy and environmental economics, Alexander and Moran (2013) apply this approach to assess the impact of perennial energy crops income variability on the crop selection of risk-averse farmers.

equal to zero:

$$\begin{aligned} EU(\pi(\overline{\chi})) &= \mu_\pi(\overline{\chi}) - \lambda\sigma_\pi(\overline{\chi}) \\ &= (\mu_p - \mu_{C_v} - c_i\overline{\chi}) - \lambda\sigma_{p,C_v} \\ &= 0 \end{aligned} \tag{5.4}$$

In contrast to the firms' risk aversion, we assume the regulator to be risk neutral. There are several reasons why environmental regulation is determined on a risk-neutral basis (see e.g. Kaufman (2014) for an extensive review). In the context of public economics, Arrow and Lind (1970) argue that with a sufficiently large population, the risk premiums converge to zero because they can be spread out among constituents. Fisher (1973) discusses the principles of Arrow and Lind in the context of risks stemming from environmental externalities. [66] Hence, we assume the regulator to maximise the expected welfare:

$$E[\mathcal{W}] = E\Big[\int_p^\infty Q(z)dz + (p-d)Q(p) + \int_0^{\overline{\chi}}(d - c_v - c_i z)dz\Big] \tag{5.5}$$

### 5.3.2. Policy ranking with damage risk

In the following, we focus on damage risk and neglect the risk of the variable production costs. Therefore, we set $\mu_{C_v} = c_v$ with $\sigma^2_{C_v} = 0$. We derive and compare the outcomes of the three carbon pricing regimes in terms of the emission-free production capacity $\overline{\chi}$ and carbon price $p$ in the presence of damage risk. We contrast the three regimes to the social optimum and conclude that

**Proposition 5.3.1.** *In the presence of damage risk and firms' risk aversion, only the hybrid policy of offering a CCfD and setting the carbon price flexibly yields an socially optimal level of* $p$ *and* $\overline{\chi}$*. A pure carbon pricing regime reaches either a socially optimal carbon price through allowing for flexibility or optimal investment through early commitment.*

As the valuation of environmental damage is not known before investing ($t_1$), while it is known after investing ($t_3$), the timing of the carbon pricing regimes changes the carbon prices and the resulting market outcomes. When setting the carbon price flexibly in $t_3$, all relevant information is available for the regulator. Hence, the *Regulatory Flexibility* regime results in the socially optimal carbon price for the market clearing. However, in this regime, firms face a risk regarding their revenues. Due to their risk aversion, firms consequently invest less than

[66] Besides the risk neutrality of the regulator, we assume that her welfare maximisation is also not affected by the firms' risk aversion. This corresponds to the concept of the literature on non-welfarist taxation, which is common practice in public economics (e.g. Heutel (2019), Kanbur et al. (2006)). In essence, the regulator's *ignorance* of the risk-averse utility of the firms can stem from either paternalistic behaviour or an insufficiently large proportion of the firms on the market.

socially optimal. When committing to a carbon price in $t_1$, the regulator cannot take into account the information becoming available in $t_3$. Hence, the carbon price under *Commitment* is ex-post either too high or too low. However, the carbon price commitment incentivises socially optimal investments. It accounts for the risk in the valuation of environmental damage; that is, the firms and the regulator face the same problem. Offering a CCfD removes the impact of damage risk for the firms and enables socially optimal investments. Furthermore, socially optimal consumption is reached as the regulator sets the carbon price in $t_3$, having complete information on the damage valuation.

*Proof.* For the proof of proposition 5.3.1, we compare the socially optimal carbon price and emission-free production capacity to the three carbon pricing regimes. Supplementary Material D.2 presents a complete derivation of the respective optimal solutions. In the following, we provide the main results and the intuition behind the finding in proposition 5.3.1.

### Social optimum

In the social optimum, the social planner sets the carbon price $p$ after the actual environmental damage revealed. Following the rationale of the risk-free setting, the socially optimal carbon price equals the realised marginal damage, i.e., $p^{Opt} = \hat{d}$. As the social planner knows the actual damage level when setting the carbon price, the damage risk does not impact her decision.

In contrast, investments are due before the actual damage reveals. Hence, the social planner must set the emission-free production capacity $\overline{\chi}$ in the presence of damage risk. The social planner sets $\overline{\chi}^{Opt}$ such that it maximises the expected welfare gain from abatement investments.

$$\overline{\chi}^{Opt} = \frac{\mu_D - c_v}{c_i} \tag{5.6}$$

The emission-free production capacity balances the expected benefit of abatement, i.e., the expectation of the avoided environmental damage and the abatement costs, consisting of variable production costs and investment costs.

### Regulatory flexibility

Similar to the social planner case, the regulator sets the carbon price after the actual damage revealed when she chooses *Regulatory Flexibility*. As the regulator and the social planner have the same objective function, both settings result in a carbon price at $p^{Flex} = p^{Opt} = \hat{d}$, i.e. the Pigouvian tax level.

In $t_2$, the firms choose to invest if their expected utility is positive, anticipating the carbon price set by the regulator in the following stage. However, the price is stochastic to firms, as it depends on the realised damage.

$$\overline{\chi}^{Flex} = \frac{\mu_{p^{Flex}} - c_v - \lambda \sigma_{p^{Flex}}}{c_i} = \frac{\mu_D - c_v - \lambda \sigma_D}{c_i} \tag{5.7}$$

Unlike in the case of a (risk-neutral) social planner, firms not only account for the expected revenues and costs of abatement but also consider a risk term stemming from the abatement revenue risk. This risk term reduces the firms' expected utility and consequently the emission-free production capacity, as firms aim to avoid situations where their investments are unprofitable. The dampening effect of risk on investments increases with the volatility of expected carbon prices and the firms' risk aversion.

### Commitment

Under *Commitment*, the firms' investment rationale is based on the carbon price known at the time of taking their decision:

$$\overline{\chi}^{Com} = \frac{p^{Com} - c_v}{c_i} \tag{5.8}$$

Following the intuition of the setting without risk, those firms invest which increase their profit by adopting the emission-free technology. As revenues are not subject to risk, the firms' risk aversion does not impact their investment decisions in $t_2$ and the resulting emission-free technology balances the marginal revenue and the marginal costs of abatement.

In $t_1$, the regulator sets the carbon price maximising expected welfare and taking into account that firms solely invest if the investment is profitable. As a result, the regulator sets the carbon price to $p^{Com} = \mu_D$, i.e., the expected Piguvian tax level. Substituting the optimal carbon price $p^{Com}$ into Equation 5.8 yields $\overline{\chi}^{Com} = \frac{\mu_D - c_v}{c_i}$, which is equal to the solution of the social planner. However, the carbon price to which the regulator commits herself in $t_1$ is ex-post not optimal. If the revealed damage is greater than expected, the carbon price is too low, and vice versa.

### CCfD

When the regulator can offer the firms a CCfD, the regulator faces the same objective function for setting the carbon price in $t_3$ as under *Regulatory Flexibility*. Hence, she chooses the Pigouvian tax level $p^{CCfD} = p^{Flex} = p^{Opt} = \hat{d}$.

In $t_2$, the firms' problem is identical to the one under *Commitment.* Here, the firms receive the strike price:

$$\overline{\chi}^{CCfD} = \frac{p_s - c_v}{c_i} \tag{5.9}$$

The rationale for investments is the same as without risk: Firms invest in the emission-free technology if it increases their profits. In $t_1$, the regulator chooses the strike price that maximises expected social welfare. She accounts for the firms' reaction function to the announced strike price and faces damage risk. The resulting strike price equals the expected marginal damage, i.e., $p_s = \mu_D$. By substituting $p_s$ in Equation 5.9, we see that under a *CCfD* regime, the emission-free production capacity equals the one under *Com* (and the social planner), i.e., $\overline{\chi}^{CCfD} = \overline{\chi}^{Com} = \overline{\chi}^{Opt}$). ■

## Welfare Comparison

We calculate and compare the ex-ante social welfare in the different carbon pricing regimes in terms of welfare.[67] We find that:

$$E[\mathcal{W}^{Opt}_{\sigma_D}] = E[\mathcal{W}^{CCfD}_{\sigma_D}] \geq E[\mathcal{W}^{Com}_{\sigma_D}] \lesseqgtr E[\mathcal{W}^{Flex}_{\sigma_D}] \tag{5.10}$$

First, the carbon price and the emission-free production capacity are identical in the social optimum and the *CCfD* regime. Consequently, the *CCfD* regime results in the social optimum.

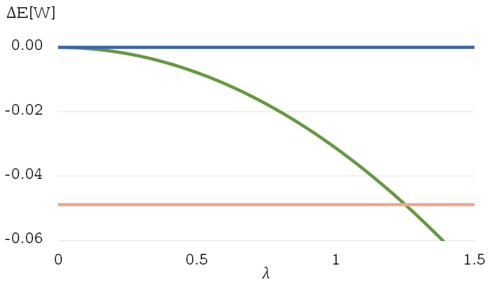
Second, we compare offering a CCfD against *Regulatory Flexibility* and *Commitment.* While the *CCfD* regime achieves the socially optimal emission-free production capacity, investments in *Flex* are lower. As the expected welfare increases in $\chi$ as long as $\chi \leq \overline{\chi}^{CCfD} = \frac{\mu_D - c_v}{c_i}$, the welfare under the *Flex* regime is lower than the social optimum or offering a CCfD. The welfare loss increases in the firms' risk aversion and the standard deviation of environmental damage. However, if firms are risk neutral, the *Flex* regime reaches the socially optimal emission-free production capacity. Figure 5.4a shows these results numerically. Note that these parameter values are illustrative and do not correspond to empirical estimates.[68] In contrast to the case of *Regulatory Flexibility*, the policy regimes *Commitment* and *CCfD* both result in the socially optimal emission-free production capacity. However, these regimes differ concerning the carbon price level and the resulting utility from consumer surplus. Under the *Com* and *CCfD* regimes, consumers bear the same carbon prices in

[67] The subscript $\sigma_D$ represents the welfare in the presence of damage risk.

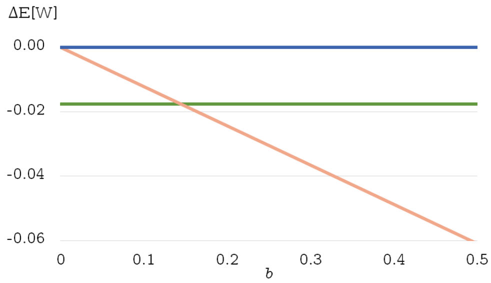
[68] Both Figure 5.4a and Figure 5.4b share the parameters regarding the distribution of the environmental damage $D \sim TN(\mu_D = 4, \sigma_D^2 = 0.25, \underline{\theta_D} = 2.5, \overline{\theta_D} = 5.5)$ and the cost parameters of the emission-free technology $c_v = 2$ and $c_i = 4$.

expectation. However, the consumer surplus is a convex function of the respective carbon price. I.e., a higher carbon price decreases the consumer surplus less than an equivalently lower carbon price would lead to an increase of the consumer surplus.[69] Hence, the difference in expected consumer surplus is positive, i.e., $E[\int_{p^{CCfD}}^{\infty} Q(z)dz] > \int_{p^{Com}}^{\infty} Q(z)dz$. With an increase in demand elasticity, the difference in consumer surplus of the *Com* and *CCfD* regimes increases. Therefore, the greater the demand elasticity, the higher the loss in ex-ante welfare arising from not setting the carbon price according to the actual marginal damage under *Com*. We illustrate this finding numerically in Figure 5.4b.

Third, it is unclear whether *Com* or *Flex* is welfare superior. *Flex* results in socially optimal carbon pricing, while *Com* allows for socially optimal emission-free production capacity. Which regime is welfare superior depends on the relevance of the two variables. In case of damage risk, setting a flexible carbon price is welfare superior to *Com* if demand elasticity is sufficiently high and the share of emission-free production is sufficiently low. The same holds vice versa for *Com*.




(a) Effect of risk aversion




(b) Effect of elasticity



Figure specific parameters in (a): $\lambda \in [0, 1.5]$, $Q(p) = 5 - 0.4p$ and (b): $\lambda = 0.75$, $Q(p) = 5 - bp$ with $b \in (0, 0.5]$.

Figure 5.4.: Difference in welfare compared to social optimum in the presence of damage risk.

### 5.3.3. Policy ranking with variable cost risk

In this chapter, we focus on variable cost risk and set $\mu_D = d$ with $\sigma_D^2 = 0$. We derive the outcomes of the three carbon pricing regimes in terms of emission-free production capacity $\overline{\chi}$ and carbon price $p$ when the firms do not know the variable costs of the emission-free technology when investing. We contrast the three regimes with the social optimum and conclude that

**Proposition 5.3.2.** *In the presence of variable cost risk, only the hybrid policy of offering a CCfD and setting the carbon price flexibly yields a socially optimal*

[69]This relation is also known as the Jensen gap stemming from Jensen's inequality.

*level of $p$ and $\overline{\chi}$. A pure carbon price in a regime with Regulatory Flexibility reaches a socially optimal carbon price $p$ but falls short of the socially optimal emission-free production capacity $\overline{\chi}$. Commitment reaches neither the socially optimal level of $p$ nor $\overline{\chi}$.*

When firms face a variable abatement costs risk, risk aversion reduces the utility from investing in the emission-free production technology. Depending on the carbon pricing regime, the regulator can mitigate this effect. The regulator can encourage firms to increase investments by setting the carbon price above the Pigouvian tax level when committing to a carbon price. However, the price increase results in inefficient consumption levels. Hence, the regulator faces a trade-off between high consumer surplus and low environmental damage, resulting in a deviation from the social optimum. When the regulator can offer a CCfD in addition to a carbon price, she does not face this trade-off. Instead, the regulator can offer a CCfD, which sufficiently compensates firms for facing risk regarding their revenue and enable socially optimal investments. Furthermore, the regulator achieves the socially optimal consumption level. She can set the carbon price to the Pigouvian tax level, indicating the benefit of having two instruments for different objectives. If the regulator cannot offer a CCfD and sets the carbon price flexibly, the regulator achieves the socially optimal consumption level but cannot alter the firms' investment decisions. Consequently, fewer firms invest than socially optimal.

*Proof.* For the proof of proposition 5.3.2, we compare the socially optimal carbon price and emission-free production capacity to the three carbon pricing regimes. Supplementary Material D.3 presents a complete derivation of the respective optimal solutions. In the following, we provide the main results and the intuition behind the finding in proposition 5.3.2.

## Social optimum

In the social optimum, the social planner maximises welfare by setting the carbon price $p^{Opt}$ after the level of variable costs revealed. She chooses the Pigouvian tax level $p^{Opt} = d$, which equals the social marginal costs of production.

The social planner sets the emission-free production capacity $\overline{\chi}^{Opt}$ under risk such that it maximises the expected welfare. The emission-free production capacity balances the marginal benefit and marginal costs from abatement. The optimisation rationale resembles the one under damage risk. However, in this case, not the benefit of emission-free production but its costs are subject to risk:

$$\overline{\chi}^{Opt} = \frac{d - \mu_{C_v}}{c_i} \tag{5.11}$$

### Regulatory flexibility

Under *Regulatory Flexibility*, the regulator faces the same optimisation problem as the social planner. Hence, she sets the carbon price to the Pigouvian tax level $p^{Flex} = p^{Opt} = d$.

In $t_2$, firms invest in the emission-free technology if the investment increases the expected utility of the firm. For this, the firms anticipate the Pigouvian tax. As firms are risk averse, the firms' utility decreases in the level of risk and risk aversion. The resulting emission-free production capacity equals:

$$\overline{\chi}^{Flex} = \frac{p^{Flex} - \mu_{C_v} - \lambda\sigma_{C_v}}{c_i} = \frac{d - \mu_{C_v} - \lambda\sigma_{C_v}}{c_i} \tag{5.12}$$

The emission-free production capacity falls short of the social optimum in case of risk aversion ($\lambda > 0$). The shortfall increases with an increasing level of risk and risk aversion.

### Commitment

Under *Commitment*, in $t_2$, firms choose to invest given the announced carbon price level. As in the case of *Regulatory Flexibility*, firms invest if they generate a positive expected utility, such that the emission-free production capacity equals:

$$\overline{\chi}^{Com} = \frac{p - \mu_{C_v} - \lambda\sigma_{C_v}}{c_i} \tag{5.13}$$

In $t_1$, the regulator sets the carbon price anticipating that her choice impacts firms' investment decisions and the consumer surplus. These two effects result in a trade-off which we can express as:

$$\frac{p - d}{p} = \frac{1}{\epsilon(p)} \frac{\partial \overline{\chi}^{Com}(p)}{\partial p} \frac{1}{Q(p)} (d - c_i \overline{\chi}^{Com}(p) - \mu_{C_v}), \tag{5.14}$$

where $\epsilon(p) = -\frac{\partial Q(p)}{\partial p} \frac{p}{Q(p)}$ is the elasticity of demand.

The resulting carbon price is higher than $d$, which we show in Supplementary Material D.3. In fact, the optimal carbon price under commitment $p^{Com}$ ranges from $[d, d + \lambda\sigma_{C_v}]$, depending on the configuration of parameters. Hence, the regulator sets a carbon price above the social marginal costs of the conventional technology, i.e. $d$, and the carbon price is higher than in the social optimum. The solution is a modified version of the Ramsey formula for monopolistic price setting under elastic demand (Höffler, 2006, Laffont and Tirole, 1996). The regulator increases the carbon price above the socially optimal level to encourage investments. This price mark-up is proportionate to the inverse price elasticity of demand and the marginal benefit from increased investments. The marginal benefit arises from the marginal increase in the share of emission-free production, i.e., $\frac{\partial \overline{\chi}^{Com}(p)}{\partial p} \frac{1}{Q(p)}$ , and the benefit of the marginal emission-free production, i.e., $d - c_i \overline{\chi}^{Com}(p) - \mu_{C_v}$. In other words, the regulator balances the loss in consumer surplus and the abatement benefits.

