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Information shocks and profitability risks for power plant investments: Impacts of policy instruments

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Information shocks and profitability risks for power plant investments – Impacts of policy instruments

HEMF Working Paper No. 05/2018

by

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Abstract

Climate change mitigation requires governmental intervention, but different choices are at hand. While economists in general advocate for first-best instruments, reality looks quite different, with especially many subsidy schemes for renewable energies being used. Supporters of these schemes often argue that investment risk reduction is essential to achieve ambitious environmental targets. In this paper we compare four different instruments (cap, tax, minimum quota and feed-in tariffs/renewable auctions) in terms of efficacy and efficiency and also quantify investment risks, assuming an uncertain investment environment, represented by different information shocks on demand, investment and fuel cost. We use a long-term electricity market equilibrium model (generalized peak load pricing model) of the future German electricity market implemented as a linear optimization problem. Starting from an equilibrium, single input parameters are varied to simulate the arrival of new information. Running the model again with partly fixed capacities then allows us to analyze the adjustment of the power plant portfolio towards the new equilibrium over time. As expected quantity-based instruments are effective in assuring achievement of quantitative goals, notably a certain emission level. Yet risks for investors are rather high in that furthermore that first-best instruments are the most efficient. Risks are lower with price solutions, especially feed-in tariffs or renewable auctions provide the possibility to limit risks extremely by diversification only inside the electricity market.

Keywords : Information shocks, Electricity system, Investment, Policy instruments

JEL-Classification : Q40, Q48

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Content

Abstract.....	I
Content	II
1 Introduction.....	1
2 Literature.....	3
2.1 Environmental policy instruments	3
2.2 Long-term equilibrium models for Electricity Markets	3
2.3 Control Theory	4
3 Model.....	4
3.1 Dynamic recursive optimization approach	4
3.2 Linear Program formulation.....	5
3.3 Calibration.....	8
4 Application	10
4.1 Input Data.....	10
4.2 Base Cases	11
5 Influence of Information Shocks	15
5.1 CO2 Emissions	15
5.2 Cost Efficiency.....	16
5.3 Investment Risk	17
6 Conclusion	21
References.....	III

1 Introduction

Economists have been advocating environmental taxes or emission certificates as so-called first best instruments for emission reduction for decades, especially in the context of Global warming. Nevertheless the on-going actual transformation of the energy system towards a low-carbon technologies does in most countries worldwide not primarily on these first-best instruments but rather strongly on a policy mix including including particularly various support mechanisms for renewable electricity generation. One argument frequently made by policy makers in favor of specific support mechanisms is the reduction of investment risk that they provide. This is considered as paramount to achieve the ambitious targets of energy system transformation and greenhouse gas emission reduction.

Analysing this risk protection in an energy economics context is yet challenging as there are two types of dynamics to be considered. One the one side there is the planned dynamics of the transformation of the energy system and on the other side there is the risk dimension, which by definition includes unplanned events.

The paper at hand borrows on concepts from control theory and stochastic dynamic macroeconomic models to provide a sound analysis focusing on the second aspect, namely the dynamics of unexpected events and their implications for investors. As rational investors form expectations about the future based on currently available information, any unexpected event must be considered as consequence of new information or “information shocks”. This argument put forward by Samuelson (1965) to explain why “properly anticipated stock prices fluctuate randomly” is also at the heart of the so-called famous efficient market hypothesis (EMH) in finance, popularized notably through the seminal work by Fama (1970, 1990).

Although the efficient market hypothesis is heavily debated in finance (e.g. Shiller 1986, Shiller, Akerlof 2007) and it is criticized on the same grounds as simple models of “homo oeconomicus” in other streams of economics, such formal frameworks provide the undoubtable advantage that they are theoretically consistent and mathematically treatable. In this framework, planned transformations – which imply corresponding, consistent expectations – may moreover be conceptually separated from the unplanned (and non-plannable) impacts of new information.

Subsequently we therefore focus on the dynamics of the latter and use stable expectations for convenience. We hence leave to later research to deepen the understanding of the interplay between expectation formation and risk apprehension which may induce precautionary actions. Such analysis may theoretically be conducted in the framework of an Arrow-Debreu world, yet its formalization for the case of energy and climate policy instruments is beyond the scope of this paper. Rather we focus on the practical implications of information shocks under different policy frameworks.

As a base model we use the so-called peak-load pricing model going back to Boiteux (1960) which describes the long-term equilibrium in electricity markets. We implement it as an optimization problem which allows to include additional elements such as a CO₂ cap to simulate carbon certificate markets or a renewable quota system. Furthermore a CO₂ tax and a renewable feed-in tariff (FIT) (or equivalently a renewable procurement auction scheme) are modelled as policy instruments. The information shocks considered include changes in demand, generation technology and fuel costs. The main objective is then to assess the impact of these information shocks on investment profitability for both renewable and conventional generation technologies. In a world without capital market frictions such return risks would only be relevant in as far as they are correlated with systematic market risk – that is the essence of the standard capital asset pricing model (CAPM) going back to the Work of (Sharpe 1964, Lintner 1965 and Moss 1965). Whether this hypothesis on the irrelevance of idiosyncratic risk carries through to real-world markets is subject to discussion (cf. e.g. Stulz 1985, Froot et al. 1993 and with applications in the energy field Schober et al. 2014, Kitzing, Weber 2015). Yet again an in-depth discussion of this issue is beyond the scope of the present paper. Rather we stop here at the step of (monetary) quantification of risk, disregarding the subsequent valuation in terms of changes in capital cost. Yet the quantification has to be done in a multiperiod setting since contrarily to standard financial assets, energy assets like power plants or wind turbines are not fungible. Even the corresponding investments lead to sunk cost and – in dynamic market equilibrium – to a devaluation (or revaluation) of the assets as a consequence of information shocks. As will be shown this change in value is gradually vanishing over time, yet a dynamic extension to the original Peak-Load-Pricing model is needed to assess the overall impact over the lifetime of an asset. The construction and evaluation of such a dynamic model and its “impulse-response function” is at the core of the present work.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature streams while section 3 describes the own modelling approach. Section 4 presents the application case including the equilibrium results. In section 5, the impacts of different information shocks on the profitability of various generation technologies under different policy frameworks are then discussed while section 6 concludes.

2 Literature

The question raised in this contribution draws on at least three strands of literature: the environmental economics literature about optimal policy instruments, the energy economics literature on long and short term equilibria in electricity markets and the control theory literature which is widely used in engineering, but has also made its way also to macroeconomic models of “stochastic dynamic equilibria”. We subsequently briefly summarize some relevant elements of these strands of literature which form the basis for the subsequent analyses.

2.1 Environmental policy instruments

The question of adequate policy instruments to deal with environmental externalities has intrigued economists since the seminal works of Pigou (1920) and Coase (1937). Environmental economics textbooks such as Requate, Phaneuf (2015) or Kolstad (2011) develop the concept of first best instruments stating a fundamental equivalence between the price-based tax solution and the quantity-based certificate solution in equilibrium.

The recent economic analysis of environmental policy has among others evolved around so-called policy mixes. While traditionally the use of multiple instruments is considered as economically inefficient, in the real world, which is often only a second-best world, multiple instruments may be actually more efficient than a single first-best instrument and thus the use of a policy mix might be justified (e. g. Jenkins (2014), Bennear, Stavins (2007)). Lehmann (2012) provides a review on research in this field.

