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Cross-border electricity market effects due to price caps in an emission trading system: An agent-based approach

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HIGHLIGHTS

- Cross-border effects of CO_2 policies were investigated with an agent-based model.
- The current EU ETS might cause CO_2 price shocks and CO_2 price volatility.
- A CO_2 auction reserve price does not lower welfare, but lowers CO_2 price volatility.
- A national CO_2 price floor lowers consumer cost in the other countries.
- A CO_2 price ceiling does not lead to an overshoot of emissions.

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ABSTRACT

The recent low CO_2 prices in the European Union Emission Trading Scheme (EU ETS) have triggered a discussion whether the EU ETS needs to be adjusted. We study the effects of CO_2 price floors and a price ceiling on the dynamic investment pathway of two interlinked electricity markets (loosely based on Great Britain, which already has introduced a price floor, and on Central Western Europe). Using an agent-based electricity market simulation with endogenous investment and a CO_2 market (including banking), we analyse the cross-border effects of national policies as well as system-wide policy options.

A common, moderate CO_2 auction reserve price results in a more continuous decarbonisation pathway. This reduces CO_2 price volatility and the occurrence of carbon shortage price periods, as well as the average cost to consumers. A price ceiling can shield consumers from extreme price shocks. These price restrictions do not cause a large risk of an overall emissions overshoot in the long run. A national price floor lowers the cost to consumers in the other zone; the larger the zone with the price floor, the stronger the effect. Price floors that are too high lead to inefficiencies in investment choices and to higher consumer costs.

1. Introduction

1.1. Motivation

The current low CO_2 prices in Europe's Emission Trading System (ETS) have triggered a discussion about policy options for improving the incentive for investing in CO_2 abatement. We introduce an agent-based electricity market model of two interlinked electricity markets which we use to test price floors and ceilings which are among these options.[1] Concerns are that the current low permit prices allow high-carbon investments, which would lock in a considerable part of future CO_2 emissions. This could lead to dynamic inefficiencies (Fankhauser and Hepburn, 2010), when later abatement efforts are more challenging than anticipated, making it more expensive to meet the emission target in the future. In addition, some policy makers fear the possibility of high price volatility, since it increases the risk premium of investors and may deter investment in the capital-intensive low-carbon technologies altogether (Department of Energy & Climate Change, 2011).

Several implementations of price caps for emission trading schemes have been discussed as possible measures to increase the dynamic efficiency and decrease price volatility of carbon markets (Fankhauser and Hepburn, 2010). A price ceiling allows unlimited emissions at a fixed maximum price. While emissions may thus exceed the targeted emission level, it serves as a “safety valve” against CO_2 prices high enough to cause substantial consumer resistance as well as possibly a loss of industrial competitiveness in comparison to countries which have no, or a lower CO_2 price.

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[1] Others are reducing the supply of credits, changing to a CO_2 tax or introducing a stability reserve.

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A price floor prevents low CO_2 prices, or at least limits the supply of permits (in the case of a reserve price) when the CO_2 price falls too low, thus providing a stable minimum incentive for low-carbon investments (Wood and Jotzo, 2011).

A national price floor has been introduced in the U.K. Department of Energy & Climate Change (2011) as a national policy measure to promote low carbon investments. This, however, poses new questions regarding cross-border effects of such a policy, both on the carbon market and on the generation portfolio. While the direct effects of different national and pan-national CO_2 price floors have been elaborated on by Wood and Jotzo (2011), the feedback loops between the carbon market and investment in electricity generation still need more research (cf. Section 1.2).

Our agent-based electricity market model *EMLab-Generation*[2] of two interlinked zones (Great Britain and Central Western Europe) provides a dynamic simulation of investment in generation capacity in response to CO_2 price floors and caps that are implemented in Great Britain, CWE or in the entire system. With Monte-Carlo simulations and sensitivity analysis, we analyse the robustness of different CO_2 price cap policies in the presence of external influences such as uncertain demand development and fuel prices. We analyse the impacts on CO_2 emissions, price levels and price volatility, as well as on total generation costs and consumer expenditures.