The trade-off under *Com* with variable cost risk is different from the case with damage risk: With damage risk, the regulator commits to a carbon price that will be sub-optimal ex-post. By committing to a carbon price, the regulator takes up the firms' risk, mitigating the negative effect of the firms' risk aversion on social welfare. With cost risk, the regulator cannot take away the firms' risk, but she can compensate the firms for taking the risk. By committing to a carbon price that includes a premium, she incentivises more investments. However, this price increase has the downside of a loss in consumer surplus and, in consequence, neither consumption nor investments are socially optimal. If demand was fully inelastic, i.e., $Q'(p) = 0$, the trade-off would diminish. The regulator would set the carbon price such that she fully compensates the firms for their profit risk, i.e. $d + \lambda\sigma_{C_v}$.

## CCfD

When the regulator can offer firms a CCfD in $t_1$, she sets the carbon price in $t_3$ after the actual variable costs revealed and firms invested in the emission-free technology. Her optimisation problem is the same as under *Regulatory Flexibility* and the social optimum. Hence, $p^{CCfD} = d$.

In $t_2$, the firms' optimisation rationale is the same as under the *Commitment*, only that they face a strike price instead of the carbon price.

$$\overline{\chi}^{CCfD} = \frac{p_s - \mu_{C_v} - \lambda\sigma_{C_v}}{c_i} \tag{5.15}$$

In $t_1$, the regulator chooses a strike price that maximises expected social welfare and accounts for the firms' reaction to the strike price.

$$p_s = d + \lambda\sigma_{C_v} \tag{5.16}$$

In contrast to the previous cases, the regulator sets the strike price above the expected benefit of abatement. By substituting $p_s^{CCfD}$ in Equation 5.15, we see that under a *CCfD* regime, the emission-free production capacity equals the choice of the social planner, i.e., $\overline{\chi}^{CCfD} = \overline{\chi}^{Opt}$. The mark-up $\lambda\sigma_{C_v}$ of the strike price compensates firms for taking the risk. The strike price equals the upper limit of the carbon price under *Commitment*, i.e., the level of $p^{Com}$ with fully inelastic demand. As the strike price does not affect the consumer surplus, the regulator can fully assume the firms' risk. In the absence of risk aversion, the regulator sets the strike price at the level of marginal damage. ■

### Welfare Comparison

This subchapter compares the ex-ante social welfare of the different carbon pricing regimes to determine which regime is socially optimal in an environment with risk regarding variable costs. We see that offering a CCfD yields the social optimum, while the other regimes fall short of it. Under *Commitment*, the carbon price is too high and the emission-free production capacity too low. With *Regulatory Flexibility*, the carbon price is socially optimal, but the emission-free production capacity is too low. We find that:

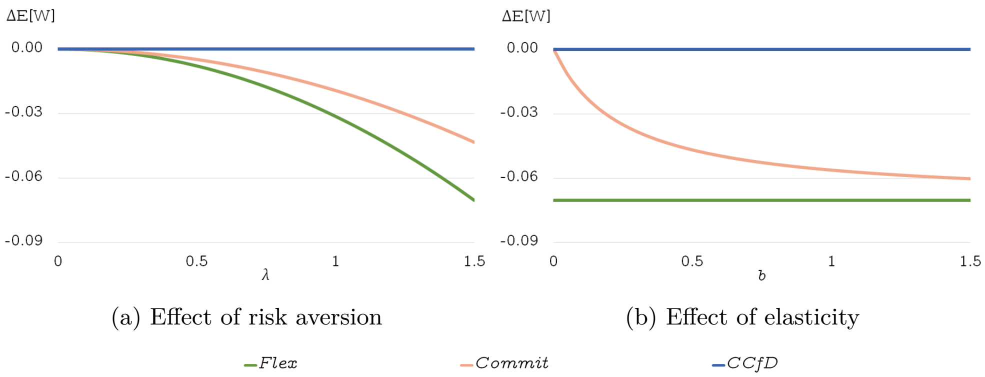
$$E[\mathcal{W}^{Opt}_{\sigma_{C_v}}] = E[\mathcal{W}^{CCfD}_{\sigma_{C_v}}] \geq E[\mathcal{W}^{Com}_{\sigma_{C_v}}] \geq E[\mathcal{W}^{Flex}_{\sigma_{C_v}}] \tag{5.17}$$

First, we compare the expected welfare in *CCfD* with the one the social planner obtains. As both the carbon price and the emission-free production capacity are identical, the *CCfD* regime results in the social optimum.

Second, we find that welfare in *Flex* falls short of the benchmark if firms are risk averse. Like in the case of damage risk, this arises due to too low investments. With increasing risk aversion, the shortfall of investments and welfare increases - a finding that can also be observed numerically in Figure 5.5a.[70]

Third, we find that welfare under *Commitment* falls short of the social optimum but is superior to *Regulatory Flexibility.* The shortfall in welfare arises as the *Com* regime reaches neither the socially optimal carbon price nor the socially optimal emission-free production capacity. The welfare superiority of *Com* compared to *Flex* emerges as the regulator can influence not only the market size but also the investments by setting the carbon price early. In contrast to the damage risk case, there is no disadvantage from setting the carbon price early as the realisation of the damage is known in $t_1$. When deciding on a carbon price under *Com*, the regulator balances the welfare gain from increased abatement arising from a higher carbon price against the welfare loss from decreased consumption. With an increasing elasticity of demand, e.g., due to an increasing slope of a linear demand function, the welfare loss from setting a higher carbon price increases. Hence, the higher the elasticity, the less the carbon price is increased compared to $p^{Flex}$ by the regulator. In consequence, the relative advantage of *Com* compared to *Flex* decreases with increasing demand elasticity. Figure 5.5b displays the finding numerically. The analytical proof showing the welfare of *Com* is superior to *Flex* can be found in Supplementary Material D.3.

[70] Both, Figure 5.5a and Figure 5.5b, share the parameters regrading the distribution of the environmental damage and the costs related to the emission-free technology of Figure 5.4. The chosen parameter values are illustrative and do not correspond to empirical estimates.




(a) Effect of risk aversion

(b) Effect of elasticity

Figure specific parameters in (a): $\lambda \in [0, 1.5]$, $Q(p) = 5 - 0.4p$ and (b): $\lambda = 1.5$, $Q(p) = 5 - bp$ with $b \in (0, 1.5]$.

Figure 5.5.: Difference in welfare compared to social optimum in the presence of cost risk.

## 5.4. Carbon pricing regimes with potentially socially not optimal production

In the previous chapter, we focused on the effects of different carbon pricing regimes in settings in which the production of the emission-free technology is always socially optimal in $t_4$, i.e., the variable costs of abatement are ex-post lower than the marginal environmental damage. In this chapter, we alleviate this assumption and allow for situations in which emission-free production may not be socially optimal.

### 5.4.1. Model framework in the presence of risk and socially not optimal production

To allow for situations in which the production of the emission-free technology is welfare reducing, we assume the environmental damage to be normally distributed instead of truncated normally distributed. That means there is a positive probability that variable costs exceed the realised damage, i.e. $P(C_V > D) > 0$ (see Figure 5.6).[71] We denote the cumulative distribution and probability density functions of $D$ as $F_D(.)$ and $f_D(.)$. To keep investment in abatement ex-ante socially optimal in all cases, we maintain the assumption that $\mu_D > \mu_{C_V}$.

To emphasise the impact of potentially welfare-reducing production on the different carbon pricing regimes, we assume firms to be risk neutral when analysing

[71] The assumption of an untruncated normal distribution implies that $\chi < Q(p(d)$ cannot hold for all $\hat{d} \in D$. Instead, we can almost ensure that the emission-free capacity cannot cover the total demand by assuming $P(Q(p(d)) < \chi) \to 0$, such that the probability of this case is infinitesimally small and can be neglected.

the problem analytically (Chapter 5.4.2). As the three carbon pricing regimes yield the same outcome in the variable cost risk case if firms are risk neutral (see Chapter 5.3.3), we focus on the damage risk case.[72] Hence, we set $\mu_{C_V} = c_v$ with $\sigma^2_{C_V} = 0$ in the following. Being risk neutral, firms invest if their expected profits are positive, i.e., $E[\pi(\chi)] > 0$. To assess the combined effect of potentially welfare-reducing production and risk aversion, we analyse the model numerically in Chapter 5.4.3.

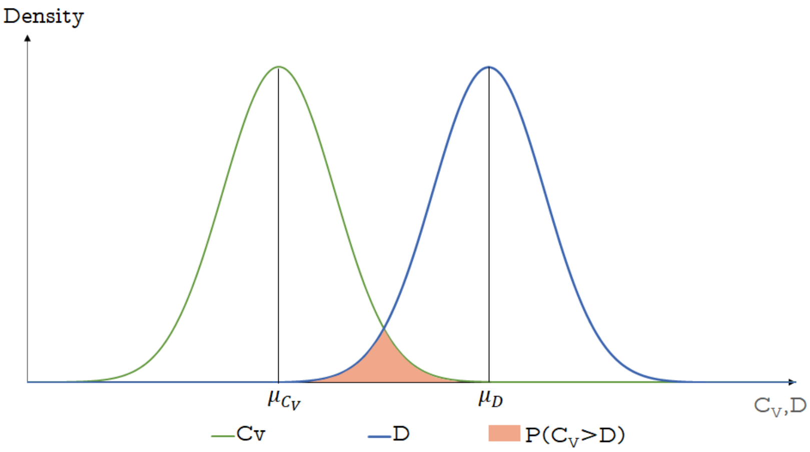



Figure 5.6.: Density of normally distributed $D$ and $C_V$ with $P(C_V > D) > 0$.

Due to the adjusted assumptions on the distribution of damage and costs, the carbon price applied in $t_4$ may be smaller than the variable costs, such that firms may not produce.[73] Firms may decide not to produce even if they invested in the emission-free technology as investment costs are sunk. The profit function can be defined as:

$$\pi(\chi) = \begin{cases} p - c_v - c_i\overline{\chi} & \text{if } c_v \leq p \\ -c_i\overline{\chi} & \text{else} \end{cases} \tag{5.18}$$

Like in Chapter 5.3, we assume the regulator to be risk neutral. Hence, she maximises the expected social welfare. As firms only produce if the carbon price exceeds the variable costs, welfare in $t_4$ is given by:

$$\mathcal{W} = \begin{cases} \int_p^\infty Q(z)dz + (p - \hat{d})Q(p) + \int_0^{\overline{\chi}}(d - c_v - c_i z)dz, & \text{if } c_v \leq p \\ \int_p^\infty Q(z)dz + (p - \hat{d})Q(p) - \int_0^{\overline{\chi}}(c_i z)dz, & \text{else} \end{cases} \tag{5.19}$$

[72]Supplementary Material D.5 shows that all carbon pricing regimes yield the social optimum if risk stems from variable costs and production is potentially welfare reducing.
[73]In Chapter 5.3.2, the realised carbon price by assumption is higher than the marginal costs of production, such that firms produce for any realisation of damage and costs.

### 5.4.2. Policy ranking with damage risk

This section analytically assess the different carbon pricing regimes when the emission-free production is potentially welfare reducing in a setting with damage risk and risk-neutral firms. We derive the outcomes of the three carbon pricing regimes regarding emission-free production capacity $\overline{\chi}$ and carbon price $p$. We contrast the three regimes to the social optimum and conclude that

**Proposition 5.4.1.** *In the presence of damage risk, potentially welfare-reducing production and risk-neutral firms, only setting a carbon price flexibly yield a socially optimal level of* $p$ *and* $\overline{\chi}$. *Offering a CCfD or committing to a carbon price falls short of the social optimum, as these regimes safeguard emission-free production even if it is ex-post socially not optimal.*

Under *Regulatory Flexibility*, the regulator can react flexibly to the actual environmental damage and sets the socially optimal Pigouvian tax level. Concurrently, as firms are risk neutral, investments are not hampered by the risk in profits. Hence, in *Flex*, the emission-free production capacity is socially optimal. In contrast, if the regulator offers a CCfD or commits to a carbon price, the firms' production decision is independent of the actual environmental damage. Hence, these regimes safeguard emission-free production even if it is ex-post socially not optimal. Although the regulator anticipates this effect and, in the *CCfD* regime, lowers the strike price, she cannot reach the social optimum. In addition to the welfare-reducing production level, committing to a carbon price early on also sets the carbon price for consumers, which is ex-post socially not optimal. As in the previous chapter, this socially not optimal carbon price level additionally lowers welfare.

*Proof.* For the proof of proposition 5.4.1, we compare the socially optimal carbon price and the emission-free production capacity to the three carbon pricing regimes. Supplementary Material D.4 presents a complete derivation of the respective optimal solutions. In the following, we provide the main results and the intuition behind the finding in proposition 5.4.1. ■

### Social optimum

In $t_3$, the social planner sets the carbon price $p^{Opt}$ when the level of damage revealed. She optimises Equation 5.19, anticipating that her choice of the carbon price impacts the production of the emission-free technology. Irrespective of the production decision, the social planner sets the carbon price equal to the actual environmental damage, i.e., the Pigouvian tax level $p^{Opt} = \hat{d}$. Hence, whether firms that invested in the emission-free technology in $t_2$ produce in $t_4$ or not depends on the realisation of marginal environmental damage.

In $t_2$, the social planner sets the emission-free production capacity $\overline{\chi}^{Opt}$ to maximise expected welfare. She considers the cases in which production of the emission-free technology may not be socially optimal, i.e., $c_v > \hat{d}$. Thereby, she knows that irrespective of the investment decision, firms will only produce if the realised damage is greater than the marginal variable costs of abatement. In the social optimum, she sets the emission-free production capacity to:

$$\overline{\chi}^{Opt} = \frac{\int_{c_v}^{\infty}(z - c_v)f_D(z)dz}{c_i} \tag{5.20}$$

The solution balances the expected benefit of abatement with its investment costs. The expected benefit of abatement is equal to the benefit from reduced environmental damage minus variable costs weighted by its probability of realisation represented by the integral over the distribution function. The integral is limited to $c_v$ as there is no emission-free production for $c_v > \hat{d}$.

### Regulatory flexibility

Under *Regulatory Flexibility*, the regulator sets the carbon price after the actual damage revealed. Hence, in $t_3$, the regulator faces the same optimisation problem as the social planner, such that $p^{Flex} = p^{Opt} = \hat{d}$.

Sunk investment costs from $t_2$ or whether the emission-free technology produces or not in $t_4$ are irrelevant for the regulator's decision.

In $t_2$, firms choose to invest if their expected utility is positive, anticipating that the Pigouvian carbon tax depends on the damage level that is not yet revealed.

The firms anticipate that they will only produce if the damage (and the respective carbon price) is large enough, i.e., $c_v \leq \hat{d}$. Thereby, the marginal firm investing in the emission-free technology is defined by

$$\overline{\chi}^{Flex} = \frac{\int_{c_v}^{\infty}(z - c_v)f_D(z)dz}{c_i} \tag{5.21}$$

In the absence of risk aversion, the investment rationales of firms and the social planner are aligned, such that *Flex* reaches the social optimum. This result extends the findings from Chapters 5.3.2 and 5.3.3 with $\lambda = 0$ to the case in which emission-free production can be ex-post welfare reducing.

### Commitment

Under *Commitment*, firms choose to invest in the emission-free technology in $t_2$ given the announced carbon price level. The investment decisions are identical to those under *Regulatory Flexibility*, only that the firms know the carbon price when making their decision. Hence, the marginal firm investing in the emission-free technology is characterised by

$$\overline{\chi}^{Com} = \begin{cases} \frac{p^{Com} - c_v}{c_i} & \text{for } c_v \leq p \\ 0 & \text{else} \end{cases} \tag{5.22}$$

In $t_1$, the regulator sets the carbon price anticipating that her choice impacts the firms' investment decision. She chooses a carbon price equal to the expected environmental damage, i.e., $p^{Com} = \mu_D$. As in Chapter 5.3.2 the carbon price is either too high or too low. By assumption, the expected damage is greater than the variable costs, i.e., $\mu_D > c_v$, which implies that investments and production occur. In cases where $\hat{d} < c_v$, the emission-free technology should not produce but does so in response to a too high carbon price. Furthermore, plugging in $p^{Com}$ in Equation 5.22 and subtracting the socially optimal investment level shows that the investment level under *Com* falls short of the social optimum:

$$\begin{aligned} \overline{\chi}^{Com} - \overline{\chi}^{Opt} &= \frac{\int_{-\infty}^{\infty}(z - c_v) f_D(z) dz}{c_i} - \frac{\int_{c_v}^{\infty}(z - c_v) f_D(z) dz}{c_i} \\ &= \frac{\int_{-\infty}^{c_v}(z - c_v) f_D(z) dz}{c_i} \\ &\leq 0 \end{aligned} \tag{5.23}$$

This result shows that the regulator incentivises less investments than socially optimal in order to limit the welfare loss arising from potentially welfare-reducing production.

## CCfD

When the regulator offers a CCfD in $t_1$, the optimisation rationale in $t_3$ is the same as in the social optimum and under *Regulatory Flexibility* (compare Equation 5.19). The solution yields the socially optimal Pigouvian tax level

$$p^{CCfD} = p^{Opt} = p^{Flex} = \hat{d} \tag{5.24}$$

In $t_2$, the investment decision of firms is identical to the rationale under the other regimes and hence:

$$\overline{\chi}^{CCfD} = \begin{cases} \frac{p_s - c_v}{c_i}, & \text{for } c_v \leq p_s \\ 0, & \text{else} \end{cases} \tag{5.25}$$

If the strike price, i.e., the firms' marginal revenue, is larger than their variable costs, they invest in the emission-free technology. Otherwise, it is not worthwhile for firms to enter a CCfD and invest.

In $t_1$, the regulator chooses a strike price that maximises social welfare. She accounts for the firms' reaction to the strike price.

$$p_s = \begin{cases} \mu_D, & \text{for } c_v \leq \mu_D \\ 0 \leq p_s < c_v, & \text{else} \end{cases} \tag{5.26}$$

By assumption $\mu_D > c_v$ holds. Hence, only the first case materialises, and the regulator offers a CCfD that incentivises investments and production. The resulting emission-free production capacity and production coincide with the one under *Commitment*. Hence, socially not optimal production occurs in those cases were $\hat{d} < c_v$. Furthermore, less investments than socially optimal are incentivised ($\overline{\chi}^{CCfD} = \overline{\chi}^{Com} = \frac{\mu_D - c_v}{c_i} < \overline{\chi}^{Opt}$) in order to limit the negative welfare effects of socially not optimal production.