While uncertainty is acknowledged in principle, an explicit treatment of the implications is frequently missing. Yet already Weitzman (1974) discusses the choice of price- versus quantity-based instruments in the context of uncertainty about actual shapes of cost and benefit functions. He establishes that from a social planner point of view, the choice between price- and quantity-based instruments depends on the curvature of the cost and benefit functions.

2.2 Long-term equilibrium models for Electricity Markets

The long-term equilibrium model for electricity markets may be traced back to Boiteux (1960) who develops a theory of optimal pricing for the (then standard) monopolistic utility. This model, also known as peak-load-pricing-model, has been developed further ever since, including inter alia contributions by Crew, Kleindorfer (1976) and Chao (1983). Sunderkötter and Weber (2013) combine the peak-load-pricing model with explicit risk considerations in a Markowitz framework whereas Steffen and Weber (2012) have included storage in a simplified way. In a recent working paper, Böcker and Weber (2018) discuss in depth analytically the drivers of storage operation and investment in this context.

2.3 Control Theory

Besides long-term and short-term static equilibria, economists are also concerned with transition and adaptation processes and with response to exogenous shocks. Modern concepts of time series analysis such as Vector Autoregressive Modells (VAR) and notably Vector Error Correction Models (VECM) strongly build on the concept of dynamic adjustments to equilibrium (e.g. Lütkepohl 2005). But also in modern macroeconomic theory stochastic dynamic equilibrium models play an important role (e.g. Ljungqvist and Sargent 2018).

Yet at the interface of energy, environment and economics, stochastic equilibrium have to the knowledge of the authors not been widely used so far. Obviously multiple studies have been undertaken to determine transition pathways towards a sustainable energy future, yet these rather optimize intertemporal transformation trajectories (e.g. FhG-ISI et al. 2017, dena 2018) than that they consider stochastic shocks and adaptation reactions in the system.

3 Model

3.1 Dynamic recursive optimization approach

The model used in this paper aims at simulating the impact of shocks on the long-term equilibrium in the electricity market. Building on the equivalence of market outcomes under perfect competition and the result of an optimization (by a perfectly informed central planner), we determine the optimal power plant and storage portfolio over multiple years and its changes over time. The model starts with a green field approach to determine the long-term equilibrium for the start year. Under the assumption of a homogeneous age structure of the optimal portfolio, each year then the same proportion of plants of one technology is decommissioned as they have reached the end of their lifetime. In the following year, the remaining plants are considered as fixed minimum installed capacities. Under stable conditions, the decommissioned plants would simply be replaced to restore the pre long-term equilibrium. However, if an information shock occurs and some input parameter changes, the new long-term optimal portfolio will differ. Yet adjustments may not occur immediately, given the remaining fixed capacities. As the model does not use a green field approach for the second year, the already installed plants hinder the adjustment process. In subsequent years the gradual decommissioning of old plants is continued and new built capacities will help to adjust to the long term equilibrium.

This setup allows investigating the impact of various information shocks: after the optimal portfolio has been determined for the first year, one input parameter is changed for simulating the next year. Due to the fixed capacities, the results for the second year can differ from the results which would be obtained using a green field approach considering the new information. Thus it

can be expected that there will still be changes in the portfolio structure during the next years, until the new equilibrium is reached.

The repeated optimization requires a few other adjustments: In order to keep operation of storages consistent, the filling level at the end of each year must equal the one at the beginning of the next year. Here this is achieved by setting the filling level to zero at the beginning of each year. It will then also be zero at the end, since using up all stored energy will help saving costs (this happens because the optimization is done separately for every single year). Other input parameters do not change between years, especially the time series for load and renewable energy remain unchanged. Furthermore, technological progress is also not taken into account. This might be unrealistic but it allows to identify the impact of the information shock much better than otherwise.

3.2 Linear Program formulation

The core of the model is a linear optimization, aiming at deriving an efficient generation and storage portfolio to cover the electricity demand in each hour at minimal system costs and considering different technical and political constraints. The long-term optimization problem is thereby formulated building on the problem formulation of Böcker and Weber (2018). The objective function minimizes the total costs:

$$\begin{aligned} \min \sum_{u_G} K_G(u_G) \cdot c_{inv\ K_G}(u_G) + \sum_{u_S} (K_S(u_S) \cdot c_{inv\ K_S}(u_S) + V_S(u_S) \cdot c_{inv\ V_S}(u_S)) \\ + \sum_{t, u_{G_C}} y_{G_C}(t, u_{G_C}) \cdot c_{fuel}(u_{G_C}) \cdot \Delta t + \sum_t LL(t) \cdot c_{VOLL} \end{aligned} \quad (1)$$

The total costs consist of the investment and operating costs for all plants. Since only one year is considered as planning horizon, investment costs are annualized over the respective lifetime. The costs of generation technologies u_G (including conventional and renewable technologies u_{G_C} and u_{G_R}) consist of investment and operating costs. The investment costs are calculated by multiplying the installed capacity $K_G(u_G)$ with the specific investment costs $c_{inv\ K_G}(u_G)$. The operating costs mainly depend on the fuel costs $c_{fuel}(u_{G_C})$ and are proportional to the electricity output $y_{G_C}(t, u_{G_C})$. For renewable generation technologies, the operating costs are assumed to be zero. Additionally, lost load $LL(t)$, i. e. the difference between demand and supply causes costs proportional to the value of lost load c_{VOLL} .

Investment costs for storage technologies u_S are divided into costs for storage capacity $K_S(u_S)$ and for storage volume $V_S(u_S)$ with the specific investment costs $c_{inv\ K_S}(u_S)$ and $c_{inv\ V_S}(u_S)$ respectively. Operating costs are assumed to be zero.

The first constraint requires supply to meet electricity demand $D(t)$ in all hourly time steps t :

$$\sum_{u_{G_C}} y_{G_C}(t, u_{G_C}) + \sum_{u_{G_R}} y_{G_R}(t, u_{G_R}) \cdot K_G(u_{G_R}) + \sum_{u_S} (y_{S_{dc}}(t, u_S) - y_{S_{ch}}(t, u_S)) + LL(t) - S(t) = D(t) \forall t \quad (2)$$

Electricity generation is composed of conventional generation $y_{G_C}(t, u_{G_C})$ and renewable generation. The latter is determined by the available energy – depending on weather conditions – given as a feed-in pattern $y_{G_R}(t, u_{u_R})$ (with values between 0 and 1) and is proportional to the installed capacity $K_G(u_{G_R})$. Storage units can increase or decrease the supply by discharging $y_{S_{dc}}(t, u_S)$ or charging $y_{S_{ch}}(t, u_S)$. Demand is assumed price-inelastic until the electricity price reaches the value of lost load. As lost load is modelled as a “virtual” power plant with no investment but very high operating costs, it can contribute to meeting the constraint. At times of high renewable feed-in, supply may be reduced by curtailment $S(t)$ in order to balance the equation. This option is used if excess energy cannot be used economically through storage. The shadow price of this constraint represents the costs of a marginal increase in demand at time t , which corresponds to the electricity price.

Conventional generation is limited by the installed capacity. Additionally, installed renewable generation capacity and storage volume are limited by the available sites in Germany. Corresponding restrictions are taken into account.