We find that moderate price floors significantly reduce CO_2 price volatility and prevent the occurrence of scarcity price periods, while they do not increase overall electricity generation costs. An additional price ceiling effectively protects consumers against the risk of price spikes. The effect of national implementations of CO_2 price floors depends strongly on the relative size of the introducing area as compared to the total market size.

In the following we will discuss the relevant existing literature and choice of modelling methodology (Section 1.2), introduce our model in Section 2, discuss and analyse the results (Section 3), discuss them in light of the model's assumptions and limitations in Section 3.7 and come to our conclusions and policy recommendations in Section 4.

1.2. Literature review and choice of methodology

In the academic debate, price caps lie between a pure price based mechanism, the Pigovian tax, which puts a price to a negative externality, and quantity-based mechanisms, which can be traced back to Coase (1960), which limit emissions by setting a cap and making them tradable via permits.[3] Price caps thus constitute *hybrid instruments*, which were first proposed by Roberts and Spence (1976), who state that in case of non-linear marginal damages, as well as uncertainty about marginal costs to prevent these damages, hybrid instruments are superior, since they allow for a closer approximation of the expected damage function for pollution.

For models of the overall economy price ceilings have been discussed widely for climate mitigation schemes[4] (e.g. Pizer, 2002; Jacoby and Ellerman, 2004). They come to the conclusion that price ceilings can lead to large welfare benefits. The discussion of price floors in carbon markets is more recent (Wood and Jotzo, 2011; Burtraw et al., 2010). Wood and Jotzo (2011) state that in principle three models for CO_2 price floors exist: A buy back of licenses by the administrator (as proposed in Hepburn, 2006), a reserve price when emissions are auctioned (Grubb and Neuhoff, 2006; Hepburn et al., 2006), and a complementary tax paid by the emitter, where the sum of the EU ETS price and the complementary tax is equal to the desired minimum CO_2 price floor, whenever the EU ETS permit price is below the price floor. Wood and Jotzo (2011) conclude that the first and the second options are not applicable for national solutions within interlinked CO_2 trading systems (e.g. within the EU ETS), since the first creates potentially unlimited liabilities and the latter might lead to emitters buying permits elsewhere, thus reducing the introducing state's source of income. The third option described by Wood and Jotzo, a complementary tax for energy producers was introduced in Great Britain.[5]

Regarding analysis discussing the effect of price floors and ceilings in the electricity sector, these have mostly been conducted from a single investor perspective (Szolgayova et al., 2008; Brauneis et al., 2013), using real options analysis. Burtraw et al. (2010) are an exception and use an equilibrium simulation model to analyse the effects of symmetric price caps, and finding them to be welfare enhancing. However, up to now no fully dynamic simulation model has to our knowledge been utilised to analyse price caps, especially not for national implementations. However, such dynamic investigations are useful, since equilibrium models often assume that systems develop into the future on a cost-optimal trajectory, but as Olsina et al. (2006) point out this can hardly be assumed, since important preconditions are not met: Production capacity for example can, as in any capital-intensive infrastructure system, only slowly be adjusted, which easily leads to business cycles. Furthermore long-run uncertainties exist, and thus perfect information and foresight should not be assumed. Thus path dependencies exist in the electricity sector, a problem that seems especially relevant to model when looking into the current debate about a EU ETS with very low prices, and the discussion whether this leads to lock-in effects into carbon intensive electricity production.

We decided to analyse national and pan-national, symmetric and asymmetric price caps with the help of an agent-based model, which is a middle way between fully flexible linguistic models and fully formalised, yet simplified analytic models (Holland and Miller, 1991). Agent-based modelling has been argued to be especially well suited to investigate out-of-the-equilibrium economics, the process of equilibrium formation and the inclusion of historical path dependencies (Arthur, 2006), which applied to generation capacity expansion models translates to the fact that earlier changes in generation capacity can strongly alter the outcome in later years. While agent-based modelling is more common for spot-market simulations of electricity markets and attached CO_2 markets (see for example Weidlich and Veit, 2008 or Guerci et al., 2010 for an overview), agent-based modelling is only being applied more recently to long-term policy issues, such as market concentration (Botterud et al., 2007), CO_2 cap and trade systems and CO_2 taxes (Chappin, 2011; Chappin and Dijkema, 2009), and to compare different CO_2 emission allocation schemes (Most et al., 2011).