## Welfare comparison

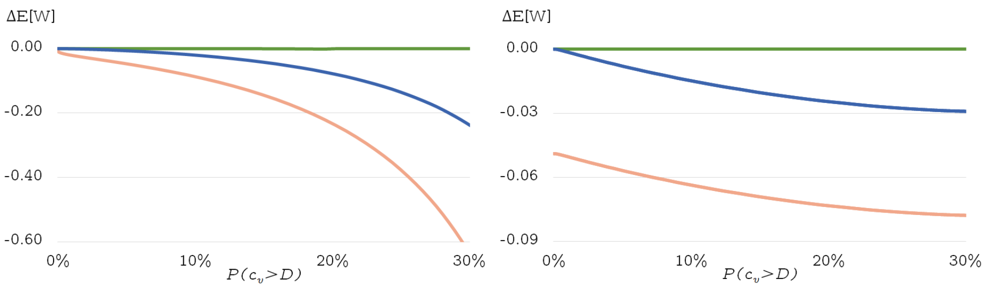
We now compare the welfare of the three carbon pricing regimes in a setting of damage risk, risk-neutral firms, and potentially welfare-reducing emission-free production. *Regulatory Flexibility* yields both the socially optimal emission-free production capacity and carbon price. Under the *CCfD* regime, the carbon price is socially optimal, but too few firms invest in the emission-free technology. *Commitment* falls equally short of the socially optimal investment level. In addition, it achieves a lower consumer surplus due to a sub-optimal carbon price. Hence we derive the ranking:

$$E[\mathcal{W}^{Opt}_{\sigma_D}] = E[\mathcal{W}^{Flex}_{\sigma_D}] \geq E[\mathcal{W}^{CCfD}_{\sigma_D}] \geq E[\mathcal{W}^{Com}_{\sigma_D}] \tag{5.27}$$

First, we find that *Regulatory Flexibility* reaches the social optimum. The firms face a carbon price equal to the marginal environmental damage and, thus, their production decision is socially optimal. Concurrently, as the firms are risk neutral, volatile profits do not impede investments.

Second, welfare falls short of the social optimum if the regulator offers a CCfD. Firms' production decision is independent of the actual carbon damage, such that emission-free production is safeguarded even if it is ex-post socially not optimal. We find that with an increasing probability of ex-post welfare-reducing production, welfare increasingly falls short of the social optimum. The probability of situations in which emission-free production is socially not optimal depends both on the variance ($\sigma_D$) and the expected value ($\mu_D$) of the environmental damage. However, the impact of these two factors differs. As the expected value of environmental damage decreases, the welfare-deterring effect of the *CCfD* regime is partially mitigated as the socially optimal emission-free production capacity decreases, too. Figure 5.7 illustrates these findings for a numerical example.[74] We provide an analytical proof showing the welfare superiority of *Regulatory Flexibility* compared to the *CCfD* regime in Supplementary Material D.4. Figure 5.7a presents welfare changes induced by an increase of the variance of the damage, $\sigma_D$, and Figure 5.7b welfare changes induced by an increase of the mean of the environmental damage, $\mu_D$.

Third, confirming the results of Habermacher and Lehmann (2020), we find that *Com* likewise falls short of the social optimum. Moreover, *Com* performs worse than offering a CCfD. In addition to the welfare-reducing production, committing to a carbon price early on does not only affect producers but also consumers. Suppose the probability of socially not optimal production increases due to an increase of the damage variance, both the production and the consumption decisions are increasingly distorted. As a result, the welfare deterring effect in comparison to the *CCfD* regime increases. In turn, if the probability of socially not optimal production increases due to a reduced difference between $\mu_D$ and $c_v$, the shortfall in welfare is unaffected. We depict these results in Figure 5.7.




(a) Change in $P(c_v > D)$ due to an increase in $\sigma_D$

(b) Change in $P(c_v > D)$ due to a decrease in $\mu_D$

Figure specific parameters in (i): $D \sim N(\mu_D = 2.75, \sigma_D^2 \in [0, 1.5]$ and (ii): $D \sim N(\mu_D \in [2.25, 3.5]), \sigma_D^2 \in (0, 1.5])$.

Figure 5.7.: Difference in welfare compared to social optimum in the presence of damage risk and potentially welfare-reducing production.

### 5.4.3. Numerical application with risk aversion

We complement our analytical results with a numerical application. The primary intention of this numerical exercise is to show how firms' risk aversion alters the effect of potentially welfare-reducing production in case of damage risk. Like

[74] These parameter values are illustrative and do not correspond to empirical estimates. Both, Figure 5.7a and Figure 5.7b, share the parameters regrading the demand $Q(p) = 5 - 0.4p$ and the costs related to the emission-free technology $c_v = 2$ and $c_i = 1$.

in Chapter 5.3, we assume the firms to have a utility which is exponential in profits (i.e., $EU[\pi(\chi)] = E[1 - e^{\pi(\chi)}]$. We find that the introduction of risk aversion reduces the superiority of *Regulatory Flexibility* and generates a trade-off for the regulator between incentivising investments and triggering socially optimal production. Note that these parameter values are illustrative and do not correspond to empirical estimates.[75] For the analysis, we vary two parameters in our model: firms' risk aversion and the distribution of the environmental damage. The latter results in different probabilities of socially not optimal production, i.e., how likely it is that variable costs of abatement are ex-post higher than the marginal environmental damage.

To illustrate the effects of these two variations, we calculate the expected welfare levels of the carbon pricing regimes and compare them to the social optimum. Figure 5.8 depicts the results. In Figure 5.8a, we analyse the impact of firms' risk aversion. Extending our analytical results for the case without risk aversion, *Commitment* and *CCfD* do not result in the social optimum, whereby the *CCfD* regime is superior to *Com*, as it sets the socially optimal carbon price. Firms' risk aversion does not impact the welfare levels as both regimes remove risk for the firms. Also reflecting the results of Chapter 5.4.2, the *Flex* regime results in the social optimum if firms are risk neutral. However, as the risk aversion increases, fewer firms invest in the emission-free technology, whereby the expected welfare of this policy regime decreases. If this investment hampering effect of risk aversion becomes sufficiently large, the *Flex* regime becomes welfare inferior to *Com* and *CCfD*. Hence, there is a trade-off between the effects identified in Chapter 5.3.2 and 5.4.2.

Figure 5.8b shows a similar effect when varying the probability of socially not optimal production by altering the variance of the marginal damage as $P(C_v > D)$ increases in $\sigma_D$.[76]

With increasing volatility, *Flex* becomes less efficient as firms' risk aversion increasingly impedes investments. Offering a CCfD and committing to a carbon price, in contrast, become less efficient due to the increasing probability of welfare-reducing production arising from increased volatility. The level of risk aversion does not impact this effect. Under *Com*, the ex-post socially not optimal carbon price also applies for consumers, such that welfare is lower than in the *CCfD* regime. With an increasing probability of socially not optimal production, the welfare-deterring effect of *CCfD* and *Com* becomes more pronounced compared to the *Flex* regime. Hence, with an increasing probability of welfare-reducing production, the *Flex* regime becomes welfare superior to *Com* and *CCfD*.[77]

[75] Figure 5.8a and Figure 5.8b share the parameters regarding the demand $Q(p) = 5 - 0.1$ and the costs related to the emission-free technology $c_v = 4$ and $c_i = 1$.

[76] In this illustrative example, all carbon pricing regimes achieve the social optimum at $P(C_v > D) = 0$. This is only the case because $\sigma_D = 0$ holds as well.

[77] When changes in the probability of socially not optimal production stem from decreasing the difference between $\mu_D$ and $c_v$, similar effects occur (see Supplementary Material D.6).


(a) Effect of risk aversion

(b) Effect of $P(c_v > D)$ due to altering $\sigma_D$

Figure specific parameters in (a): $\lambda \in [0, 1.5]$, $D \sim N(\mu_D = 2.75, \sigma_D^2 = 0.7803)$ such that $P(c_v > D) = 10\%$ and (b): $\lambda = 1.5$, $D \sim N(\mu_D = 5, \sigma_D^2 \in (0, 2])$.

Figure 5.8.: Difference in welfare compared to social optimum in the presence of damage risk, potentially welfare-reducing production and risk aversion.

Both numerical simulations show that the superiority of the respective carbon price regime is ambiguous and depends on specific parameters. However, if the regulator had to choose between offering a CCfD and committing to a carbon price early on, i.e., before the risk resolves, it is always beneficial to provide a CCfD.

## 5.5. Discussion

In the previous chapters, we showed under which circumstances offering a CCfD can be a valuable policy measure. CCfDs could increase welfare compared to a flexible carbon price if the regulator expects that, first, firms will significantly under-invest in an abatement technology in the presence of risk and, second, the probability of welfare-reducing emission-free production is low. In other words, a CCfD is only beneficial if the benefit from the additional abatement that it incentivises outweighs the risk that it supports a technology that is socially not optimal.

There are several considerations beyond our model setup determining whether a CCfD is an efficient policy instrument. First, it matters who can enter a CCfD. While policy constraints may imply that a regulator should offer CCfDs only to limited sectors, for instance, heavy industry, our research indicates that they may be helpful in a broader range of settings in which agents make insufficient investments for decarbonisation because of the presence of risk. Second, the variance of the variable at risk may increase with a longer duration of the CCfD. Hence, the probability of supporting an ex-post welfare-reducing technology may increase with the duration. Third, the process of how the regulator grants a CCfD determines its impact on welfare. Suppose the CCfD only addresses the risk regarding the valuation of damage. In that case, the strike price should equal the regulator's damage expectation, and she can offer the CCfD to any interested party. If, however, the regulator aims to address private information, for instance, on the expected variable costs or firms' risk aversion, an auction process may be preferable to minimise costs for the regulator. Likewise, this holds if the CCfD involves an additional subsidy.

In addition to the carbon price risk, the regulator may introduce an instrument, similar to a CCfD, that assumes risks on the firms' variable costs. For instance, the proposal of the German funding guidelines for large-scale decarbonisation investments in the industrial sector includes such an extended risk assumption by the government (BMU, 2021). The extended risk-bearing could reduce complementary investment subsidies from the regulator to risk-averse firms, as shown by Richstein et al. (2021).[78] However, the regulator would safeguard firms in situations with ex-post socially not optimal production, i.e., unexpectedly high variable costs which exceed marginal damage. Thereby, the probability of financing an ex-post socially not optimal technology would increase, decreasing welfare. This measure would need a reasonable justification, for instance, a significant level of firms' risk aversion or a sufficiently low probability that the low-carbon technology is socially not optimal.

Our research relies on several assumptions that, if relaxed, might dampen the identified effects and potentially change the policy rankings. Noteworthy, we assume the absence of shadow cost of public funding. Because taxation has distortionary effects, public expenses might come at a cost (e.g. Ballard and Fullerton, 1992, for a review). Including shadow costs of public funds into our model might yield two effects. First, the carbon price would optimally be higher than the marginal environmental damage. The regulator would value one unit of revenue from the carbon price at more than one unit of consumer surplus because it allows other distortionary taxes to be reduced (see, e.g., Helm et al., 2003, for a discussion of this *weak form* of a double-dividend). Second, offering a CCfD would be more costly, and the regulator might require a premium for providing the contract and safeguarding the investments. If this is the case, the benefits of offering a CCfD would partially diminish. We expect a trade-off between the benefit of increased investments and the costs of additional public funds when comparing a *CCfD* regime with *Regulatory Flexibility* and *Commitment*.

Similarly, the regulator may also be risk averse. In this case, we can see the three carbon pricing regimes from the angle of who bears the risk (see Hepburn, 2006, for a discussion of risk-sharing between the government and the private sector). While the risk remains with the firms under *Regulatory Flexibility*, the regulator assumes the risk under *Commitment* and *CCfD*. Suppose a risk-averse regulator bears the risk in the presence of an unknown valuation of environmental damage. To reduce the negative welfare effects in case of great environmental

[78] In our model, e.g., in Chapter 5.3.3, such a scheme would lower the average strike price to the expected damage and reduce the average spending of the regulator.

damage, she would set a higher strike price when offering a CCfD or increase the carbon price under *Commitment*. In contrast, with variable cost risk, she prefers incentivising a lower level of investment to reduce her risk. This aspect may change the policy ranking of the three carbon pricing regimes.

We analyse a setting where carbon prices determined by the marginal environmental damage result in a demand that exceeds the optimal emission-free production capacity. However, we could think of settings, in which demand can be covered entirely by the emission-free production. In these settings, the conventional technology would not produce. Hence, the marginal utility of consumption, given the production capacity of the emission-free technology, would determine the product price. In consequence, if firms would assume the product price to be set by the conventional technology, some of the firms using the emission-free technology would incur a loss. Instead, firms would anticipate a product price below the carbon price and reduce their investment. The marginal firm would avoid a loss by balancing its investment costs with the contribution margin, which is reduced to lower prices. If the firm cannot pass through its investment costs, it would not invest in the first place. The model would not have an equilibrium.

Broadly speaking, if the regulator aims to fully replace the conventional technology, offering a CCfD is not an adequate policy. The instrument implicitly assumes that the profit of the emission-free technology is linked to the carbon price. This is only the case if the conventional technology sets the market price because the emission-free technology is not subject to the carbon price. For the same reason, CCfDs can only support a technology switch in an existing product market but not the market ramp up for a new product.

Our model results focus on the effects of each type of risk separately. In reality, stakeholders likely face damage and cost risk simultaneously. If the two risks are uncorrelated, their effects are additive. Variable cost risk can lead to an investment that is too low. Damage risk can affect both investment and consumption. Hence, the welfare ranking in Equation 5.10 holds and the superiority of Commitment or Regulatory Flexibility depends on the concrete circumstances. If risks are positively correlated, high environmental damage indicates high variable costs and vice versa. In this case, the emission-free production is likely to be ex-post socially optimal as $\mu_{C_V} > \mu_D$ holds. Results are then similar to the setting in Chapter 5.3. If risks are negatively correlated, high environmental damage indicates low variable costs and vice versa. In the case of high damage and low variable costs, emission-free production is socially optimal. In the case of low damage and high variable costs, in turn, the emission-free production is likely to be welfare reducing. Hence, if risks are negatively correlated, the situation is similar to the setting in Chapter 5.4.

The last simplification of our model we like to stress is the assumption of constant marginal environmental damage. We do not expect our main findings regarding the ranking of the carbon pricing regimes to change if we alleviate this assumption. If the marginal environmental damage was non-constant, the regulator would still choose the Pigouvian tax level after the firms have invested. In contrast to our assumption, the tax level would depend on the number of firms using the emission-free technology, i.e., total emissions. If markets are competitive, the impact of an individual firm on total emissions is negligible, and firms' investment decisions would not change compared to our model.

## 5.6. Conclusion

The decarbonisation of the industry sector requires large-scale irreversible investments. However, the profitability of such investments is subject to risk, as both, the underlying revenue and the associated costs of switching to an emission-free production process, are unknown and cannot be sufficiently hedged. The European Commission's Hydrogen Strategy and the *Fit for 55* package propose Carbon Contracts for Differences (CCfDs) to support firms facing large-scale investment decisions. Such contracts effectively form a hedging instrument to reduce the firms' risks.

With this research, we contribute to the understanding of how regulators should design this instrument and under which circumstances it is beneficial to offer a CCfD. We analyse the effects of a CCfD in the presence of risks stemming from environmental damage and variable costs on the decisions of a regulator and risk-averse firms facing an irreversible investment decision. Applying an analytical model, we compare three carbon price regimes against the social optimum: *Regulatory Flexibility*, *Commitment*, and offering a *CCfD*.

We conclude that a CCfD can be a welfare-enhancing policy instrument, as it encourages investments when firms' risk aversion would otherwise impede them. Additionally, offering a CCfD is always better than committing early to a carbon price as CCfDs incentivise investments in the same way while keeping the possibility to set the carbon price flexibly if new information,e.g., on the environmental damage, is available. However, if it is likely that the production of the emission-free technology turns out to be socially not optimal, CCfDs have the disadvantage that the regulator is locked in her decision, and she may distort the market clearing. In these situations, *Regulatory Flexibility* can be welfare superior to offering a CCfD. The comparison of *Regulatory Flexibility* and *Commitment* depends on the type of risk involved. With damage risk, *Regulatory Flexibility* is superior to *Commitment* if the level of risk aversion is low and the elasticity of demand is high. With variable cost risk, in contrast, *Regulatory Flexibility* performs worse than *Commitment*. While the regulator can only set the carbon price after the firm's investment under *Regulatory Flexibility*, she can balance additional investment incentives and the consumption level under *Commitment*.

This research focuses on the effects of CCfDs, aiming at mitigating the impact of risk regarding investments in emission-free technologies. Further research analysing CCfDs with more complex features and the interactions between CCfDs and other policy instruments may broaden our understanding of this instrument. To begin with, regulators may combine a CCfD with a subsidy payment to firms. This combination may be justified if the future carbon price is too low to incentivise sufficient emission-free investments, e.g., in the presence of learning effects or other positive externalities. Research could focus on whether combining a CCfD and a subsidy has advantages over offering both instruments separately. Additionally, proposals for the use of CCfDs focus on sectors competing in international markets. Our model assumes complete cost pass-through of the carbon price and, hence, increased revenues for firms investing in abatement. If not all firms on an international market face a (similar) carbon price, this may not hold. It remains open how the design of CCfDs would need to change in such settings to ensure investments' profitability. Future analyses could consider the possibility of introducing carbon border adjustment mechanisms, such that producers from countries without a carbon price at the domestic level cannot offer the goods at a lower price. The question how other hedging instruments offered by private actors compare to CCfDs is also worth analysing in more detail. Moreover, future research could assess the role of shadow costs of public funds by extending our model in this regard. As pointed out in Chapter 5.5, we assume payments under a CCfD to be welfare-neutral. Considering shadow costs of public funds may worsen the welfare ranking of CCfDs compared to pure carbon pricing regimes.