Including storage requires additional constraints. First, filling levels of storages have to comply with a continuity restriction:

$$L_S(t + 1, u_S) = L_S(t, u_S) + y_{S_{ch}}(t, u_S) \cdot \eta_{ch}(u_S) \cdot \Delta t - y_{S_{dc}}(t, u_S) / \eta_{dc}(u_S) \cdot \Delta t - \frac{1}{2} \cdot (L_S(t + 1, u_S) + L_S(t, u_S)) \cdot sd(u_S) \cdot \Delta t \forall t, u_S \quad (3)$$

The storage filling level at the next time step $L_S(t + 1, u_S)$ results from the level at the current time step $L_S(t, u_S)$ by adding the charged amount of energy $y_{S_{ch}}(t, u_S) \cdot \eta_{ch}(u_S)$ and subtracting the discharged amount $y_{S_{dc}}(t, u_S) / \eta_{dc}(u_S)$ during the time step. The efficiency is divided into the charging efficiency $\eta_{ch}(u_S)$ and the discharging efficiency $\eta_{dc}(u_S)$. In addition, the self-discharging rate $sd(u_S)$ causes a reduction of the stored energy that depends on the mean storage level $0,5 \cdot (L_S(t + 1, u_S) + L_S(t, u_S))$ in the current time step. Additionally, the storage levels have to be zero at the beginning and the levels are limited by the installed volumes.

Second, cycle stability is relevant for the life time of batteries and may be a restrictive factor:

$$\sum_t y_{S_{dc}}(t, u_S) \leq V_S(u_S) * cs(u_S) \forall u_S \quad (4)$$

It is defined as the maximum number of full cycles during life time. Assuming that the units are used similarly during their life time, this number is converted into a maximum number of full cycles per year $cs(u_s)$. The constraint limits the possible sum of all discharging of the storage unit. Moreover, charging and discharging are both limited by the installed storage capacities.

Other possible technical restrictions like transmission or ramping constraints are not taken into account.

However, implementing political instruments into the model is achieved by adding more constraints. The instruments examined here are an absolute CO2 limit, a renewable minimum quota, a CO2 tax and fixed feed-in tariffs (or equivalent in the present context: renewable auctions).

The CO2 limit restricts the total amount of CO2 emitted by the generation units:

$$\sum_{t, u_{G_C}} y_{G_C}(t, u_{G_C}) * e_{CO_2}(u_{G_C}) \leq f_{CO_2} \quad (5)$$

The conventional generation technologies are assigned an emission factor $e_{CO_2}(u_{G_C})$. Multiplying it with the sum of the output gives the CO2 emissions of the corresponding generation technology. The sum of all CO2 emissions is limited by a maximum value f_{CO_2} . This inequality in principle resembles the restriction of a limited resource, which allows finding a shadow price. This shadow price corresponds to the value of emitting one more ton of CO2, i. e. the price of a CO2 certificate.

The minimum renewable energy quota sets a minimal amount of energy to be supplied using renewable generation technologies:

$$\sum_t \left(\sum_{u_{G_R}} y_{G_R}(t, u_{G_R}) * K_G(u_{G_R}) - \sum_{u_S} (y_{S_{ch}}(t, u_S) - y_{S_{dc}}(t, u_S)) - S(t) \right) \geq f_{RE} * \sum_t D(t) \quad (6)$$

The minimum share of renewable energies f_{RE} , multiplied by the total demand, gives the minimum amount of electricity that must be covered by renewable generation. However, since in scenarios with a high share of renewables stored energy is typically a surplus from renewables, the entire storage losses are subtracted from renewable generation. Similarly, curtailment usually occurs during hours with high renewable feed-in, thus it is also subtracted from renewable generation. Hence, only renewable generation that actually contributes to covering the demand is taken into account in this constraint. The shadow price of this restriction corresponds to the price of green electricity certificates.

The CO₂ tax is implemented in the objective function via an additional cost term. Equation (1) is thus rewritten as:

$$\begin{aligned}
\min \sum_{u_G} K_G(u_G) * c_{inv K_G}(u_G) + \sum_{u_S} (K_S(u_S) * c_{inv K_S}(u_S) + V_S(u_S) * c_{inv V_S}(u_S)) \\
+ \sum_{t, u_{G_C}} y_{G_C}(t, u_{G_C}) * (c_{fuel}(u_{G_C}) + c_{CO_2 Tax} * e_{CO_2}(u_{G_C})) \\
+ \sum_t lL(t) * c_{VolL}
\end{aligned} \tag{7}$$

The tax payment for conventional generation technologies is calculated by multiplying the tax rate per ton CO₂ $c_{CO_2 Tax}$ with the emission factor $e_{CO_2}(u_{G_C})$ and the generation $y_{G_C}(t, u_{G_C})$. Thus the costs of emissions will be taken directly into account when minimizing costs.

Fixed feed-in tariffs are not straightforward to implement in this model framework. But assuming that policy makers use them to achieve certain policy targets in terms of renewable penetration, they may be considered as equivalent to procurement auctions for renewables (as introduced in 2017 in Germany). Therefore they are modelled here through three constraints, one for each renewable generation technology:

$$K_G(u_{G_R}) \geq K_{G fit}(u_{G_R}) \forall u_{G_R} \tag{8}$$

This implementation is in fact more similar to a tender-based model as currently in place in Germany.¹ For each renewable technology a minimum capacity $K_{G fit}(u_{G_R})$ is determined exogenously because in these mechanisms, e. g. the German Renewable Energy Act („Erneuerbare-Energien-Gesetz“, EEG), renewable energy plants are put outside of the market. The actual level of the fixed feed-in tariff is only calculated ex-post in the model and used for analytical purposes. It is equal to the annualized cost of investment $c_{inv K_G}(u_G)$ divided by the sum of full load hours $y_{G_R}(t, u_{G_R})$, i. e. it is technology-specific. The subsidized plants receive the fixed feed-in tariffs (auction remuneration) over their whole lifetime (20 to 25 years).

In the following we apply the instruments only one-by-one, we leave the impact analysis for combinations of different instruments to the future research.

3.3 Calibration

Since different instruments and different information shocks shall be compared, comparability must be ensured between different scenarios. In particular, two major problems may occur: First, in order to compare the effectiveness of different instruments, their parameters should be calibrated such that the base-case CO₂ emissions are identical in all four scenarios. Second, the availability of sites for renewable generation and some storage technologies is limited, meaning there are upper limits for the capacities of each renewable technology and for storage volumes.

¹ This is relevant as changes in investment cost of renewable energies are thus reflected in the feed-in tariffs investors receive, since it is assumed that investors bid their marginal cost in tenders.

These restrictions may lead to scarcity rents for those technologies and thus make interpreting the influence of information shocks on investor's profits more difficult. Therefore we replace the upper bounds by the corresponding scarcity costs as discussed below.

Calibrating the CO₂ limit is the simplest, as the amount of CO₂ is directly controlled by the limit set. The shadow price of the CO₂ limit restriction is then set as the tax payment for the CO₂ tax scenario. The renewable minimum quota is determined via an iterative approach that stops when the resulting emissions match the CO₂ limit. Finally, the fixed capacities for the feed-in tariff / renewable procurement auction case have to be set. As there are three values to be set, multiple solutions are possible. To reduce the degrees of freedom, the relation of the three capacities is chosen as the same as for the minimum quota scenario, i. e. the optimal renewable capacities of the minimum quota case are taken and multiplied by the same factor. This factor is then iteratively adjusted such that the CO₂ emissions again match the value as for the other cases.

To avoid scarcity rents for plant operators due to site restrictions, these restrictions shall be removed from the model. However, a simple elimination may induce very unrealistic capacities for some technologies, hence these must be limited by other means. This is achieved by the following method: Optimization with the site restrictions leads to shadow prices for some technologies. The shadow prices differ between the different political instruments. The highest shadow price occurring for each technology is taken and added on the annuity of the respective investment costs. Herein, only the CO₂ limit and the minimum renewable quota are considered, as the CO₂ tax corresponds to the CO₂ limit and thus gives the same shadow prices. The feed-in tariffs are not considered because their calibration does directly depend on the minimum quota. Even though this approach is not able to guarantee that no technology exceeds the available sites limit, it is good enough to effectively prevent extremely high values.

Since shadow prices obtained in one case are then implemented as cost components for all cases, this may induce slightly different CO₂ emissions in some cases. Therefore, calibration is repeated one more time after the restrictions have been removed.

4 Application

4.1 Input Data

Subsequently we apply the model for a time frame from 2030 to 2050, with input data assumptions corresponding to 2040. The main input parameters used are shown in Table 1.

Table 1: Technical input parameters of the model

	Capacity cost	Capacity maintenance cost	Volume cost	Lifetime	Efficiency	Fuel cost	CO ₂ emission factor
Unit	TEUR/MW	%/year	TEUR/MWh	years	%	EUR/MWh _{el}	t/MWh _{el}
Lignite	1500	2,4	/	20	48,5	8,2	0,74
Hard coal	1200	2,7	/	20	51	23,9	0,67
CCGT	700	3,1	/	20	62	50,5	0,32
OCGT	400	4	/	20	41	76,3	0,49
Wind offshore	2223,4 ²	4,9	/	20	/	0	/
Wind onshore	1200	2,9	/	20	/	0	/
Photovoltaic	800	2,6	/	25	/	0	/
PHS	840	2	26,5 ^a	50	81 ³	0	/
Li-Ion battery	100	2	150	20	90,25 ⁴	0	/

^a investment cost after adjustments with shadow prices (cf. section 3.3).

Original values 1600 (capacity wind offshore) and 20 (volume PHS)

Source: Böcker, Weber (2018) and own calculations

Generation technologies include lignite, hard coal, CCGT⁵ and OCGT⁶ as well as wind onshore, wind offshore and photovoltaic. Additionally PHS and Li-Ion batteries are taken into account as storage technologies.

Lignite and hard coal are typical base load technologies as they have high investment but low operational costs. On the contrary, the two gas-based technologies are rather peak load technologies as their operational costs are high but investment costs are low.

Wind onshore, wind offshore and photovoltaics are well established renewable technologies. They all have a high potential but are also characterized by their dependence on the energy supply and thus high volatility. Their feed-in pattern is taken from the time period July 2011 to June 2012. In the following this will be referred to as 2011 for readability. Yearly full load hours result

² Originally 1600 (capacity wind offshore) and 20 (volume PHS), see explanation in subchapter 3.3.

³ Efficiency for charging and discharging: 90%.

⁴ Efficiency for charging and discharging: 95%.

⁵ Combined Cycle Gas Turbine

⁶ Open Cycle Gas Turbine

according to the meteorological conditions in Germany to 3500h, 1800h and 900h for wind offshore, wind onshore and photovoltaic respectively.

Similar to base and peak load technologies, there are storage technologies for long-term and for short-term balancing. PHS has relatively high capacity costs and low volume costs and thus the reservoir size will be rather large, so it is suitable for longer-term balancing. In contrast, investment costs for Li-Ion batteries are dominated by volume cost, thus they are more suitable for short-term balancing. While self-discharge and cycle stability usually can be neglected for PHS, it cannot for Li-Ion batteries. It is assumed that these battery units can reach 8000 cycles before their capacity significantly drops. These cycles are assumed to be equally distributed over the unit's lifetime, resulting in 400 cycles per year. The self-discharge rate is assumed to be 2% per month.

Lifetimes are assumed to be 50 years for PHS, 25 years for photovoltaic and 20 years for all other technologies. While this is realistic for the technical lifetime of renewables, it is not the technical lifetime of conventional power plants. However, there are two reasons for assuming such a relatively short lifetime: First, since this analysis simulates the system for 21 years from 2030 to 2050, a lifetime of 20 years is convenient for modelling, as most plants built in 2030 are then shut down again until 2050 – hence the new equilibrium is reached at the latest in 2050. Second, it can be assumed that political uncertainties for conventional plants, especially coal-based technologies, will increase, due to environmental concerns. It may thus be reasonable for investors to assume a shorter time in which such investments must refinance themselves.

The target for emission reduction is chosen to align roughly to the targets of the German federal government: A reduction of CO₂ emissions of 80% in the electricity sector compared to the level in 1990. For the emissions of electricity generation, this implies an emission cap of 71.6 Mio. tons per year. The first calibration of the minimum renewable quota induces the same emission level.

The original site restrictions are 54 GW for wind offshore, 198 GW for wind onshore and 275 GW for photovoltaic, while the maximum storage volume for PHS is limited to 2 TWh.

The considered information shocks include changing fuel prices for lignite, hard coal and gas, changing investment costs for wind onshore, wind offshore, photovoltaic, PHS and Li-Ion batteries as well as a changing demand. Reductions and Increases by 10% and 20% are considered, leading to a total of 36 possible shocks.

4.2 Base Cases

The base cases for each of the four political instruments are obtained without any information shock present, thus allowing optimal planning under perfect information. Since a green field approach is used for the first year and nothing changes for the following years, the portfolio is

optimal and stays the same for all years, with old decommissioned plants simply being replaced by the same type of plant. The carbon emissions are the same in all base cases.

In the first model run, the site related-restrictions are only binding for wind offshore and PHS, the highest in both cases for the minimum renewable quota scenario. Removing the restrictions and adding the shadow prices on the annualized specific investment costs, then calculating total specific investment costs yields the results indicated in Table 1. Those may be interpreted as an increase of prices for appropriate sites, which are scarce. The results for the minimum quota case stay the same, but the optimal portfolio will change for the other cases. This is acceptable as it is not the main goal of this analysis to provide a model of the German power system.

After removal of site restrictions, the second calibration leads to a CO₂ tax of 149.95€ per ton, a minimum renewable quota of 81.36% and fixed capacities funded by feed-in tariffs of 86,4 GW, 60,3 GW and 178,1 GW for wind onshore, wind offshore and photovoltaic respectively.

The optimal portfolio for the base cases is shown in Figure 1. The installed capacities are characterized by a high share of renewable energies for all four cases. In accordance with economic theory, the cases with CO₂ cap and CO₂ tax lead to exactly the same results for the base case. Installed capacities are the triple of the peak load for these first best instruments and more than four times higher for feed-in tariffs / RE auctions, with the minimum renewable quota ranging in between. Nowadays, the installed generation capacity in Germany is only about the double of the maximum load.