# A. Supplementary Material for Chapter 2

## A.1. Optimal spot market result

Consider a social planner solving the optimization problem (A.1a-A.1e). The social planner maximizes overall welfare, consisting of the consumer surplus from the participation at the spot market minus the electricity generation costs. Thus, she jointly optimizes the cost-minimal dispatch at the spot market level. The solution is constrained by the equilibrium condition, which requires supply to equal demand (A.1b-A.1c) and the restriction of the transmission line (A.1d).

$$\max_{l,\mathbf{q},\mathbf{D}} W = \int_0^{D_n} [p_n(z)]\, \mathrm{d}z + \int_0^{D_s} [p_s(z)]\, \mathrm{d}z - \sum_i c_i q_i \tag{A.1a}$$

$$s.t. \quad D_n + l = q_n \tag{A.1b}$$

$$D_s - l = q_s \tag{A.1c}$$

$$|l| \leq \overline{L} \tag{A.1d}$$

$$q_n, q_s, D_n, D_s \geq 0 \tag{A.1e}$$

The optimal solution yields a node-specific result. The optimal level of generation in each node is given by (A.2) and depends on the spatial choice of the demand investment.

$$q_i^* = \begin{cases} D_n^* + \overline{L} & \text{for } i = n \\ D_s^* - \overline{L} & \text{for } i = s \end{cases} \tag{A.2}$$

Since by assumption, generation costs are higher in the south and demand exceeds the capacity limit of the transmission line, the network is congested and fully utilized up to the capacity limit, i.e. $l^* = \overline{L}$. The prices reflect the marginal costs at the respective nodes with $p_n^* = c_n$ and $p_s^* = c_s$ and thus, producer surplus equals zero. Due to the price difference between the nodes and the quantity transmitted from node $n$ to node $s$, a positive congestion rent $(c_s - c_n)\overline{L}$ results, which is accounted to the TSO budget.

## A.2. Fixed network tariffs

The first-order conditions of the Lagrangian of the optimization problem (2.2a-2.2c) are:

$$\frac{\partial L}{\partial f_n} = \lambda\omega_n - \mu = 0 \tag{A.3}$$

$$\frac{\partial L}{\partial f_s} = \lambda\omega_s + \mu = 0 \tag{A.4}$$

$$\frac{\partial L}{\partial \lambda} = \sum_i \omega_i f_i - F + (c_s - c_n)\overline{L} = 0 \tag{A.5}$$

$$\mu\frac{\partial L}{\partial \mu} = \mu[c_s\overline{D} + f_s - c_n\overline{D} - f_n] = 0 \tag{A.6}$$

$$\frac{\partial L}{\partial \mu} = c_n\overline{D} + f_n \leq c_s\overline{D} + f_s \tag{A.7}$$

$$\mu \geq 0 \tag{A.8}$$

The complementary slackness condition (A.6) is true if either (1) $\mu = 0$, (2) $c_n\overline{D} + f_n = c_s\overline{D} + f_s$, or (3) both.

**Case 1:** $\mu = 0$. Plugging $\mu = 0$ into the first two equations yield $\lambda = 0$, as $\omega_i > 0$. The fixed network tariffs $\boldsymbol{f}$ can take every possible values that satisfy equation (A.5) and (A.7).

**Case 2:** $\mu > 0$ and $c_n\overline{D} + f_n = c_s\overline{D} + f_s$. Using the equality, we can solve for the fixed network tariffs, e.g. $f_s = \frac{F-(c_s-c_n)(\overline{L}+\overline{D}\omega_n)}{\omega_n+\omega_s}$. In addition, $\lambda = \frac{-\mu}{\omega_s}$ and $\lambda = \frac{\mu}{\omega_n}$. We can rule this case out, as it would require $\omega_n = -\omega_s$.

**Case 3:** $\mu = 0$ and $c_n\overline{D} + f_n = c_s\overline{D} + f_s$. Again, we can solve for the fixed network tariffs, e.g. $f_s = \frac{F-(c_s-c_n)(\overline{L}+\overline{D}\omega_n)}{\omega_n+\omega_s}$. Again, plugging $\mu = 0$ into the first equation yields $\lambda = 0$.

Hence, cases 1 and 3 are possible solutions of the optimization and both require $\lambda = 0$. As the shadow variable of the budget constraint is zero, the constraint (and the fixed network tariffs) has no influence on social welfare. Hence, fixed network tariffs can be considered as a welfare neutral payment.

## A.3. Volume-based network tariffs

### A.3.1. Deriving the Ramsey-Boiteux inverse elasticity rule

We use equation (2.7), substitute $p_i = c_i + \tau_i$ on the right-hand side and make use of the relationship $\tau_i = p_i - c_i$ to expand the equation. We denote the elasticity of demand with

$$\epsilon_i(p_i) = -\frac{\partial D_i(p_i)/\partial p_i}{D_i(p_i)/p_i} \tag{A.9}$$

Plugging the elasticity in, we then obtain the Ramsey-Boiteux formula, which is the classical inverse elasticity rule:

$$\frac{p_i - c_i}{p_i} = \frac{\lambda}{\lambda+1} \cdot \frac{1}{\epsilon_i(p_i)} \tag{A.10}$$

We can see that a change in price $\partial p_i$ is equivalent to a change in network tariff $\partial \tau_i$.

### A.3.2. Solution for restricted volume-based network tariffs and boundary for binding dynamic consistency constraint

To solve for the optimal volume-based network tariff with a binding dynamic consistency constraint, we use the relation of network tariffs from (2.4b) and (2.4c). As (2.4c) is binding, it follows that $\tau_n = \tau_s + c_s - c_n$. Using the budget constraint (2.4b), we yield

$$\hat{\tau}_s = \frac{F - (c_s - c_n)(\overline{L} + D_n(c_n + \hat{\tau}_n))}{D_s(c_s + \hat{\tau}_s) + D_n(c_n + \hat{\tau}_n)} \tag{A.11}$$

and

$$\hat{\tau}_n = c_s - c_n + \frac{F - (c_s - c_n)(\overline{L} + D_n(c_n + \hat{\tau}_n))}{D_s(c_s + \hat{\tau}_s) + D_n(c_n + \hat{\tau}_n)}. \tag{A.12}$$

To derive the boundary at which the dynamic efficiency constraint is binding, we plug in the optimal static volume-based network tariff (2.9) into $c_n + \tau_n^* = c_s + \tau_s^*$:

$$c_n + \frac{F - (c_s - c_n)\overline{L}}{\frac{\rho_n(\tau_n^*)}{\rho_s(\tau_s^*)} D_s(c_s + \tau_s^*) + D_n(c_n + \tau_n^*)} = c_s + \frac{F - (c_s - c_n)\overline{L}}{\frac{\rho_s(\tau_s^*)}{\rho_n(\tau_n^*)} D_n(c_n + \tau_n^*) + D_s(c_s + \tau_s^*)}, \tag{A.13}$$

which simplifies to

$$\frac{\frac{\partial D_s(c_s+\tau_s^*)}{\partial \tau_s^*} D_n(c_n + \tau_n^*) - \frac{\partial D_n(c_n+\tau_n^*)}{\partial \tau_n^*} D_s(c_s + \tau_s^*)}{\frac{\partial D_n(c_n+\tau_n^*)}{\partial \tau_n^*} D_s(c_s + \tau_s^*)^2 + \frac{\partial D_s(c_s+\tau_s^*)}{\partial \tau_s^*} D_n(c_n + \tau_n^*)^2} = \frac{c_s - c_n}{F - (c_s - c_n)\overline{L}}. \tag{A.14}$$

The solution depends on the costs that need to be recovered, the relation of the generation costs and the relation of the demand functions in the respective nodes.

### A.3.3. Volume-based network tariffs under uniform pricing

To solve for the case that the dynamic efficiency constraint is non-binding, i.e., $\mu = 0$, we make use of equation (2.11) and substitute the quasi-elasticity $\rho_i$.

$$\tau_s^* = \frac{\rho_n(\tau_n^*)}{\rho_s(\tau_s^*)}\tau_n^* + c_s - c_n \tag{A.15}$$

It still holds that the elasticity in one node affects the network tariff in the other node. In addition, the network tariffs also depend on marginal generation costs. Again, we can solve for the respective network tariffs using the budget constraint of the TSO. The network tariff in the south is equal to:

$$\tau_s^* = \frac{F - (c_s - c_n)\overline{L}}{\frac{\rho_s(\tau_s^*)}{\rho_n(\tau_n^*)}D_n(c_n + \tau_n^*) + D_s(c_n + \tau_s^*)} + c_s - c_n, \tag{A.16}$$

while the structure of the solution for the north is similar to the one under zonal pricing:

$$\tau_n^* = \frac{F - (c_s - c_n)\overline{L}}{\frac{\rho_n(\tau_n^*)}{\rho_s(\tau_s^*)}D_s(c_n + \tau_s^*) + D_n(c_n + \tau_n^*)} \tag{A.17}$$

For the case that the dynamic efficiency constraint is binding, we can use (2.10b) and (2.10c). This yields:

$$\hat{\tau}_s = \hat{\tau}_n = \frac{F - (c_s - c_n)(\overline{L} + D_s(c_s + \hat{\tau}_s))}{D_s(c_s + \hat{\tau}_s) + D_n(c_n + \hat{\tau}_s)} \tag{A.18}$$

We can check when the dynamic efficiency constraint gets binding, by substituting (A.16) and (A.17) into $\tau_n \leq \tau_s$ :

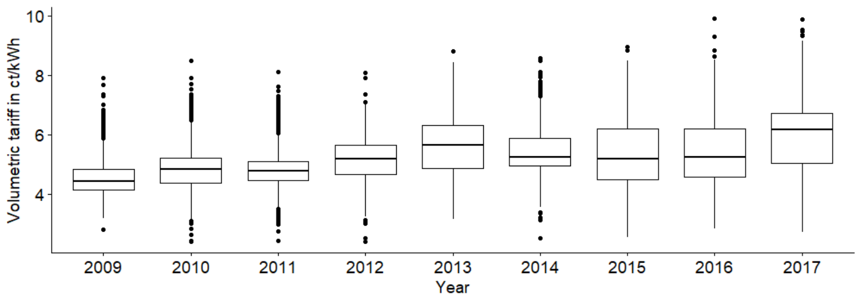
$$D_n(c_n + \tau_n^*)\frac{\partial D_s(c_s+\tau_s^*)}{\partial \tau_s^*}[R + (c_n - c_s)D_s(c_s + \tau_s^*)] \leq \frac{\partial D_n(c_n+\tau_n^*)}{\partial \tau_n^*}D_s(c_s + \tau_s^*)[R + (c_n - c_s)D_n(c_n + \tau_n^*)]$$
$$\text{with} \quad R = F - (c_s - c_n)\overline{L} \tag{A.19}$$

The result is similar to the regulatory setting with zonal pricing and depends on the costs that need to be recovered, the relation of the generation costs and the relation of the demand functions in the respective nodes.

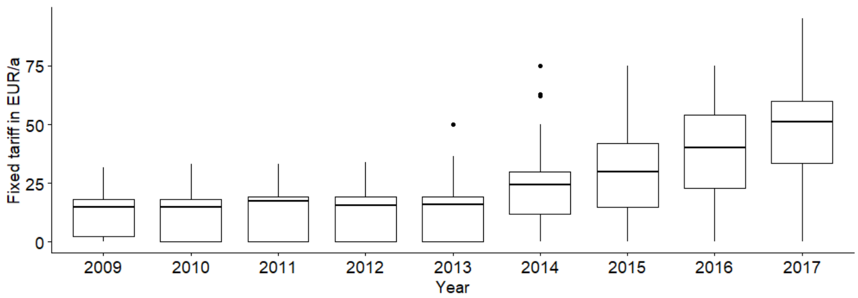
# B. Supplementary Material for Chapter 3

## B.1. Further data statistics

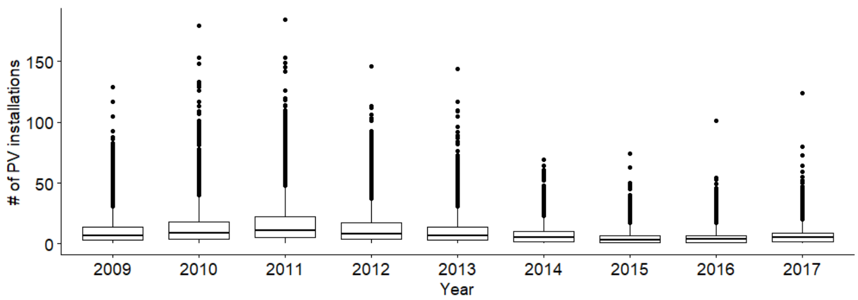
Figure B.1 illustrates the variation of the volumetric network tariffs, the fixed network tariff and the number of PV installations between the years 2009 and 2017.




(a)




(b)




(c)

Figure B.1.: Temporal variation of (a) the volumetric network tariffs, (b) the fixed network tariff, and (c) the number of PV installations

As shown in figure B.1 (a) and (b) network tariffs have risen steadily over the period under consideration. In particular, the median fixed tariff more than doubled between 2009 and 2017. In addition, one can see that for both the volumetric and fixed tariff the regional dispersion in the 25th to 75th percentile across postcode areas has increased substantially, while the regional dispersion of the number of PV installations has tended to decrease (see figure B.1 (c)).

## B.2. Further robustness checks

With the following robustness checks in table B.1, we additionally check our assumption that households respond to the previous years' tariffs, i.e., $tariff_{i,t-1}$, by including tariffs further in the past. We test a regression with $tariff_{i,t-2}$ and one alternative with $tariff_{i,t-3}$ instead of $tariff_{i,t-1}$.

Table B.1.: Further robustness checks: time lags

| Model: | (11) | (12) | (13) |
|---|---|---|---|
| Dependent Variable: | # of PV | # of PV | # of PV |
| tariff$_{t-1}$ | | | 0.0231** |
| | | | (0.0086) |
| tariff$_{t-2}$ | 0.0245*** | | -0.0107 |
| | (0.0071) | | (0.0091) |
| tariff$_{t-3}$ | | -0.0050 | -0.0031 |
| | (0.0081) | (0.0082) | |
| income (log of) | -0.1004 | -0.4194 | -0.4253 |
| | (0.2140) | (0.3182) | (0.3184) |
| housetype | -0.0014 | 0.0034 | 0.0038 |
| | (0.0047) | (0.0054) | (0.0054) |
| age | 0.0366* | 0.0331 | 0.0336* |
| | (0.0155) | (0.0170) | (0.0171) |
| buildings (log of) | -0.0403 | 0.01267 | 0.1075 |
| | (0.1839) | (0.2178) | (0.2186) |
| *Fit statistics* | | | |
| observations | 56,269 | 48,084 | 48,083 |
| AIC | 282,959.3 | 235,622.8 | 235,605.7 |
| BIC | 426,858.3 | 376,482.9 | 376,483 |
| Log-Likelihood | -125,380.6 | -101,769.4 | -101,758.9 |

*Robust standard errors clustered at the postcode level.*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The results show that the impact of the lagged network tariffs $tariff_{i,t-2}$ and $tariff_{i,t-3}$ decreases compared to the impact of $tariff_{i,t-1}$. An encompassing test further supports this finding. The coefficient of $tariff_{i,t-1}$ is the only significant variable, at least at a 5 percent level, compared to $tariff_{i,t-2}$ and $tariff_{i,t-3}$. Hence, the results further support our assumption.

Table B.2.: Further robustness check: regional results

| Model: | (14) | |
|---|---|---|
| Dependent Variable: | # of PV | |
| BW × $\text{tariff}_{t-1}$ | 0.1652*** | (0.0197) |
| BY × $\text{tariff}_{t-1}$ | 0.0290*** | (0.0085) |
| BE × $\text{tariff}_{t-1}$ | -0.1352 | (0.0929) |
| BB × $\text{tariff}_{t-1}$ | 0.0559* | (0.0232) |
| HB × $\text{tariff}_{t-1}$ | 0.2740** | (0.0872) |
| HH × $\text{tariff}_{t-1}$ | 0.0659 | (0.1405) |
| HE × $\text{tariff}_{t-1}$ | -0.0058 | (0.0238) |
| MV × $\text{tariff}_{t-1}$ | 0.0869* | (0.0368) |
| NI × $\text{tariff}_{t-1}$ | 0.0607** | (0.0192) |
| NW × $\text{tariff}_{t-1}$ | 0.0570** | (0.0198) |
| RP × $\text{tariff}_{t-1}$ | -0.0678** | (0.0255) |
| SL × $\text{tariff}_{t-1}$ | -0.0508 | (0.0624) |
| SN × $\text{tariff}_{t-1}$ | 0.1360*** | (0.0257) |
| ST × $\text{tariff}_{t-1}$ | 0.0678* | (0.0300) |
| SH × $\text{tariff}_{t-1}$ | 0.1550*** | (0.0309) |
| TH × $\text{tariff}_{t-1}$ | 0.2682*** | (0.0432) |
| income (log of) | -0.0273 | (0.1487) |
| housetype | 0.0044 | (0.0043) |
| age | 0.0158 | (0.0136) |
| buildings (log of) | -0.1350 | (0.1685) |
| *Fit statistics* | | |
| observations | 64,531 | |
| AIC | 329,958 | |
| BIC | 476,636 | |
| Log-Likelihood | -148,816 | |

*Robust standard errors clustered at the postcode level.*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

In another model variation (14, table B.2), we include an interaction term between binary dummy variables for the 16 German states and the network tariff. This estimation allows us to compare the regional effect of network tariffs on PV investments. The model specification is based on the assumption that while the effect of the network tariffs differs between states, the effects of the covariates and time-specific fixed effects do not. The results suggest that network tariffs significantly impact PV investments in a selection of states (BW, BY, SN, SH, TH), with the highest effect being in HB and the lowest in BY. An explanation for the different sizes of the effect could be differences in awareness for PV investments in different states. A reason why we cannot identify a significant effect for most states could be the low within-variance of network tariffs in the respective state. Because of the low within-variance of the state-specific tariffs and because the results depend on the assumptions made about the effects of the covariates and the annual fixed effects, the results should be treated with caution. Therefore, we interpret the results as indicative of the existence of regional differences in the effect of network tariffs on PV investments. However, a detailed analysis of these differences is outside the scope of this paper and remains subject to future research.