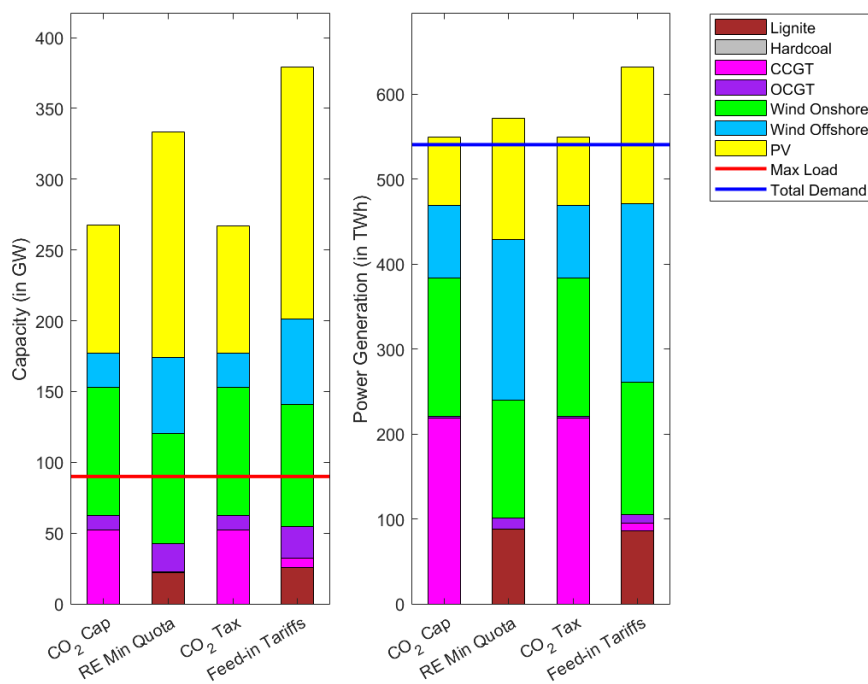


Figure 1: Generation capacities and power generation of the efficient portfolio under different instruments

Pricing CO₂ increases the competitiveness of gas-based technologies compared to coal power plants. Thus lignite is not part of the efficient portfolio under these instruments (hard coal is not part of the efficient portfolio in any case). However, lignite accounts for a significant share of the portfolio under an RE quota and feed-in tariffs / RE auction, as it is cheaper than gas except for peak load, this leads to conventional electricity being mostly generated by lignite power plants. Since CO₂ emissions are by calibration identical in all base cases, and given that lignite plants are more emission-intensive than gas plants, the renewable share in electricity generation is higher in the two latter cases. Both scenarios have to deal with significant curtailment (and partly storage losses), whereas this is rather limited in the first best case. Notably feed-in tariffs / RE auctions lead to a lot of curtailment, since there is no incentive to store renewable energy if it is not cost-efficient. On the contrary, the implementation of a renewable energy quota used here rewards storage of renewable energy in some hours when it is actually not cost-efficient, because storing renewable energy contributes to fulfilling the quota, thus limiting curtailment. It is important to point out that curtailment in this model is not due to any grid congestion but only because generation and usage do not occur at the same time and intertemporal storage is too expensive.

Also the storage installations shown in Figure 2 underline the strong tendency to store excessive renewable energy under a renewable quota, as it leads to much higher storage capacities and especially volumes than the other instruments. Note that CO₂ pricing instruments lead to higher short-term storage in form of lithium-ion batteries compared to the other cases.

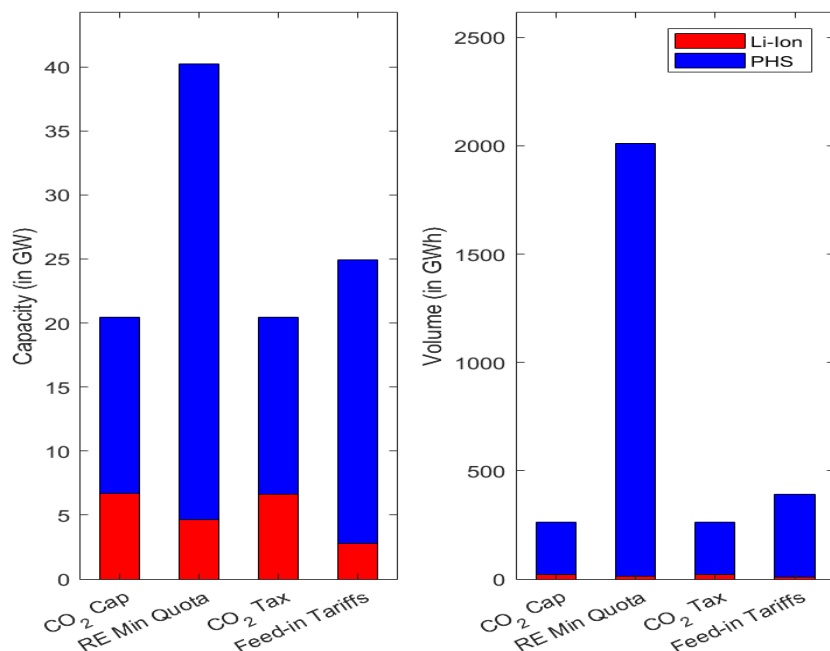


Figure 2: Capacity and volume of storage installations in the efficient portfolio under different instruments

Looking at the system costs for the different portfolios, a CO₂ cap leads to the best result, as expected, as does the CO₂ tax, since they are both first-best instruments. Note that the tax payment

increases the system cost in the optimization, but since this money is not actually spent on labor or capital, it must not be considered when comparing instruments in terms of cost efficiency. The government as receiver of this cash flow can use it to substitute other taxes or too lower end-consumer energy bills. It is important to keep in mind that also the other policy instruments implicitly involve cash flows between the government (i.e. the social planner) and the power plant operators: the payments by emitters for CO₂ certificates under a CO₂ cap, the payments by the government for green certificates for the renewable quota or the (capacity or market) premia paid in the context of feed-in tariffs /RE auctions. However, these payments do not explicitly appear in the system cost function because they are implemented via constraints.

Costs are more than 10% higher under a renewable quota and nearly 20% higher under feed-in tariffs, because these instruments do not directly promote CO₂ reduction but they foster renewable generation technologies instead and thus reduce carbon emissions as a side effect.

The cost structure differs between different instruments as well. While CO₂ pricing instruments lead to roughly 75% of the money being spent for investment in generation capacity, 25% for fuel and only very small amounts for storage installations, the first share is much higher under renewable subsidies instruments, up to about 90%. It is noteworthy that storage investment account for only approximately 10% of the costs under a renewable quota, even with such huge pumped hydro storage capacities. Fuel cost are small for cases with specific renewable instruments, because the main conventional generation is done by lignite power plants with quite cheap fuel, while the CO₂ pricing cases induce conventional generation by gas only, which is rather expensive.

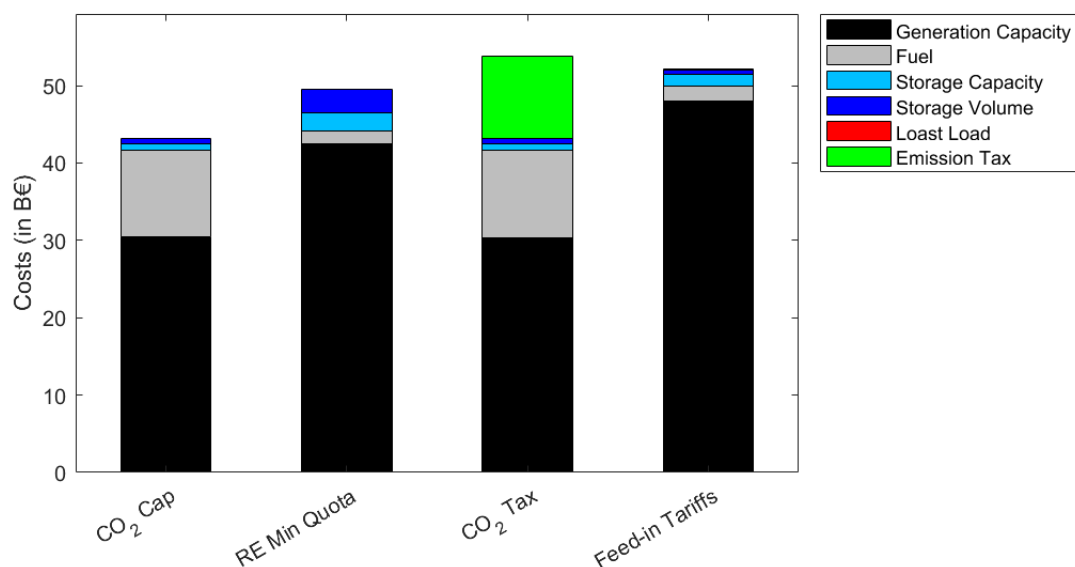


Figure 3: Cost structure of the optimal portfolio under different instruments

5 Influence of Information Shocks

This chapter evaluates the performance of the four political instruments under the influence of different information shocks occurring right in the second year, after the equilibrium state being established for each instrument in the previous year. The instruments are thereby not adjusted after the shock. The instruments are evaluated using the following indicators: the ability to maintain a certain level of total emissions (effectiveness), the ability to reach this result with minimal cost (efficiency) and the potential risks for investors. Especially the latter may shed light on the question which instrument is the most suitable given prevalent uncertainty.