## B.3. Within-variance of the covariates in our sample

Using a fixed effects approach, we exploit the within-region variation of our explanatory variables to identify their impact on our dependent variable. By including time fixed effects, we control for overall developments over time. While this allows us to isolate the effects under investigation, i.e., the effect of network tariffs on PV investments, it prevents us from making statements about the influence of covariates that have little or no within-region variation after controlling for time fixed effects. By regressing the explanatory variables on our fixed effects, we calculate the variation in these variables used to estimate the coefficients in our fixed effects model. The standard deviations of these residuals, calculated for the preferred specification of our model (1) and the specification without the postcode-specific slope (7), are shown in table B.3. The given values may aid in interpreting and classifying the estimated treatment effects of the explanatory variables. For a detailed analysis on the interpretation of fixed effects, refer to Mummolo and Peterson (2018).

Table B.3.: Within standard deviation

| Model: | (1) | (7) |
|---|---|---|
| tariff$_{t-1}$ (ct/kWh) | 0.34 | 0.49 |
| income (log of) | 0.02 | 0.03 |
| housetype (%) | 0.63 | 0.96 |
| age | 0.18 | 0.43 |
| buildings (log of) | 0.02 | 0.02 |

# C. Supplementary Material for Chapter 4

## C.1. Synthetic RES generation and forecast error samples

This section reports the outcomes of the stochastic modeling processes applied to wind and solar power generation. Detailed statistics on the forecasts for wind and solar generation are presented in Table C.2 and C.1. The columns labeled 'Min.' and 'Max.' denote the years with the minimum and maximum average generation, respectively, highlighting the inter-annual variability in renewable output. The stochastic process effectively replicates the average production levels and their associated volatility, while also capturing the observed range between annual generation volumes.

Table C.1.: Summary of PV capacity factor samples and actual data in [%].

| | Actuals | | | Samples | | |
|---|---|---|---|---|---|---|
| | Min. | Mean | Max. | Min. | Mean | Max. |
| Mean | 9 | 10 | 11 | 9 | 10 | 11 |
| Std. | 14 | 15 | 17 | 14 | 15 | 17 |
| CoV | 152 | 153 | 152 | 152 | 154 | 154 |
| Min. | 0 | 0 | 0 | 0 | 0 | 0 |
| Max. | 59 | 69 | 67 | 59 | 77 | 81 |

Table C.2.: Summary of Wind capacity factors samples and actual data in [%].

| | Actuals | | | Samples | | |
|---|---|---|---|---|---|---|
| | Min. | Mean | Max. | Min. | Mean | Max. |
| Mean | 17 | 20 | 23 | 17 | 20 | 23 |
| Std. | 13 | 16 | 18 | 14 | 16 | 17 |
| CoV | 78 | 79 | 77 | 84 | 78 | 75 |
| Min. | 1 | 0 | 0 | 1 | 1 | 0 |
| Max. | 73 | 86 | 78 | 88 | 86 | 89 |

To evaluate the performance of the stochastic model in replicating forecast errors, Table C.3 presents standard forecast accuracy metrics, specifically the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

These metrics are benchmarked against observed historical data. The results indicate that the Gaussian Mixture Models (GMMs) effectively capture both the magnitude and distribution of absolute and relative forecast deviations.

Table C.3.: Summary of forecast errors metrics for wind and solar.

| | Wind | | | | PV | | | |
|---|---|---|---|---|---|---|---|---|
| | MAE [MWh] | | MAPE [%] | | MAE [MWh] | | MAPE [%] | |
| | Actual | Samples | Actual | Samples | Actual | Samples | Actual | Samples |
| Mean | 267 | 277 | 14 | 13 | 98 | 106 | 10 | 13 |
| Min. | 224 | 258 | 13 | 11 | 82 | 89 | 8 | 13 |
| Max. | 298 | 299 | 16 | 14 | 143 | 124 | 14 | 14 |

## C.2. Regression results

Figure C.1 presents the in-sample forecast based on the regression estimates for the day-ahead market for the year 2024.

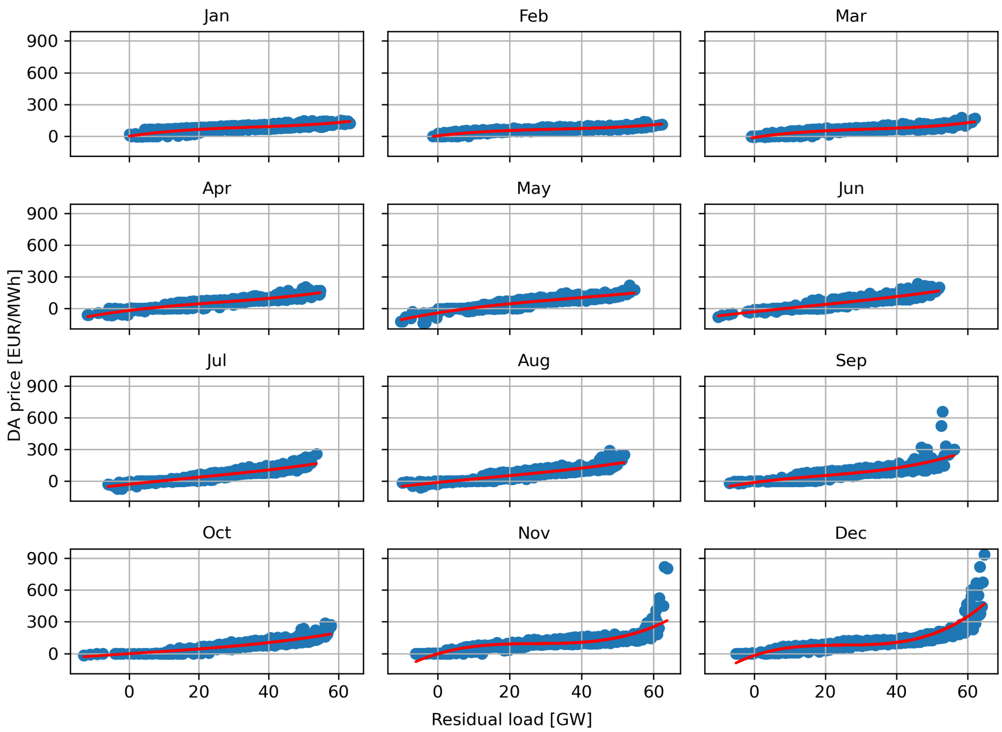



Figure C.1.: Day-ahead regression results by month.

The results for the intraday market regression are reported in Table C.4. In this context, forecast errors are defined as the difference between realized and forecasted generation, where positive values indicate excess supply, which have a negative effect on intraday prices. The estimated coefficients are broadly consistent with the magnitudes reported in earlier literature, such as Kulakov and Ziel (2021). The intercept reflects the observed intraday price premium in 2024, which may be attributed to the presence of a forward or risk premium (Obermüller, 2017) or to unobserved factors such as unplanned outages, which have a price-increasing effect on the intraday market.

PV forecast errors exert a stronger influence on intraday prices than wind forecast errors. This differential impact may stem from the temporal patterns of PV forecast errors, which typically occur during midday ramps — periods when flexible thermal generation units are either offline or undergoing their own ramping processes, thus limiting system flexibility. The existence of threshold effects related to the share of demand met by renewable energy sources is shown by Kiesel and Paraschiv (2017).

Table C.4.: ID regression results.

| | Coefficients | Standard Errors | t-values | p-values |
|---|---|---|---|---|
| $\beta_0$ | 2.45 | 0.522 | 4.696 | 0.000 |
| $\beta_1(p_t^{DA})$ | 1.07 | 0.006 | 167.119 | 0.000 |
| $\beta_2(FE_t^{PV})$ | -2.66 | 0.118 | -22.654 | 0.000 |
| $\beta_3(FE_t^{PV})^2$ | 0.15 | 0.012 | 12.289 | 0.000 |
| $\beta_4(FE_t^{Wind})$ | -1.96 | 0.070 | -27.917 | 0.000 |
| $\beta_5(FE_t^{Wind})^2$ | -0.02 | 0.006 | -3.598 | 0.000 |

## C.3. An application of Modern Portfolio Theory to hybrid PV-BESS assets

Given the negative correlation between PV and BESS margins, Modern Portfolio Theory (MPT) can be used to determine the optimal ratio between the PV and BESS assets. MPT suggests that investors can optimize their portfolios to achieve the highest expected return for a given level of risk, emphasizing the importance of diversification. Combining assets with varying but correlated returns, such as renewable generation assets and batteries, minimizes overall portfolio risk. MPT introduces the concept of an efficient frontier, representing the set of portfolios that offer the best risk-return trade-offs. To construct the efficient frontier, the returns for each technology are calculated by dividing the respective contribution margins by the corresponding annuities, based on the cost data in Table 4.1. Given these returns, the average, standard deviation, and covariance matrix are computed. Varying the financial weights of the technologies, while ensuring their sum equals one, yields different portfolio combinations. Portfolio returns and standard deviations are then determined using standard portfolio theory formulas. The efficient frontier comprises all portfolios that maximize expected return for a given level of risk. The capital allocation line is based on the optimal portfolio determined by the Sharpe ratio. The Sharpe ratio measures the risk-adjusted return of an investment by comparing its excess return over a risk-free rate to the standard deviation of its returns. The calculation assumes a risk-free rate of 2.41% based on the interest rate for a 10-year German government bond (European Central Bank, 2025). Finally, the physical weights of each technology are derived by scaling the financial weights by their respective annuities. Unlike financial weights, the physical weights represent the share of each respective technology in megawatts (MW). Figure C.2 shows the efficient frontier for the hybrid PV-BESS systems in the base case and the corresponding physical weights of the technologies. The selection of the optimal portfolio depends on the risk aversion of investors.

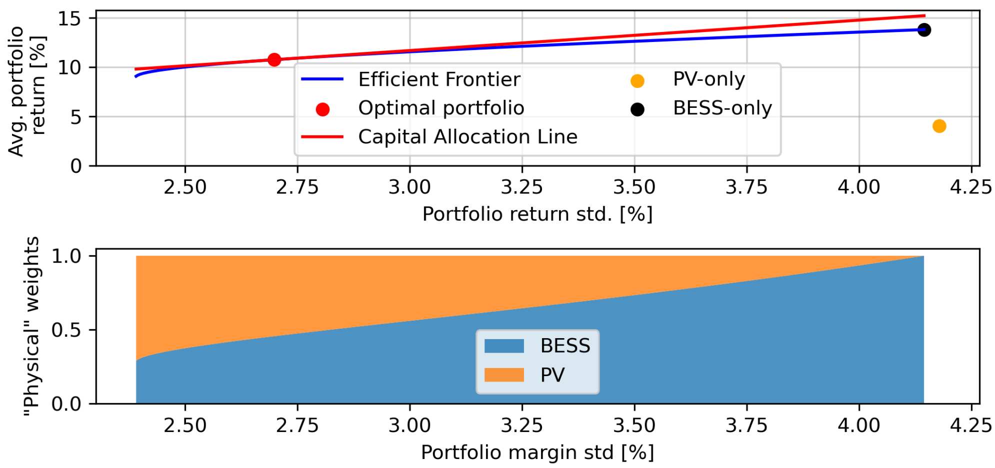



Figure C.2.: Efficient frontier of hybrid PV-BESS system and analysis of respective weights.

The optimal portfolio, based on the Sharpe ratio, and the respective standalone assets are highlighted. The optimal hybrid PV-BESS system has a PV-to-BESS ratio of 1.2:1. For a total system capacity of 4 MW in the base case, this translates to a configuration of 2.2 MW PV and 1.8 MW battery capacity. As investors' risk appetite increases, the share of batteries in the portfolios along the efficient frontier rises. In contrast to a standalone BESS, a standalone PV asset (PV-only) is not part of the efficient frontier. PV-only assets deliver comparatively low returns while exhibiting a high risk. Therefore, an investment in a standalone PV asset would not be profitable in this case study.

It is important to note that the financial performance of each asset depends on the underlying electricity price structure (cf. Section 4.4.5). Investment decisions require an assessment of expected price trajectories over the full asset's operational lifetime. Nevertheless, the proposed methodology offers a robust framework that is applicable over extended horizons. Moreover, investment and financing costs play a major role in determining the optimal portfolio. Future research could enhance the approach with different technology options, such as wind or electrolysis, and consider a broader market portfolio as an alternative investment.

## C.4. Grid connection charges in Germany

Efficiently designed network tariffs play a critical role in guiding investment decisions and supporting market design, particularly in power systems operating under uniform pricing regimes (Arnold et al., 2022, Jeddi and Sitzmann, 2021). Such tariffs include grid connection charges —upfront, one-time payments required for new grid connections — which are intended to signal grid-related costs and steer investments accordingly (Jeddi and Sitzmann, 2019). In Germany, the regulatory framework surrounding grid connection charges for batteries is currently under legal and regulatory scrutiny. Historically, BESS assets have been subject to the same principles as other consumers, with charges based on the system's grid withdrawal capacity and the applicable capacity tariff at the corresponding voltage level of the DSO or TSO. However, a recent court decision classified this practice as discriminatory, prompting the BNetzA to refer the matter to the Federal Court of Justice (OLG Düsseldorf, 2024). In its subsequent position paper, the BNetzA reaffirmed the general appropriateness of applying grid connection charges to BESS based on capacity tariffs (BNetzA, 2024). The paper proposes a tiered system for TSOs, consisting of five levels, with the highest tier reflecting the full capacity charge and the lowest set at 20% of that amount. The applicable tier is to be determined by the locational value of the connection, reflecting grid congestion levels and the need for expansion. This locational differentiation aims to incentivize siting in grid-favorable areas. Based on the current proposal and the published capacity tariffs of German TSOs, the current proposal would imply a cost of approximately EUR 20–100 per kW for BESS connections to the extra-high voltage grid. This range corresponds to roughly 3–13% of the capital expenditure (CAPEX) for a two-hour duration BESS. It is important to note that capacity charges vary substantially across voltage levels and among DSOs. As a significant share of planned BESS installations are expected to connect at the high-voltage level via DSOs, the average grid connection charge for this voltage level is calculated based on published figures from the four largest DSOs in Germany, as reported by the BNetzA. The resulting average charge is presented in Table C.5.[79] The resulting average connection charge for the high-voltage grid is 133 EUR/kW, or an annuity of 15 EUR/kW.

[79]The four largest DSOs by overhead line length—excluding the German railroad network—are identified as Westnetz GmbH, Avacon Netz GmbH, Bayernwerk Netz GmbH, and Netze BW GmbH.

Table C.5.: Overview of BKZ for 2025 and (annuity) in EUR/kW.

| | TSO | DSO average (High-voltage) | DSO average (Medium-voltage) |
|---|---|---|---|
| Full capacity charge (100%) | 103 (10) | 139 (14) | 152 (15) |
| Reduced capacity charge (20%) | 21 (2) | 18 (3) | 30 (3) |

## C.5. Optimal grid connection capacities under various marginal grid connection costs

This sensitivity analysis investigates how the optimal configuration of grid access for hybrid PV-BESS systems responds to variations in the connection costs for grid injection and withdrawal capacity. The analysis is based on identifying the configuration that maximizes the CVaR. Figure C.3 presents the results, illustrating the optimal levels of grid withdrawal (left panel) and injection (right panel) capacity across a range of grid connection costs. The findings indicate that a complete restriction on grid charging is suboptimal under moderate marginal withdrawal costs. In contrast, limiting grid injection capacity is optimal even when grid connection costs are moderate. The analysis reveals a notable interaction between the connection costs of grid injection and withdrawal capacity. Under asymmetric charging schemes, an increase in grid injection costs leads to a reduction in both the optimal grid injection and withdrawal capacities. Higher injection costs diminish the economic value of feeding electricity to the grid, which in turn reduces the value for grid-based charging. As a result, the battery charges more from the PV asset. Furthermore, lower grid withdrawal capacity constrains the system's ability to capitalize on short-duration price spikes. This dynamic underscores the importance of considering not only absolute grid connection costs but also their interactions when designing grid charging schemes for hybrid renewable systems.

## C.6. The impact of market premia on standalone wind and PV assets

This section presents the impact of grid injection restrictions on contribution margins of standalone renewable energy assets, distinguishing between cases with and without market premium payments. The analysis compares solar and wind generation to evaluate how their respective characteristics influence sensitivity to grid constraints. PV assets exhibit a lower contribution margin reduction than wind assets. This outcome is primarily driven by two factors: the generally lower market value of PV generation and the less frequent occurrence of high-capacity utilization. As a result, restricting grid access imposes a comparatively smaller

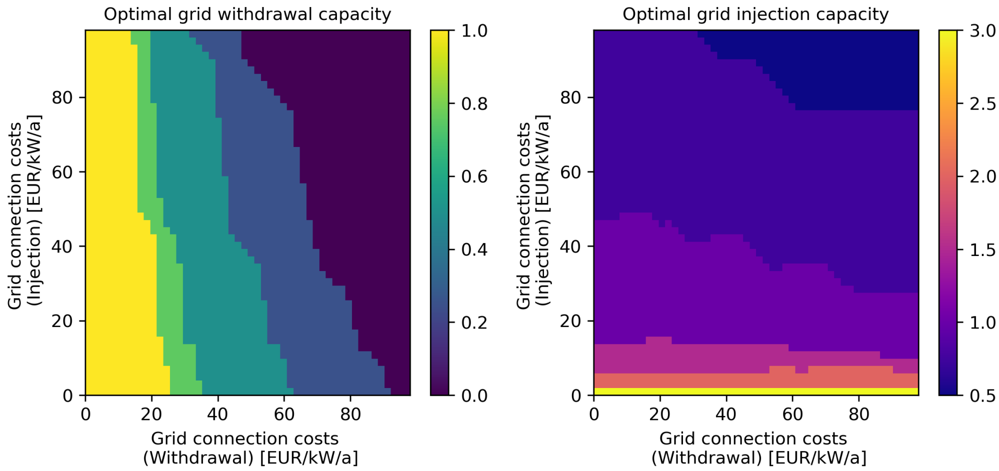



Figure C.3.: Optimal grid connection configurations depending on the marginal grid connection costs.

economic loss on PV systems. Market premium payments increase the loss from grid injection restrictions for both technologies. However, the magnitude of this effect differs. The increase is less pronounced for wind assets, reflecting their typically lower market premia. In contrast, PV assets experience a stronger sensitivity, as market premia are higher.

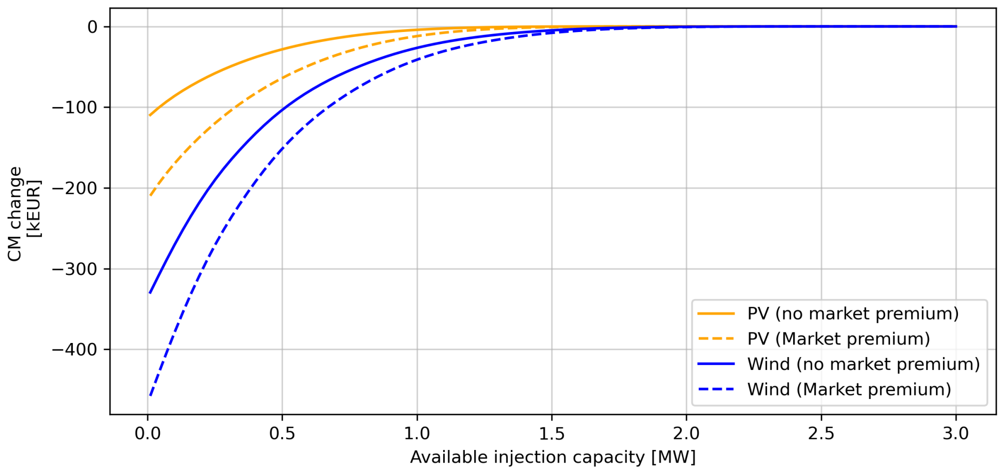



Figure C.4.: Contribution margin changes for different RES assets with and without market premium payments.

## C.7. Sensitivity analysis of different storage durations and PV-to-BESS ratios

Given the significance of charging restrictions for hybrid PV-BESS systems in the German EEG innovation tender scheme, this section examines how different asset configurations influence their impact. Notably, all analyzed cases exclude market premia.

Table C.6 presents contribution margin statistics for storage durations of two and four hours in the base case and for configurations with grid charging restrictions. The findings reveal three key insights. First, doubling the storage duration does not result in a proportional increase in contribution margin, indicating diminishing marginal benefits of additional storage — consistent with previous studies (e.g., Mercier et al., 2023). Second, the relative risk of contribution margins remains nearly unchanged for systems with two- and four-hour storage durations, particularly in the base case. This suggests that longer storage durations do not significantly influence risk. Third, the effect of charging restrictions on average contribution margins increases in absolute terms as storage durations increase.

Table C.6.: Impact of different storage durations on the absolute contribution margin.

| | 2h duration | | | 4h duration | | |
|---|---|---|---|---|---|---|
| | Grid charging | No grid charging | Difference [%] | Grid charging | No grid charging | Difference [%] |
| Mean [kEUR] | 225.84 | 170.83 | -24.36 | 273.11 | 196.23 | -28.15 |
| Std. [kEUR] | 5.02 | 5.58 | +11.21 | 6.14 | 6.05 | -1.56 |
| CoV [%] | 2.22 | 3.27 | +47.03 | 2.25 | 3.08 | +37.01 |

Beyond storage duration, PV-to-BESS ratios also shape the impact of charging restrictions. Figure C.5 illustrates how contribution margins vary with installed BESS capacity. In the base case, where the grid connection is not constrained, the contribution margin increases linearly with installed BESS capacity. The relative contribution margin remains constant when grid charging is permitted, as grid injection capacity scales with the combined PV-BESS capacity. However, in cases with charging restrictions, the contribution margin increase follows a concave pattern. A higher PV-to-BESS ratio limits the amount of PV generation available for charging. Yet, even for very high ratios (1:1), revenue continues to increase, as the BESS can discharge more stored electricity at the highest price.

Nonetheless, the marginal benefit of this increased flexibility declines. Consequently, the impact of charging restrictions intensifies with the PV-to-BESS ratio, meaning the restrictions imposed by the EEG innovation tender regulation become more severe as the ratio increases. The findings indicate that investors would favor smaller PV-to-BESS ratios.

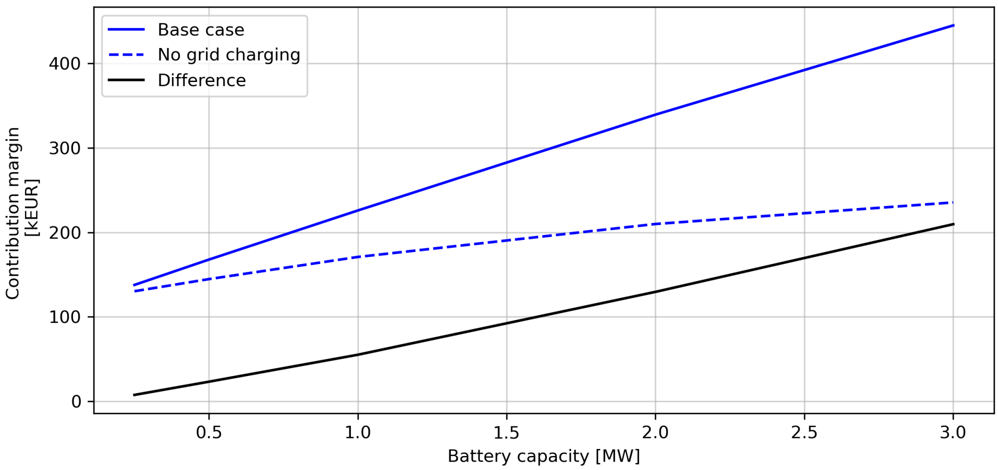



Figure C.5.: Contribution margins for different PV-BESS ratios.

# D. Supplementary Material for Chapter 5

## D.1. Proof of Proposition 1

For the proof of Proposition 5.2.1, we compare the socially optimal outcome to the three carbon pricing regimes. In the following, we derive the outcomes of these regimes.

### Regulatory flexibility

In a setting with *Regulatory flexibility*, the regulator sets the carbon price after the firms have invested in the emission-free technology. The regulator faces the optimisation problem:

$$\max_{p} \mathcal{W} = \int_{p}^{\infty} Q(z)dz + (p-d)Q(p) + \int_{0}^{\overline{\chi}} (d - c_v - c_i z)dz \tag{D.1}$$

We derive the optimal solution by deriving the first-order conditions:

$$\frac{\partial \mathcal{W}}{\partial p} = -Q(p) + Q(p) + Q'(p)(p-d) = 0 \longrightarrow p^{Flex} = d \tag{D.2}$$

As in the social optimum, the carbon price equals the damage of one additional unit of the good. In $t_3$, the investments are already set, and, hence, the social planner and the regulator face identical problems. The carbon price does not influence the emission-free production capacity but only determines the optimal level of consumption and, in consequence, pollution.

In $t_2$, the firms choose to invest in the emission-free technology, as long as the associated profits are positive. Firms anticipate the carbon price that arises in the subsequent stage. The profit of the marginal firm investing in the emission-free technology is zero and, hence, the emission-free production capacity is defined by

$$\begin{aligned} \pi(\overline{\chi}) &= p^{Flex} - c_v - c_i\overline{\chi} = 0 \\ \longrightarrow \overline{\chi}^{Flex} &= \frac{p^{Flex} - c_v}{c_i} \end{aligned} \tag{D.3}$$

The optimal emission-free production capacity is at the socially optimal level, as the carbon price set in $t_3$ equals the marginal damage ($p^{Flex} = d$), i.e. $\overline{\chi}^{Flex} = d - c_v/c_i$.

## Commitment

When the regulator commits to a carbon price, she faces no decision in $t_3$. In $t_2$, the firms choose to invest in the emission-free technology if the associated profits are positive, such that the marginal firm investing is defined by:

$$\begin{aligned} \pi(\overline{\chi}) &= p - c_v - c_i\overline{\chi} = 0 \\ \longrightarrow \overline{\chi}^{Com} &= \frac{p - c_v}{c_i} \end{aligned} \tag{D.4}$$

In $t_1$, the regulator chooses the carbon price that maximises the social welfare function while anticipating the reaction function of firms to the announced price.

$$\begin{aligned} \max_p \mathcal{W} &= \int_p^\infty Q(z)dz + (p-d)Q(p) + \int_0^{\overline{\chi}(p)} (d - c_v - c_i z)dz \\ \frac{\partial \mathcal{W}}{\partial p} &= -Q(p) + Q(p) + Q'(p)(p-d) + \overline{\chi}'(p)(d - c_v - c_i\overline{\chi}) = 0 \end{aligned} \tag{D.5}$$

Inserting the optimal investment level $\overline{\chi}^{Com}$ from (D.4), the expression yields:

$$Q'(p)(p-d) = \overline{\chi}'(p)(p-d) \longrightarrow \quad p^{Com} = d \tag{D.6}$$

As under *Regulatory flexibility*, the solution yields the social optimum. In the absence of risk, there is no difference for the regulator in setting the carbon price in $t_1$ or $t_3$.

## CCfD

When the regulator offers a CCfD, she sets the carbon price in $t_3$ after the firms invested in the emission-free technology. The solution yields the same result as under *Regulatory flexibility*, as the regulator can only control the size of the market at this stage.

$$\begin{aligned} &\max_p \mathcal{W} = \int_p^\infty Q(z)dz + (p-d)Q(p) + \int_0^{\overline{\chi}} (d - c_v - c_i z)dz \\ &\longrightarrow \ p^{CCfD} = d \end{aligned} \tag{D.7}$$

In $t_2$, the firms choose to invest in the emission-free technology according to their profit function, which depends on the strike price of the CCfD. The carbon price is irrelevant to the firms.

$$\begin{aligned} \pi(\overline{\chi}) &= p_s - c_v - c_i\overline{\chi} = 0 \\ \longrightarrow \overline{\chi}^{CCfD} &= \frac{p_s - c_v}{c_i} \end{aligned} \tag{D.8}$$

The result is the socially optimal emission-free production capacity that balances the marginal costs and the benefit of abatement, i.e., savings from reduced payment of the strike price. In $t_1$, the regulator chooses the strike price that she offers to the firms. She faces the following optimisation problem:

$$\begin{aligned} \max_{p_s} \mathcal{W} &= \int_p^\infty Q(z)dz + (p-d)Q(p) + \int_0^{\overline{\chi}(p_s)} (d - c_v - c_i z)dz \\ \frac{\partial \mathcal{W}}{\partial p_s} &= [d - c_v - c_i\overline{\chi}(p_s)]\overline{\chi}'(p_s) = 0 \end{aligned} \tag{D.9}$$

Inserting the optimal investment level $\overline{\chi}^{CCfD}$ from (D.8), the expression yields $p_s^{CCfD} = d$. Hence, the strike price equals marginal damage, and the strike price and carbon price have the same level in the absence of risk. Firms and consumers receive the same signal regarding the benefit from investments or the damage from consumption, respectively. Both prices are at the socially optimal level.

### Welfare ranking

As all three carbon pricing regimes result in the socially optimal carbon price and the socially optimal emission-free production capacity, it is straightforward that the respective welfare is equal to the social optimum.

## D.2. Proof of Proposition 2

For the proof of Proposition 5.3.1, we derive the optimal solutions in the respective carbon pricing regimes and under the assumption of a social planner.

### Social optimum

In the social optimum, the social planner sets the carbon price $p$ in $t_3$ after the actual environmental damage revealed. She optimises:

$$\max_p \mathcal{W} = \int_p^\infty Q(z)dz + (p-\hat{d})Q(p) + \int_0^{\overline{\chi}} (\hat{d} - c_v - c_i z)dz \tag{D.10}$$

Given the first-order conditions, the optimal solution is equal to:

$$\frac{\partial \mathcal{W}}{\partial p} = -Q(p) + Q(p) + Q'(p)(p-\hat{d}) = 0 \longrightarrow p^{Opt} = \hat{d} \tag{D.11}$$

The investments are due before the actual damage reveals. Hence, the social planner must choose the emission-free production capacity in the presence of risk. The social planner optimises the expected welfare with respect to the emission-free production capacity $\overline{\chi}$.

$$\max_{\overline{\chi}} E[\mathcal{W}] = E\left[\int_{p}^{\infty} Q(z)dz + (p-d)Q(p) + \int_{0}^{\overline{\chi}}(d - c_v - c_i z)dz\right] \tag{D.12}$$

Given the expected damage, the optimal solution is equal to:

$$\frac{\partial E[\mathcal{W}]}{\partial \overline{\chi}} = E[d] - c_v - c_i\overline{\chi} = 0 \longrightarrow \overline{\chi}^{Opt} = \frac{E[d] - c_v}{c_i} = \frac{\mu_D - c_v}{c_i} \tag{D.13}$$

### Regulatory flexibility

Under *Regulatory flexibility*, similar to the assumption of a social planner, the regulator sets the carbon price after the actual damage revealed. As shown in D.1, in this case, the regulator and the social planner have the same objective function. Hence, in *Flex*, the regulator optimises (D.10), which yields $p^{Flex} = \hat{d}$.

In $t_2$, the firms choose to invest in the emission-free technology, as long as the associated profits are positive. They anticipate the subsequent carbon price:

$$\begin{aligned} EU(\pi(\overline{\chi})) &= E[p^{Flex}] - c_v - c_i\overline{\chi} - \lambda\sigma_{p^{Flex}} = 0 \\ \longrightarrow \overline{\chi}^{Flex} &= \frac{p^{Flex} - c_v - \lambda\sigma_{p^{Flex}}}{c_i} = \frac{\mu_D - c_v - \lambda\sigma_D}{c_i} \end{aligned} \tag{D.14}$$

where the last step stems from replacing the statistical moments of the carbon price in *Flex* with the ones of the environmental damage, i.e., $E[p^{Flex}] = \mu_D$ and $\sigma_{p^{Flex}} = \sigma_D$. The emission-free production capacity decreases with the volatility of the environmental damage and firms' risk aversion, as $\frac{\partial \overline{\chi}^{Flex}}{\partial \lambda} = -\frac{\sigma_D}{c_i}$ and $\frac{\partial \overline{\chi}^{Flex}}{\partial \sigma_D} = -\frac{\lambda}{c_i}$ are both smaller than zero.

### Commitment

When the regulator commits to a carbon price, she faces no decision in $t_3$. In $t_2$, the firms make their investment decision given the announced carbon price level. In this setting, all parameters are known, such that firms face no risk:

$$\begin{aligned} \pi(\overline{\chi}) &= p - c_v - c_i\overline{\chi} = 0 \\ \longrightarrow \overline{\chi}^{Com} &= \frac{p - c_v}{c_i} \end{aligned} \tag{D.15}$$

In $t_1$, the regulator sets the carbon price maximising expected welfare and accounting for the firms' reaction function to the announced price:

$$\begin{aligned}\max_p E[\mathcal{W}] &= E\Big[\int_p^\infty Q(z)dz + (p-d)Q(p) + \int_0^{\overline{\chi}(p)} (d-c_v-c_i z)dz\Big]\\ \frac{\partial E[\mathcal{W}]}{\partial p} &= -Q(p) + Q(p) + Q'(p)(p-\mu_D) + \overline{\chi}'(p)(\mu_D - c_v - c_i\overline{\chi}) = 0\end{aligned} \tag{D.16}$$

Inserting the resulting emission-free production capacity $\overline{\chi}^{Com}$ from (D.15), the expression yields:

$$Q'(p)(p-\mu_D) = \overline{\chi}'(p)(p-\mu_D) \longrightarrow \quad p^{Com} = \mu_D \tag{D.17}$$

### CCfD

When the regulator offers a CCfD, she sets the carbon price in $t_3$ after the firms made their investment decision. Hence, she optimises (D.10), and the solution is identical with the one of the social planner and under *Regulatory flexibility*, i.e., $p^{CCfD} = \hat{d}$.

In $t_2$, the firms choose to invest accounting for the strike price of the CCfD. The carbon price is irrelevant to firms. Hence, the maximisation problem is identical to (D.8), and the solution is equal to:

$$\overline{\chi}^{CCfD} = \frac{p_s - c_v}{c_i} \tag{D.18}$$

In $t_1$, the regulator chooses the strike price that maximises the expected social welfare:

$$\begin{aligned}\max_{p_s} E[\mathcal{W}] &= E\Big[\int_p^\infty Q(z)dz + (p-d)Q(p) + \int_0^{\overline{\chi}(p_s)} (d-c_v-c_i z)dz\Big]\\ \frac{\partial E[\mathcal{W}]}{\partial p_s} &= [\mu_D - c_v - c_i\overline{\chi}(p_s)] = 0\end{aligned} \tag{D.19}$$

Inserting the optimal investment level $\overline{\chi}^{CCfD}$ from (D.18), the first-order condition yields $p_s^{CCfD} = \mu_D$. Hence, the strike price equals the expected marginal damage. Inserting $p_s^{CCfD}$ into (D.18) shows that the investment level is socially optimal and equals the solution under *Commitment*.

### Welfare ranking

As shown before, the carbon price and the emission-free production capacity are identical in the social optimum and in the *CCfD* regime. Thus, welfare in the *CCfD* regime and in the social optimum is identical, i.e., $E[\mathcal{W}_{\sigma_D}^{Opt}] = E[\mathcal{W}_{\sigma_D}^{CCfD}]$.

The emission-free production capacity under *Regulatory flexibility* is lower than the under the *CCfD* regime, as:

$$\overline{\chi}^{CCfD} - \overline{\chi}^{Flex} = \frac{\mu_D - c_v}{c_i} - \frac{\mu_D - c_v - \lambda\sigma_D}{c_i} = \frac{\lambda\sigma_D}{c_i} \geq 0 \tag{D.20}$$

Expected welfare increases with the number of firms investing in the emission-free technology, as long as $\overline{\chi} \leq \overline{\chi}^{CCfD} = \frac{\mu_D - c_v}{c_i}$, since $\frac{\partial E[\mathcal{W}]}{\partial \overline{\chi}} = \mu_D - c_v - c_i\overline{\chi}$ which is a positive number for all $\overline{\chi} < \frac{\mu_D - c_v}{c_i}$. Hence, welfare under regulatory flexibility is lower than socially optimal, i.e., $E[\mathcal{W}_{\sigma_D}^{CCfD}] \geq E[\mathcal{W}_{\sigma_D}^{Flex}]$.