5.1 CO₂ Emissions

The main purpose of government intervention regarding climate change is to limit carbon emissions. Thus an important measure of instrument performance is the ability to ensure that a certain emission level is met. Strictly speaking not only too high but also too low emissions may interfere with this goal, as too low emissions would indicate too much investment into renewables while this money could have been used somewhere else instead. Of course this is true only if we assume that the exact emission level chosen by the planner is really the optimal one in terms of climate change.

In the model world the CO₂ cap by nature ensures that the total CO₂ emissions equal the amount set by the planner.

The CO₂ tax on the other hand, even though it leads to the same result in the base case, is much more sensitive to information shocks (Figure 4 upper right tile). The strongest impact results from shocks on demand and on gas prices. Lower gas prices lead to higher emissions and vice versa, because the equilibrium includes only gas and renewable technologies, lignite being never part of the generation mix under a CO₂ tax.

The minimum renewable quota leads to quite stable emissions regarding most shocks (Figure 4 lower left). Only demand shocks have very strong effects. This stability is a consequence of the base case portfolio: The minimum renewable quota implies a maximum quota for conventional generation. This conventional generation is almost exclusively from lignite and as such emission-intensive, so that a further increase in emissions is almost impossible. A decrease would however require significant changes in the costs structure between lignite and gas (a shift towards even more renewable generation would relieve the quota constraint, thus making it superfluous, which would require extreme cost reductions for renewables).

Under feed-in tariffs and RE auctions, CO₂ emissions are extremely sensitive to demand shocks (Figure 4 lower right), much more sensitive than under other instruments. This is due to the fact that this instrument is not market-based unlike the other three. The absolute amount of

renewable feed-in is constant and any change in the demand only affects conventional generation technologies. Some other shocks also have a significant influence, most notably PSH investment cost, because the prices of storage affect usability of excess renewable generation.

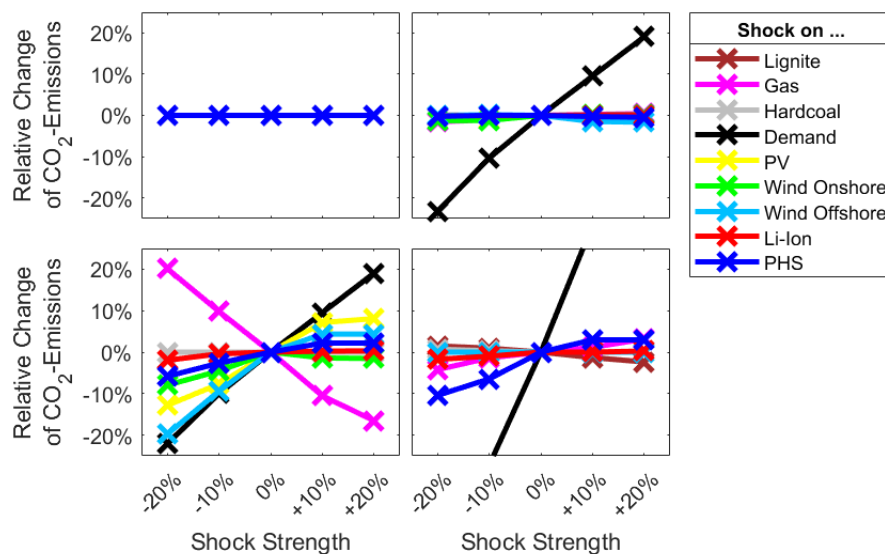


Figure 4: Relative change of carbon emissions for different shocks under a CO₂ cap (upper left), a min RE quota (upper right), a CO₂ tax (lower left), and feed-in tariffs (lower right)

To conclude, in terms of effectiveness, the CO₂ cap obviously leads to the best results. The minimum renewable quota also shows a rather good performance, with only demand shocks having strong impact, while the CO₂ tax is quite sensitive to many types of shocks and feed-in tariffs are also quite sensitive and additionally show extreme results for demand shocks.

5.2 Cost Efficiency

Ideally, the policy instruments shall not only ensure that the emission objective is met but shall do so at lowest possible cost, i.e. they should be cost efficient. We define cost efficiency as the average cost to reduce emissions by one ton of CO₂. Therefore, we optimize the system again without any political intervention (and without any information shock), this leads to emissions of 8406*10⁶ t and costs of 220 B€ (net present value) within 21 years from 2030 to 2050. The average abatement costs are then the quotient of cost increase and emission reduction for scenarios with political instruments. The lower these costs, the more efficient is the instrument.

Pricing CO₂ leads to average abatement costs of about 48.3€/t in the base case. Again, demand has the biggest effect on cost efficiency for both first-best instruments (Figure 5 upper and lower left tiles), but this effect does not only result from abatement but also simply from the changes in absolute demand. The effect is slightly stronger for the CO₂ cap, because it needs to keep emissions constant meaning the additional demand needs to be covered entirely by renewables.

Furthermore, gas prices have a significant impact, as costs for gas make up one quarter of the total costs in the base case for these instruments. This is stronger for a CO₂ tax, because under this instrument the gas price change affects the power plant portfolio, while the certificate price under a CO₂ cap adjusts accordingly to keep variable costs for gas-fired power plants constant (and because there are no other conventional technologies except gas-based- ones). Investment costs for renewables also slightly affect cost efficiency, especially reductions of investment costs.

The minimum renewable quota leads to average abatement costs of 60.1€/t in the base case, significantly higher than under CO₂ pricing solutions. Even though the efficiency is quite stable except for demand shocks, it is always less efficient than those two (Figure 5 upper right).

Feed-in tariffs have average abatement costs of 65.0€/t in the base case, which is the worst of all four base case scenarios. Demand shocks have a big impact, mostly because of high changes in emissions, as renewable capacities are constant (Figure 5 lower right). Investment costs for renewables and for pumped hydro storage also have an impact on cost efficiency. However, feed-in tariffs are always less efficient than the other instruments.

In terms of cost efficiency, instruments pricing carbon emissions yield the best results, with only small differences between a cap and a tax on CO₂. Even though the minimum RE quota and the feed-in tariffs seem to be a little more stable regarding shocks, their efficiency is much lower.

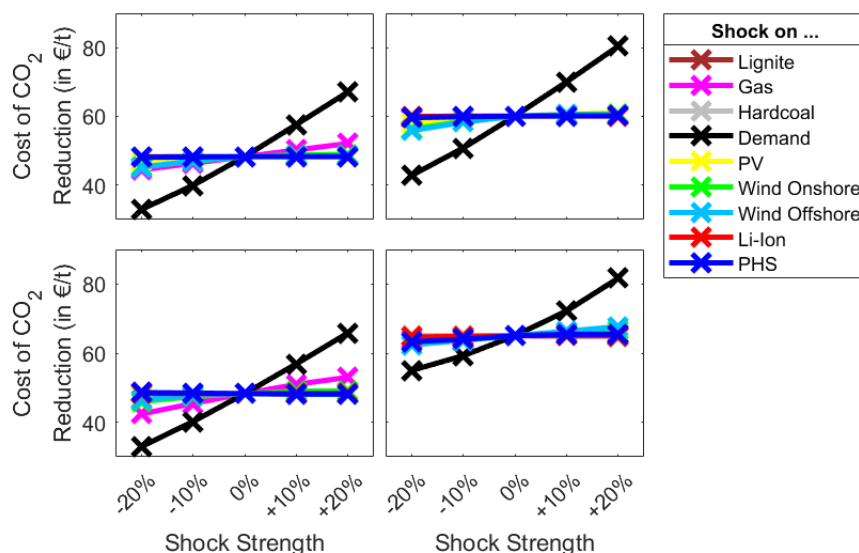


Figure 5: Cost of emission reduction for different shocks under a CO₂ cap (upper left), a min RE quota (upper right), a CO₂ tax (lower left), and feed-in tariffs (lower right)

5.3 Investment Risk

Investors want to earn a return on their investment and are usually risk-averse, i.e. they prefer lower risk at same levels of expected return on investments. The riskiness of investments depends on the technologies but also on the political interventions into the market. If policy instruments

lower the risk for investors, they are likely to attract similar amounts of investment at lower (capital) cost and hence lower cost to society. Thus, a political instrument leading to lower risks than another one is preferable.

We evaluate the effect of information shocks on the relative net present profit of investors who invested before the information shock happened. The net present profit of an investment is computed as the discounted difference of revenues from electricity sales minus variable costs of production and investment over the time period from 2030 to 2050 minus the upfront investment cost. Additionally, investors may receive subsidies or have to pay money for their emissions, depending on the political instrument and those receipts respectively payments have also to be considered. Dividing this profit by the discounted sum of investment gives a relative value, which describes the relative loss or gain in wealth, which accrues to the investor as consequence of the information shock. E.g. -0.1 would mean that the present value of the revenues after shock are 10% lower than the original investment.⁷

As the optimization does not differentiate between old and new installations, we attribute the operation margins proportional to the capacity shares to the old installations (built in 2030 and still in operation) and to the later installations. However, for storage technologies such a straight forward allocation is not possible, because the C-rate of the storage (i.e. capacity divided by volume) may change. We therefore attribute half of the contribution margins for storages on a per volume basis and the other half on a per capacity basis.

The figures in this section show these relative net present profits for different technologies under different shocks. One circle represents the impact of one specific shock on one specific technology under one specific instrument. The last column provides the relative net present profits of a mixed portfolio, consisting of shares of all technologies according to their shares on the total investment sum.

Under a CO₂ cap, the largest source of risk demand deviations (Figure 6). Conventional technologies and storages suffer high losses if the demand turns out to be lower than expected, this effect is much smaller for renewables. However, changes in investment costs of renewables also pose a significant risk, especially for older installations of the same renewable technology and for other renewables, but they also affect storage investors. Storage investment cost changes may cause significant risks for themselves and other storage technologies, and also, slightly, for OCGT.

⁷ Pumped hydro storage and photovoltaic plants have longer lifetimes than these 21 years, thus there will be additional cash flows in later years. Cash flows and investment annuities occurring after 2050 are not considered.

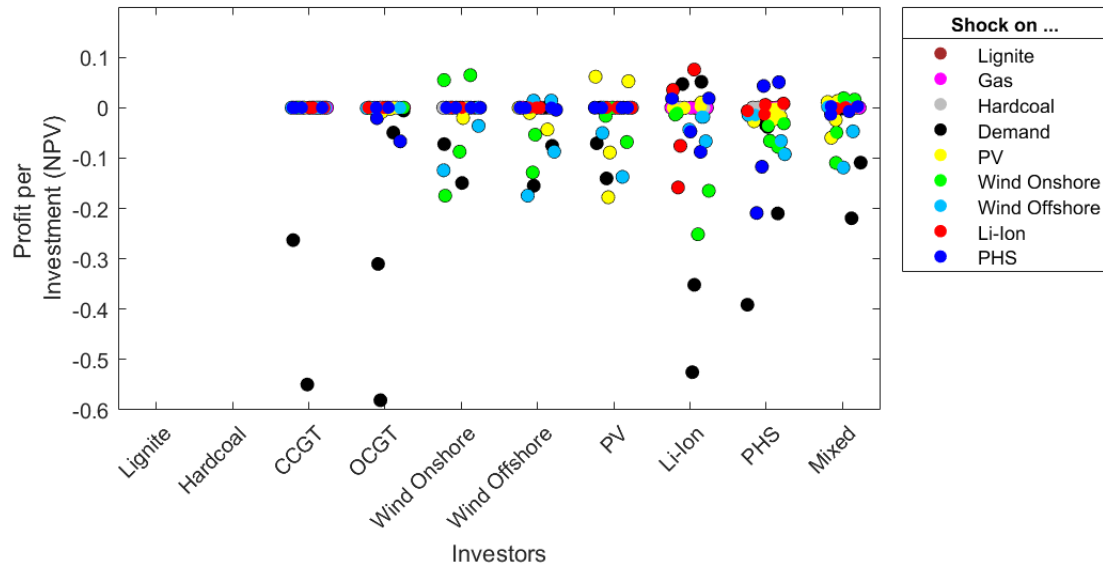


Figure 6: Investment risk under a CO₂ cap

Risks are in general smaller under a carbon tax (Figure 7): the impact of demand shocks is significantly smaller than under a cap regime, even though they are still the main risk for conventional technology investors and one of the major risks for storages. The risk of changes in renewable investment costs are rather similar to those under a CO₂ cap, albeit slightly smaller in some cases. Most notably, gas price shocks cause a significant risk for storage technologies, especially pumped hydro and for OCGT.

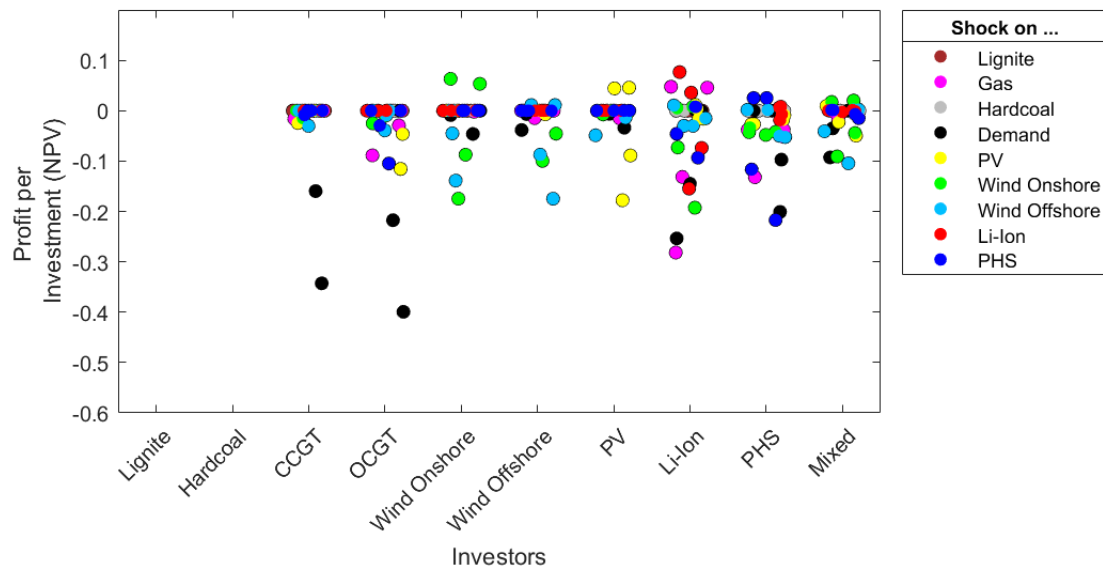


Figure 7: Investment risk under a CO₂ tax

With a minimum renewable quota, demand shocks have a big impact on all investors, notably also on renewables. Even though extreme values are not as high as for a CO₂ cap, demand shocks now lead to giant losses even for mixed portfolios. Risks for renewables are otherwise similar to those

under carbon pricing instruments, caused only by shocks on renewable investment costs. However, storages are much less affected by those renewable shocks. Except demand shocks only shocks on storage investment costs have a somewhat bigger impact on them.