The difference in welfare between the policy regimes of *Commitment* and *CCfD* stems from the difference in consumer surplus, as the respective emission-free production capacity are identical. Since the consumer surplus is a convex function, the welfare difference is positive:[80]

$$E[\mathcal{W}_{\sigma_D}^{CCfD}] - E[\mathcal{W}_{\sigma_D}^{Com}] = E[\int_D^{\infty} Q(z)dz] - \int_{\mu_D}^{\infty} Q(z)dz \geq 0 \tag{D.21}$$

Hence, it holds that $E[\mathcal{W}_{\sigma_D}^{CCfD}] \geq E[\mathcal{W}_{\sigma_D}^{Com}]$.

Whether the difference in expected welfare between *Flex* and *Com* is positive or not, is ambiguous. The difference is equal to

$$\begin{aligned} E[\mathcal{W}_{\sigma_D}^{Flex}] - E[\mathcal{W}_{\sigma_D}^{Com}] = & \underbrace{E[\int_D^{\infty} Q(z)dz] - \int_{\mu_D}^{\infty} Q(z)dz}_{\geq 0} \\ & \underbrace{+(\mu_D - c_v)(\overline{\chi}^{Flex} - \overline{\chi}^{Com}) - \int_{\overline{\chi}^{Com}}^{\overline{\chi}^{Flex}} (c_i z)dz}_{\leq 0}, \end{aligned} \tag{D.22}$$

where the first part, i.e., difference in consumer surplus, is positive and the second part, i.e., the difference in abatement benefit, is negative.

## D.3. Proof of Proposition 3

For the proof of Proposition 5.3.2, we derive the optimal solutions in the respective carbon pricing regimes and under the assumption of a social planner.

[80]This relation is also known, as Jensen gap stemming from Jensen's inequality.

### Social optimum

In the social optimum, the social planner sets in $t_3$ the carbon price $p$ after the actual level of variable costs revealed. She optimises:

$$\begin{aligned}\max_p \mathcal{W} &= \int_p^{\infty} Q(z)dz + (p-d)Q(p)\int_0^{\overline{\chi}}(d-\hat{c_v}-c_i z)dz \\ \frac{\partial \mathcal{W}}{\partial p} &= -Q(p)+Q(p)+Q'(p)(p-d)=0\end{aligned} \tag{D.23}$$

Given the first-order condition, the optimal solution is equal to $p^{Opt} = d$.

The investments are due before the level of variable costs reveals. Hence, the social planner must set the emission-free production capacity in the presence of risk. The social planner optimises the expected welfare with respect to the emission-free production capacity $\overline{\chi}$, as depicted in (D.12). Given the expected variable costs, the optimal solution is equal to:

$$\frac{\partial E[\mathcal{W}]}{\partial \overline{\chi}} = d - E[c_v]c_i - \overline{\chi} = 0 \longrightarrow \overline{\chi}^{Opt} = \frac{d-\mu_{C_v}}{c_i} \tag{D.24}$$

### Regulatory flexibility

As under the assumption of a social planner, the regulator sets the carbon price in $t_3$. Again, the regulator and the social planner have the same objective function. Hence, under *Regulatory flexibility*, the regulator optimises (D.23), which yields $p^{Flex} = d$.

In $t_2$, the firms take their investment decision, anticipating the risk in variable costs that arises in the subsequent stage:

$$\begin{aligned}&EU(\pi(\overline{\chi})) = p^{Flex} - E[c_v] - c_i\overline{\chi} - \lambda\sigma_{C_v} = 0 \\ &\longrightarrow \overline{\chi}^{Flex} = \frac{p^{Flex}-\mu_{C_v}-\lambda\sigma_{C_v}}{c_i} = \frac{d-\mu_{C_v}-\lambda\sigma_{C_v}}{c_i}\end{aligned} \tag{D.25}$$

where the last step stems from replacing the optimal carbon price in *Flex.* The emission-free production capacity decreases with the volatility of the variable costs and the firms' risk aversion, as $\frac{\partial\overline{\chi}^{Flex}}{\partial\lambda} = -\frac{\sigma_{C_v}}{c_i}$ and $\frac{\partial\overline{\chi}^{Flex}}{\partial\sigma_{C_v}} = -\frac{\lambda}{c_i}$, which both are smaller than zero.

### Commitment

When the regulator commits to a carbon price, she faces no decision in $t_3$. In $t_2$, the firms choose to invest in the emission-free technology given the announced carbon price level. In this setting, the firms still face a risk, stemming from the variable costs. The firms invest if their expected utility is greater than zero.

Hence, the marginal firm investing in the emission-free technology is characterised by:

$$\begin{aligned} EU(\pi(\overline{\chi})) &= p^{Com} - E[c_v] - c_i\overline{\chi} - \lambda\sigma_{C_v} = 0 \\ \longrightarrow \overline{\chi}^{Com} &= \frac{p^{Com} - \mu_{C_v} - \lambda\sigma_{C_v}}{c_i} \end{aligned} \tag{D.26}$$

In $t_1$, the regulator sets the carbon price maximising expected welfare and accounting for the reaction function of the firms to the announced price:

$$\begin{aligned} \max_p E[\mathcal{W}] &= E\Bigg[\int_p^\infty Q(z)dz + (p-d)Q(p)\int_0^{\overline{\chi}}(d - \hat{c_v} - c_i z)dz\Bigg] \\ \frac{\partial E[\mathcal{W}]}{\partial p} &= Q'(p)(p-d) + \overline{\chi}'(p)(d - \mu_{C_v} - c_i\overline{\chi}(p)) = 0 \\ \longrightarrow p - d &= \frac{\overline{\chi}'(p)}{-Q'(p)}(d - \mu_{C_v} - c_i\overline{\chi}(p)) \end{aligned} \tag{D.27}$$

Rearranging the first-order condition and substituting $\epsilon(p) = -\frac{\partial Q(p)}{\partial p}\frac{p}{Q(p)}$ yields the expression in (5.14). Additionally, we define $\eta = \frac{\overline{\chi}'(p)}{-Q'(p)}$. Substituting $\eta$ in (D.27) and using $\overline{\chi}(p)^{Com}$ from (D.26), yields

$$p^{Com} = d + \frac{\eta}{1+\eta}\lambda\sigma_{C_v} \tag{D.28}$$

The resulting carbon price is greater than the environmental damage $d$, as $\eta$ is a positive number.

## CCfD

When the regulator offers a CCfD, she sets the carbon price in $t_3$ after the firms made their investment decision. Hence, she optimises (D.23), and the solution is identical with the one of the social planner and under *Regulatory flexibility*, i.e., $p^{CCfD} = d$.

In $t_2$, the firms invest in the emission-free technology accounting for the strike price of the CCfD. As in the other carbon pricing regimes, the firms face a risk in variable costs. The marginal firm investing in the emission-free technology is characterised by:

$$\begin{aligned} EU(\pi(\overline{\chi})) &= p_s - E[c_v] - c_i\overline{\chi} - \lambda\sigma_{C_v} = 0 \\ \longrightarrow \overline{\chi}^{CCfD} &= \frac{p_s - \mu_{C_v} - \lambda\sigma_{C_v}}{c_i} \end{aligned} \tag{D.29}$$

In $t_1$, the regulator chooses the strike price that maximises the expected social welfare:

$$\begin{aligned} &\max_{p_s} E[\mathcal{W}] = E\Big[\int_p^\infty Q(z)dz + (p-d)Q(p) + \int_0^{\overline{\chi}(p_s)} (d - c_v - c_i z)dz\Big] \\ &\frac{\partial E[\mathcal{W}]}{\partial p_s} = d - \mu_{C_v} - c_i\overline{\chi}(p_s) = 0 \end{aligned} \tag{D.30}$$

Inserting the optimal investment level $\overline{\chi}^{CCfD}$ from (D.29), the first-order condition is equal to

$$(\frac{d-\mu_{C_v}}{c_i} - \frac{p_s - \mu_{C_v} - \lambda\sigma_{C_v}}{c_i}) = 0 \tag{D.31}$$

, which yields $p_s^{CCfD} = d + \lambda\sigma_{C_v}$. Inserting $p_s^{CCfD}$ into (D.29) shows that the emission-free production capacity is equal to tne one under a social planner, i.e., $\overline{\chi}^{CCfD} = \frac{d-\mu_{C_v}}{c_i}$

## Welfare ranking

As shown before, the carbon price and the emission-free production capacity are identical in the social optimum and in the *CCfD* regime. Thus, welfare in the *CCfD* regime and in the social optimum is identical, i.e., $E[\mathcal{W}_{\sigma_{C_v}}^{Opt}] = E[\mathcal{W}_{\sigma_{C_v}}^{CCfD}]$.

Similar to the case of damage risk in D.2, the emission-free production capacity under *Regulatory flexibility* is lower than the under the *CCfD* regime, as:

$$\overline{\chi}^{CCfD} - \overline{\chi}^{Flex} = \frac{\lambda\sigma_{C_v}}{c_i} \geq 0 \tag{D.32}$$

Expected welfare increases in the emission-free production capacity $\overline{\chi}$, as long as $\overline{\chi} \leq \overline{\chi}^{CCfD} = \frac{d-\mu_{C_v}}{c_i}$, since $\frac{\partial E[\mathcal{W}]}{\partial \overline{\chi}} = d - \mu_{C_v} - c_i\overline{\chi}$. Hence, welfare in *Flex* is lower than socially optimal, i.e., $E[\mathcal{W}_{\sigma_{C_v}}^{CCfD}] \geq E[\mathcal{W}_{\sigma_{C_v}}^{Flex}]$.

To show that offering a CCfD is welfare superior to *Commitment*, we first compare the strike price with optimal carbon price in *Com*. Inserting $\overline{\chi}^{Com}$ and rearranging (D.28), yields:

$$p^{Com} - p_s = d + \frac{\eta}{1+\eta}\lambda\sigma_{C_v} - (d + \lambda\sigma_{C_v}) = (\frac{\eta}{1+\eta} - 1)\lambda\sigma_{C_v} \tag{D.33}$$

As $\eta$ is a positive number, the first expression is negative and the difference is negative. Hence, we see that the optimal carbon price under commitment $p^{Com}$ is smaller than the strike price of the CCfD. Consequently, the emission-free production capacity in *Com* is lower than when offering a CCfD, i.e., $\overline{\chi}^{CCfD} \geq \overline{\chi}^{Com}$. Similarly, it is straightforward to show that the carbon price under the

*Com* regime is higher than under the *CCfD* regime. Both variables lead to lower welfare and, hence, we show that $E[\mathcal{W}^{CCfD}_{\sigma_{C_v}}] \geq E[\mathcal{W}^{Com}_{\sigma_{C_v}}]$.

To show that in this setting, *Commitment* to a carbon price is welfare superior to *Regulatory flexibility*, we can make use of the optimality of the carbon price in *Com*. The regulator sets a price above the marginal environmental damage to incentivise additional investments. She could, however, choose not to. We show the optimality by comparing:

$$
\begin{aligned}
&E[\mathcal{W}^{Com}_{\sigma_{C_v}}] \\
&\quad = E\Big[\int_{p^{Com}}^{\infty} Q(z)dz + (p^{Com} - d)Q(p) + d\overline{\chi}^{Com} - \frac{c_i}{2}(\overline{\chi}^{Com})^2 - c_v\overline{\chi}^{Com})\overline{Q}\Big] \\
&\quad \geq E\Big[\int_{p^{Flex}}^{\infty} Q(z)dz + (p^{Flex} - d)Q(p) + d\overline{\chi}^{Com} - \frac{c_i}{2}(\overline{\chi}^{Com})^2 - c_v\overline{\chi}^{Com})\overline{Q}\Big] \\
&\quad \geq E\Big[\int_{p^{Flex}}^{\infty} Q(z)dz + (p^{Flex} - d)Q(p) + d\overline{\chi}^{Flex} - \frac{c_i}{2}(\overline{\chi}^{Flex})^2 - c_v\overline{\chi}^{Flex})\overline{Q}\Big] \\
&\quad = E[\mathcal{W}^{Flex}_{\sigma_{C_v}}],
\end{aligned}
\tag{D.34}
$$

where the first inequality is given by the optimality of $p^{Com}$ and the second by the fact that $\overline{\chi}^{Flex} \leq \overline{\chi}^{Com}$ (c.f. Chiappinelli and Neuhoff, 2020).

## D.4. Proof of Proposition 4

For the proof of Proposition 4, we derive the optimal solutions in the respective carbon pricing regimes and under the assumption of a social planner.

### Social optimum

In $t_3$, the social planner sets the carbon price $p$ after the actual environmental damage revealed, by optimising (D.10). Hence, the optimal carbon price is equal to $p^{Opt} = \hat{d}$.

In $t_2$, the social planner sets the emission-free production capacity under risk such that it maximises the expected welfare. She considers the cases in which production may not be optimal, i.e., $c_v > \hat{d}$.

$$\begin{aligned}
\max_{\overline{\chi}} E[\mathcal{W}] =& P\Big(\int_p^\infty Q(z)dz + (p-\hat{d})Q(p) + \int_0^{\overline{\chi}} (\hat{d} - c_v - c_i z)dz \mid c_v \leq p\Big) \\
&+ P\Big(\int_p^\infty Q(z)dz + (p-\hat{d})Q(p) - \int_0^{\overline{\chi}} (c_i z)dz \mid c_v > p\Big) \\
&= \int_p^\infty Q(z)dz + (p-\mu_D)Q(p) - \int_0^{\overline{\chi}} (c_i z)dz + \int_{c_v}^\infty \overline{\chi}(z-c_v) f_D(z)dz
\end{aligned} \tag{D.35}$$

, where $f_D(z)$ is the density function of the environmental damage. Given the first-order condition, the optimal solution is equal to:

$$\frac{\partial E[\mathcal{W}]}{\partial \overline{\chi}} = \int_{c_v}^\infty (z-c_v) f_D(z)dz - c_i\overline{\chi} = 0 \longrightarrow \overline{\chi}^{Opt} = \frac{\int_{c_v}^\infty (z-c_v) f_D(z)dz}{c_i} \tag{D.36}$$

## Regulatory flexibility

As under the assumption of a social planner, the regulator sets the carbon price after the actual damage revealed with the same objective function. Hence, she sets $p^{Flex} = \hat{d}$.

In $t_2$, the firms invest in the emission-free technology if the associated expected utility is positive. They anticipate that the Pigouvian carbon tax depends on the damage level that is not yet revealed. The marginal firm investing in the emission-free technology is characterised by:

$$\begin{aligned}
EU(\pi(\overline{\chi})) &= P\Big(p^{Flex} - c_v - c_i\overline{\chi} \mid c_v \leq p^{Flex}\Big) + P\Big(- c_i\overline{\chi} \mid c_v > p^{Flex}\Big) \\
&= \int_{c_v}^\infty (z-c_v) f_D(z)dz - c_i\overline{\chi} = 0 \\
&\longrightarrow \overline{\chi}^{Flex} = \frac{\int_{c_v}^\infty (z-c_v) f_D(z)dz}{c_i}
\end{aligned} \tag{D.37}$$

The emission-free production capacity equals the socially optimal level, as the carbon price set in $t_3$ equals the marginal damage ($p^{Flex} = \hat{d}$), i.e. $\overline{\chi}^{Flex} = \overline{\chi}^{Opt}$.

## Commitment

In $t_2$, the firms make their investment decision given the announced carbon price level. In this setting, the firms know all parameters affecting their profits, such that the firms face no risk. However, the profit functions of firms depend on the carbon price level, and they have to distinguish two cases.

$$\pi(\chi) = \begin{cases} p - c_v - c_i\chi, & \text{for } c_v \leq p \\ -c_i\chi, & \text{else} \end{cases} \tag{D.38}$$

Given the indifference condition of the marginal firm investing in the emission-free technology:

$$\overline{\chi}^{Com} = \begin{cases} \frac{p^{Com} - c_v}{c_i}, & \text{for } c_v \leq p \\ 0, & \text{else} \end{cases} \tag{D.39}$$

In $t_1$, the regulator sets the carbon price anticipating that her choice impacts the firms' investment decision:

$$\max_p E[\mathcal{W}] = \begin{cases} \int_p^\infty Q(z)dz + (p - \mu_D)Q(p) & \\ \quad + \int_0^{\overline{\chi}(p)} \int_{-\infty}^\infty (t - c_v)f_D(t) - (c_i z)dtdz, & \text{if } c_v \leq p \\ \int_p^\infty Q(z)dz + (p - \mu_D)Q(p), & \text{else} \end{cases} \tag{D.40}$$

For the second case, is straightforward to show that the regulator sets carbon price equal to the expected damage. The solution for the first case is identical to the optimisation in (D.16). In both cases, the optimal carbon price equals the expected environmental damage and, thus,

$$p^{Com} = \begin{cases} \mu_D, & \text{if } c_v \leq p \\ \mu_D, & \text{else} \end{cases} \tag{D.41}$$

As by assumption the expected damage is higher than the variable costs, i.e., $\mu_D > c_v$, only the first case materialises. Thus, the optimal emission-free production capacity is equal to $\overline{\chi}^{Com} = \frac{\mu_D - c_v}{c_i}$.

## CCfD

When the regulator offers a CCfD, she sets the carbon price in $t_3$ after the firms made their investment decision. Hence, she optimises (D.10), and the solution is identical with the one of the social planner and under *Regulatory flexibility*, i.e., $p^{CCfD} = \hat{d}$.