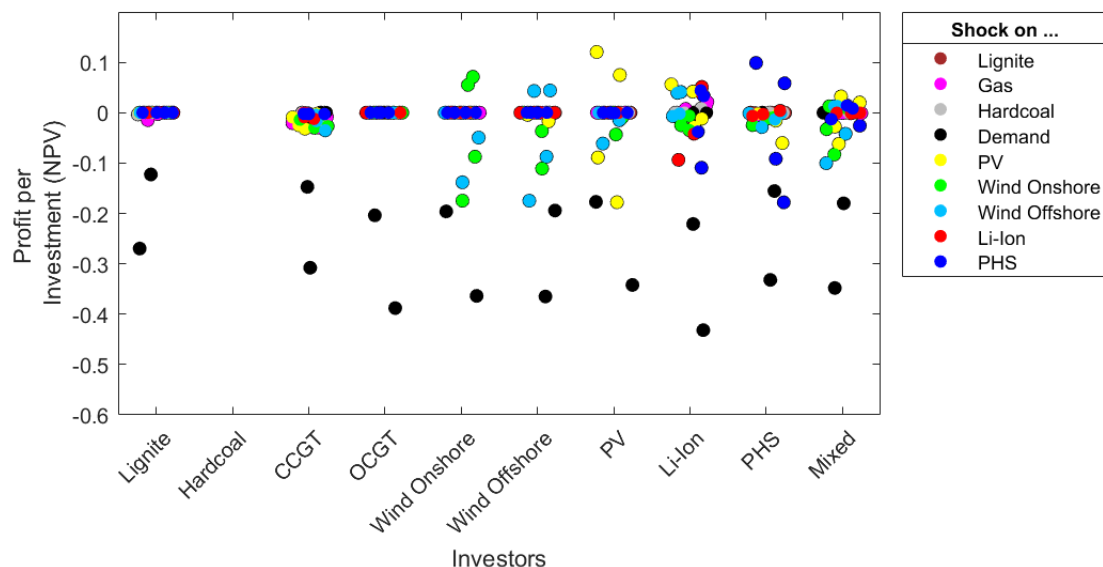


Figure 8: Investment risk under a min RE quota

Guaranteed feed-in tariffs or RE procurement auctions strongly reduce risks (Figure 9): Due to the nature of this instrument, renewables are not affected by any shock and shocks on renewable investment costs may not affect any investors. Demand shocks still pose a large risk for investors in conventional or storage technologies, though. Storages are also affected by shocks on investment costs of storage technologies. Overall, risks are quite small for a mixed portfolio under this regime, because investment into renewables yields (in the model) a risk-free return.

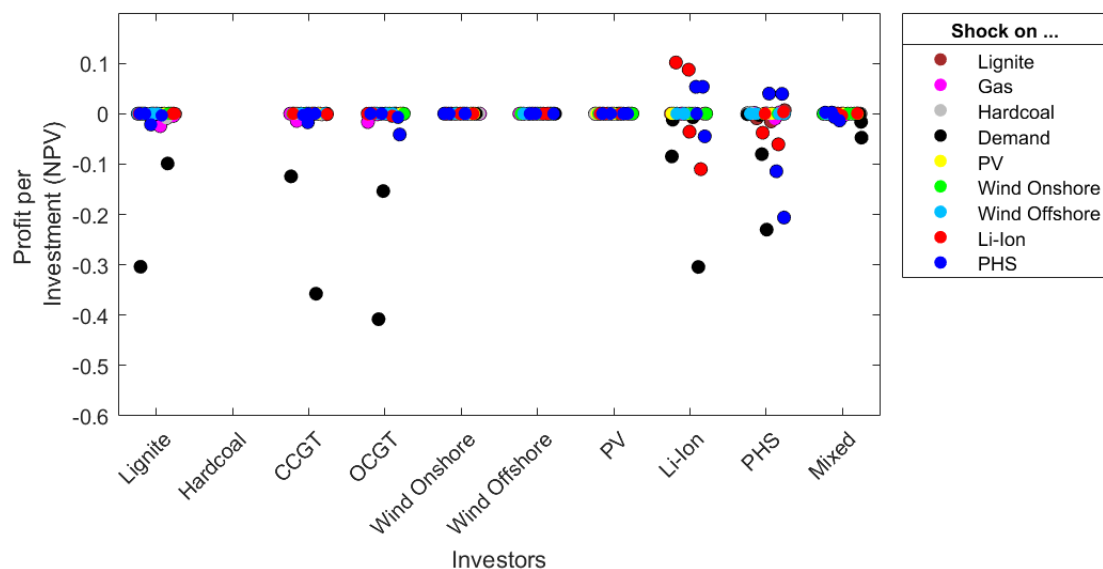


Figure 9: Investment risk under feed-in tariffs

Investment risks are smaller under price-based solutions, i.e. carbon taxes or feed-in tariffs, especially the guaranteed revenues of feed-in tariffs make this instrument beneficial for investors. Yet one should not forget that the purely price-based feed-in tariffs have caused in the past very important deviations in quantity goals: when PV module prices and interest rates fell in the aftermath of the 2008/09 global financial and economic crisis, PV uptake in Germany literally exploded, boosting also the renewable levy paid by electricity customers.

6 Conclusion

In this paper, we have analyzed the impact of information shocks on effectiveness, efficiency and dynamics of various political instruments for climate change mitigation. We developed an approach to quantify roughly the risks that different information shocks impose on investors under these instruments.

In terms of effectiveness and efficiency, our results show the expected outcome that quantity solutions like a CO₂ cap and a minimum renewable quota are favorable for achieving a certain quantity goal, while the first-best instruments CO₂ cap and CO₂ tax reduce emissions at the lowest cost (efficiency).

The results show that fixed feed-in tariffs and renewable procurement auctions reduce risks for investors significantly, as often argued by their supporters. The CO₂ tax, as another price-based solution, provides lower risks than the quantity solutions, but risks are significantly higher than under feed-in tariffs.

Feed-in tariffs do not only prevent risks for investment in renewables but also reduce risks for investment in storages, as the investment cost of renewables do not affect the market any longer. Except demand shocks, reductions in investment costs for renewables are the main source of risk for mixed portfolios. Only feed-in tariffs can reduce them, other regimes lead to quite similar results for these shocks. This overall risk reduction is large enough to allow creating electricity-market-only portfolios with low risk, as even the effect of demand reductions by 20% leads to losses of maximum 5% over 21 years. Whether this risk is diversifiable, notably by including non-electricity assets depends on the reasons for demand reductions. Notably an economic downturn as a major cause for demand reductions implies that this risk has at least partly a systematic component.

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