In $t_2$, the firms take their investment decision and account for the strike price of the CCfD. The carbon price is irrelevant to the firms. However, the firms only invest, if the strike price is above the variable costs.

$$\pi(\chi) = \begin{cases} p_s - c_v - c_i\chi, & \text{for } c_v \leq p_s \\ -c_i\chi, & \text{else} \end{cases} \longrightarrow \overline{\chi}^{CCfD} = \begin{cases} \frac{p_s - c_v}{c_i}, & \text{for } c_v \leq p_s \\ 0, & \text{else} \end{cases} \tag{D.42}$$

In $t_1$, the regulator chooses the strike price that maximises the expected social welfare:

$$\max_{p_s} E[\mathcal{W}] = \begin{cases} \int_p^\infty Q(z)dz + (p-\mu_D)Q(p) \int_0^{\overline{\chi}(p_s)} \int_{-\infty}^{\infty} (t-c_v) f_D(t) - (c_i z) dt dz, & \text{if } c_v \leq p_s \\ \int_p^\infty Q(z)dz + (p-\mu_D)Q(p), & \text{else} \end{cases} \tag{D.43}$$

For the second case, the strike price can take any realisation between zero and $c_v$, as firms would not invest. For the first case, the solution is identical to (D.30). Hence, the result is equal to

$$p_s = \begin{cases} \mu_D \\ 0 \leq p_s < c_v \end{cases} \tag{D.44}$$

Again, only the first case materialises, as by assumption $\mu_D > c_v$. Inserting $p_s^{CCfD}$ into (D.42) shows that the investment level is equal to $\overline{\chi}^{CCfD} = \frac{\mu_D - c_v}{c_i}$.

## Welfare ranking

As shown before, the carbon price and the emission-free production capacity are identical in the social optimum and under *Regulatory flexibility*. Thus, welfare in this carbon pricing regime is identical to the social optimum, i.e., $E[\mathcal{W}_{\sigma_D}^{Opt}] = E[\mathcal{W}_{\sigma_D}^{Flex}]$.

To compare *Flex* and *CCfD*, we evaluate the difference of expected welfare. Since $p^{Flex} = p^{CCfD}$, there is only a difference regarding welfare from production with the emission-free technology. Taking the derivatives of (5.19), we see that the expected social welfare is increasing in investments as long as $\overline{\chi} \leq \overline{\chi}^{Opt} = \overline{\chi}^{Flex}$:

$$\begin{aligned} \frac{\partial E[\mathcal{W}]}{\partial \overline{\chi}} &= \int_{c_v}^{\infty} (z-c_v) f_D(z) dz - c_i \overline{\chi} > 0 \; \forall \; \overline{\chi} < \frac{\int_{c_v}^{\infty} (z-c_v) f_D(z) dz}{c_i} \\ \frac{\partial^2 E[\mathcal{W}]}{\partial \overline{\chi}^2} &= -c_i < 0 \end{aligned} \tag{D.45}$$

As $\overline{\chi}^{CCfD} \leq \overline{\chi}^{Flex}$, we conclude that $E[\mathcal{W}_{\sigma_D}^{Flex}] \geq E[\mathcal{W}_{\sigma_D}^{CCfD}]$.

Lastly, it is straightforward to show that *Commitment* is welfare-inferior to the *CCfD* regime. As investments are identical in both regimes, the difference in welfare stems form the consumer surplus. Again, applying Jensen's inequality, it holds that

$$E[\mathcal{W}_{\sigma_D}^{CCfD}] - E[\mathcal{W}_{\sigma_D}^{Com}] = E[\int_D^\infty Q(z)dz] - \int_{\mu_D}^\infty Q(z)dz \geq 0. \tag{D.46}$$

## D.5. Regulatory solutions with variable cost risk and potentially socially not optimal production

Under variable cost risk and potentially welfare-reducing production, the increase in marginal production costs might be so high that firms using the emission-free technology do not produce in $t_4$. As the investments in abatement are sunk, they do not impact the production decision. Overall welfare in $t_4$ is given by:

$$\mathcal{W} = \begin{cases} \int_p^\infty Q(z)dz + (p-d)Q(p) + \int_0^{\overline{\chi}}(d - \hat{c_v} - c_i z)dz, & \text{for } \hat{c_v} < d \\ \int_p^\infty Q(z)dz + (p-d)Q(p) - \int_0^{\overline{\chi}}(c_i z)dz, & \text{for } \hat{c_v} \geq d \end{cases} \tag{D.47}$$

### Social optimum

In the social optimum, the social planner sets the carbon price $p^{Opt}$ after the level of variable costs revealed. The optimisation is identical to maximising (D.10). Hence, it holds that $p^{Opt} = d$. The social planner sets the emission-free production capacity $\overline{\chi}^{Opt}$ such that it maximises expected welfare:

$$\begin{aligned} \max_{\overline{\chi}} E[\mathcal{W}] =& P\left( \int_p^\infty Q(z)dz + (p-d)Q(p) + \int_0^{\overline{\chi}}(d - c_v - c_i z)dz \mid c_v \leq d \right) \\ =& \int_p^\infty Q(z)dz + (p-d)Q(p) - \int_0^{\overline{\chi}}(c_i z)dz + P((d - c_v)\overline{\chi} \quad \mid c_v < d) \\ =& \int_p^\infty Q(z)dz + (p-d)Q(p) - \int_0^{\overline{\chi}}(c_i z)dz + \int_{-\infty}^d (d-z)\overline{\chi} f_{C_v}(z)dz \end{aligned} \tag{D.48}$$

We solve the problem using the first-order conditions:

$$\begin{aligned} \frac{\partial E[\mathcal{W}]}{\partial \overline{\chi}} =& - c_i\overline{\chi} + \int_{-\infty}^d (d-z) f_{C_v}(z)dt = 0 \\ \longrightarrow \overline{\chi}^{Opt} =& \frac{\int_{-\infty}^d (d-z)f(z)dt}{c_i} \end{aligned} \tag{D.49}$$

The integral of the distribution function represents the marginal benefit from abatement (damage minus variable costs) weighted by its probability of realisation. The integral is limited to $d$ as beyond this point production does not occur and the marginal benefit, hence, is zero.

### Regulatory flexibility

As under the assumption of a social planner, the regulator sets the carbon price after the firms made their investment. Hence, she optimises (D.23) and sets $p^{Flex} = \hat{d}$, which is the Pigouvian tax.

In $t_2$, the firms choose to invest if their expected utility is greater than zero, given the risk regarding its future variable costs and anticipating the Pigouvian carbon tax rational of the regulator. The marginal firm investing in the emission-free technology is characterised by:

$$\begin{aligned} EU(\pi(\overline{\chi})) &= P\Big(p^{Flex} - c_v - c_i\overline{\chi} \mid c_v \leq p^{Flex}\Big) + P\Big( - C(\overline{\chi}) \mid c_v > p^{Flex}\Big) = 0 \\ &= \int_{-\infty}^{d} (d-z) f_{C_v}(z)dz - c_i\overline{\chi} = 0 \\ &\longrightarrow \overline{\chi}^{Flex} = \frac{\int_{-\infty}^{d}(d-z)f_{C_v}(z)dz}{c_i} \end{aligned} \tag{D.50}$$

, where we inserted the optimal carbon price ($p^{Flex} = d$). As in the case of damage risk without risk aversion, *Regulatory flexibility* reaches the social optimum.

### Commitment

Under *Commitment*, the firms choose to invest after the regulator has announced the carbon price. The rationale for investments is identical to the one of *Regulatory flexibility*, as no damage risk exists. Hence, the structural solution is identical with one under the flexible carbon price regime.

$$\overline{\chi}^{Com} = \frac{\int_{-\infty}^{p}(p-z)f_{C_v}(z)dz}{c_i} \tag{D.51}$$

In $t_1$, the regulator sets the carbon price anticipating that her choice impacts the firms' investment decision:

$$\begin{aligned} \max_p E[\mathcal{W}] &= \int_p^{\infty} Q(z)dz + (p-d)Q(p) - \int_0^{\overline{\chi}(p)} (c_i z)dz + \int_{-\infty}^{p} \overline{\chi}(d-t) f_{C_v}(t)dt \\ &\longrightarrow p^{Com} = d \end{aligned} \tag{D.52}$$

The result is identical to the one of *Regulatory flexibility* and the social planner. As the firms are not risk averse, the regulator chooses the Piguvian tax level, that they can perfectly anticipate.

### CCfD

When the regulator can offer firms a CCfD in $t_1$, she sets the carbon price in $t_3$ after the actual variable costs revealed and the firms made their investment decision. The firms using the emission-free production technology produce, if their variable costs are lower than the conventional technology, i.e., if $c_v < p_s$. The solution yields the socially optimal Pigouvian tax, i.e. $p^{CCfD} = d$. In $t_2$, the firms invest in the emission-free technology given the announced strike price. The costs remain risky, hence the marginal firm investing in the emission-free technology is characterised by:

$$\begin{aligned} EU(\pi(\overline{\chi})) &= P\Big(p_s - c_v - c_i\overline{\chi} \mid c_v \leq p_s\Big) + P\Big(-c_i\overline{\chi} \mid c_v > p_s\Big) = 0 \\ &= \int_{p_s}^{\infty} (p_s - z) f_{C_v}(z) dz - c_i\overline{\chi} = 0 \\ &\longrightarrow \overline{\chi}^{CCfD} = \frac{\int_{-\infty}^{p_s} (p_s - t) f_{C_v}(z) dz}{c_i} \end{aligned} \tag{D.53}$$

In $t_1$, the regulator chooses a strike price that maximises expected welfare. She accounts for the firms' reaction to the strike price:

$$\begin{aligned} &\max_{p_s} E[\mathcal{W}] = \int_p^{\infty} Q(z)dz + (p-d)Q(p) - \int_0^{\overline{\chi}(p)} (c_i z)dz + \int_{-\infty}^{p_s} \overline{\chi}(d-t) f_{C_v}(t) \\ &\quad\longrightarrow p_s = d \end{aligned} \tag{D.54}$$

### Welfare ranking

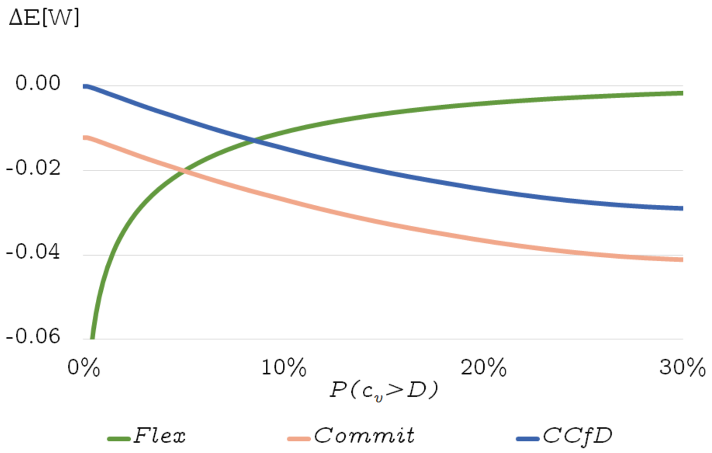
As all carbon pricing regimes result in the socially optimal carbon price and emission-free production capacity, there is no difference in welfare. The absence of risk aversion in this setting leads to equivalent welfare expectations.

## D.6. Welfare difference compared to the social optimum in the presence of damage risk, and (ex post) potentially socially not optimal abatement due to an increase in $\sigma_D$

Figure D.1 shows a similar effect, when varying the probability of socially not optimal production, $P(C_v > D)$, by altering the expected value of the marginal damage, $\mu_D$.

The welfare of *CCfD* and *Commitment* is not affected by the presence of risk aversion (compare Figure D.1 (with risk aversion) with Figure 7b (no risk aversion)). Hence, as explained in section 4.2, the shortfall in welfare increases with an increased probability of socially not optimal production. Furthermore, the effect is concave in the probability of socially not optimal emission-free production as the welfare-deferring effect is mitigated by decreasing socially optimal investments.

The *Regulatory flexibility* regime does not result in the social optimum if the firms are risk averse. However, as the socially optimal emission-free production capacity decreases, the absolute gap in welfare compared to the social optimum decreases.




$D \sim N(\mu_D \in [4.25; 5.5], \sigma_D^2 = 0.25)$ , $\lambda = 1.5$, $Q(p) = 5 - 0.1p$, $c_v = 4$, $c_i = 1$.

Figure D.1.: Difference in welfare compared to social optimum due to change in $P(c_v > D)$ by altering $\mu_D$ in the presence of damage risk and potentially welfare-reducing production.

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**CURRICULUM VITAE**

# Samir Jeddi

## PERSONAL DATA

| | |
|---|---|
| Date of Birth | 5th March 1991 |
| Place of Birth | Haan |
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## RESEARCH INTERESTS

Electricity Markets, Market Design, Regulation

## ACADEMIC EDUCATION

| | |
|---|---|
| since 10/2017 | **Institute of Energy Economics (EWI)** and<br>**Department of Economics, University of Cologne**<br>Doctoral Candidate in Economics |
| 10/2014 - 05/2017 | **TU Dresden**<br>Master of Science in Business Administration |
| 09/2015 - 01/2016 | **ISCTE – Instituto Universitário de Lisboa**<br>Study abroad |
| 10/2010 - 05/2014 | **Heinrich-Heine-University Duesselforf**<br>Bachelor of Science in Business Chemistry |
| 06/2010 | **Gymnasium Haan, Haan**<br>Maturity/Abitur |

## PROFESSIONAL EXPERIENCE

| | |
|---|---|
| since 02/2023 | **Statkraft Germany, Düsseldorf**<br>Head of Commercial Analysis |
| 02/2022 - 02/2023 | **Statkraft Germany, Düsseldorf**<br>Senior Commercial Analyst |
| 10/2017 - 02/2022 | **Institute of Energy Economics at the University of Cologne (EWI)**<br>Research Associate |
| 07/2019 - 12/2019<br>and<br>07/2020 - 09/2020 | **International Energy Agency (IEA), Paris**<br>Research Consultant |
| 11/2018 - 01/2022 | **Verein der Absolventen und Freunde des Energiewirtschaftlichen Instituts an der Universität zu Köln**<br>Managing Director |
| 05/2015 - 07/2017 | **WSB Service Deutschland GmbH, Dresden**<br>Working student |

## LANGUAGES

| | |
|---|---|
| German | Mother tongue |
| English | Proficient |

## PUBLICATIONS

**Articles in Peer-Reviewed Journals:**

- Arnold, F., Jeddi, S., and Sitzmann, A. (2022). How prices guide investment decisions under net purchasing - An empirical analysis on the impact of network tariffs on residential PV. *Energy Economics*, Vol. 112:106-177. DOI: 10.1016/j.eneco.2022.106177.
- Jeddi, S., and Sitzmann, A. (2019). Netzentgeltsystematik in Deutschland - Status-Quo, Alternativen und europäische Erfahrungen. *Zeitschrift für Energiewirtschaft*, Vol. 43(4):245-267. DOI: 10.1007/s12398-019-00265-6
- Hennes, O., Jeddi, S., Madlener, R., Schmitz, H., Wagner, J., Wolff, S., Zinke, J. (2021). Auswirkungen von CO2-Preisen auf den Gebäude-, Verkehrs-und Energiesektor. *Zeitschrift für Energiewirtschaft*, 45(2):91-107. DOI: 10.1007/s12398-021-00305-0
- Farag, M., Jeddi, S., Kopp, J. H. (2025). Global Natural Gas Market Integration: The Role of LNG Trade and Infrastructure Constraints. *The World Economy*. DOI: 10.1111/twec.13699
- Visse, R., Fidan, M., Götzinger, A., Motzny, A., Jeddi, S., Braun, M. (2018). Enantioselective palladium-catalyzed N-allylation of lactams. *ChemistrySelect*, 3(18), 5216-5219. DOI: 10.1002/slct.201801233

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- Farag, M., Jeddi, S., Kopp, J. H. (2023). Global natural gas market integration in the face of shocks: Evidence from the dynamics of European, Asian, and US gas futures prices. *EWI Working Paper*, No 23/03.
- Jeddi, S., Lencz, D., Wildgrube, T. (2021). Complementing carbon prices with carbon contracts for difference in the presence of risk: When is it beneficial and when not? *EWI Working Paper*, No 21/09.
- Arnold, F., Jeddi, S., and Sitzmann, A. (2021). How prices guide investment decisions under net purchasing - An empirical analysis on the impact of network tariffs on residential PV. *EWI Working Paper*, No 21/07.
- Jeddi, S., and Sitzmann, A. (2021). Network tariffs under different pricing schemes in a dynamically consistent framework. *EWI Working Paper*, No 21/01.

**Further Publications:**

- Jeddi, S., Sitzmann, A., Frank, D., Schmid, E., Fett, D., and Fraunholz, C. (2022). Die Auswirkungen einer Netzentgeltreform auf PV-Anlagen, Batteriespeicher und das Gerechtigkeitsempfinden, *et - Energiewirtschaftliche Tagesfragen*, Vol. 72(3):10-13.
- Frings, C., Jeddi, S., and Sitzmann, A. (2019). Netzdienliches Flexibilitätspotenzial von Haushalten mit elektrischer Wärmeversorgung, *et - Energiewirtschaftliche Tagesfragen*, Vol. 69(9):14-16.
- Scholz, Y., Fuchs, B., Borggrefe, F., Cao, K.-K., Wetzel, M., von Krbek, K., Cebulla, F., Gils, H. C., Fiand, F., Bussieck, M., Koch, T., Rehfeldt, D., Gleixner, A., Khabi, D., Breuer, T., Rohe, D., Hobbie, H., Schönheit, D., Ümitcan Yilmaz, H., Panos, E., Jeddi, S., Buchholz, S. (2022). Speeding up energy system models – a best practice guide.
- Jeddi, S., Zipf, M. (2018). A model-based market power analysis of the German market for frequency containment reserve. *2018 15th International Conference on the European Energy Market (EEM) (pp. 1-6)*. IEEE.

## PRESENTATIONS AND TALKS

- A model-based market power analysis of the German market for frequency containment reserve. *15$^{th}$ International Conference on the European Energy Market (EEM)*. June 2018. Lodz, Poland.
- A model-based market power analysis of the German market for frequency containment reserve. *41$^{st}$ IAEE International Conference*. June 2018. Groningen, Netherlands.