2. Model description and assumptions

We use an agent-based model to simulate the impact of different carbon policies on a hypothetical electricity sector that consists of two interconnected zones, based on Great Britain (GB) and Central Western Europe (CWE, consisting of Belgium, Germany, France, Luxembourg and The Netherlands). The capacity of the interconnector is allocated through market coupling.

[2] Part of the EMLab suite of energy models, http://emlab.tudelft.nl.

[3] The advantages of prices versus quantities and vice versa were given by Weitzman (1974).

[4] See Fankhauser and Hepburn (2010) for a comprehensive overview of other ETS design options.

[5] Northern Island is excluded due to fears of loss of competitiveness of generators due to the large interconnection with Ireland.

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In addition to the EU ETS (the European CO_2 cap-and-trade scheme, which is implemented as one single trading period with banking), our model includes the options to implement separate carbon price caps and floors in each zone, where the lower of the two price floors or a common price floor is treated as a CO_2 auction reserve price. The model is an extension of the long-term agent-based model EMLab-Generation, which makes use of the Agent-Spring modelling framework (Chmieliauskas et al., 2012) and prior work in (Chappin, 2011; de Vries et al., 2013).

The main agents in our model are electricity generation companies. They make decisions regarding short-term bidding and the procurement of fuels and CO_2 as well as about investment. They are driven by a profit motive. The generation companies interact with each other and with other agents in markets, and so affect their own state (e.g. cash position) and their direct surroundings (foremost among them the power plants, which are implemented as discrete objects with their own states). These and the behaviour of other agents (such as fuel suppliers and electricity spot markets), are described algorithmically and implemented in Java. The source code and input data used to run this model are openly accessible.[6] In order to facilitate Monte-Carlo simulations, several simplifying assumptions needed to be made to keep the model computationally feasible.

2.1. General model structure and agents

The model's time step is one year. Each year, the generation companies determine the fuel mix of their power plants (if multiple fuels are available), buy fuels, determine their bids for the power exchange and, after the market is cleared, they dispatch their generation units. They receive revenues from the power exchange market and pay any applicable policy costs (such as for carbon credits).

As the agents decide about investing in and decommissioning plant, the evolution of the power plant mix is an emergent result of the individual agents' investment decisions in each annual time step. In their investment decisions, they take into consideration the expected electricity prices and CO_2 prices, which the agents derive by comparing estimations of the merit order and demand, and expected fuel prices, which they estimate from past observed data (cf. Section 2.5). The fact that the agents' knowledge of the future is limited is an important characteristic of the model. It leads to sub-optimal decisions, which corresponds to reality in that expectations often differ from outcomes.[7]

In the following, the most relevant parts of the model are described. A more extensive description of the model is given by de Vries et al. (2013).

2.2. Power plant operation and spot market bidding

An initial fuel mix of multi-fuel power plants is determined at the beginning of each year using linear optimisation, based on the CO_2 prices in the previous year. However, if the CO_2 price changes during the combined electricity and CO_2 market clearing iterations, the fuel mix of the power plants is updated, so that electricity and CO_2 markets are in short-term equilibrium (cf. Section 2.3). This is done with a linear program that uses current fuel prices (which are known), the CO_2 price, power plant efficiencies and the fuel mix constraints given in Table A1. The resulting variable fuel costs $vc_{g,t}$ per MWh_{el} for power plant g in time step t are then determined as the product of the volumes of the fuels (f) in fuel mix $s_{g,f,t}$ and the fuel prices $p_{f,t}$:

$$vc_{g,t} = \sum_f \frac{p_{f,t} \cdot s_{g,f,t}}{\eta_g} \tag{1}$$

We assume that variable power plant costs are solely determined by their fuel costs and that the market price includes a 10% mark-up m on variable costs. (This implies the presence of a certain amount of market power. Modelling market power is beyond the scope of this model, but this markup appears to be a reasonable assumption, cf. Eager et al., 2012.) Therefore the bidding price $p_{z,s,g,t}$ (cf. (3)) for all agents is defined as

$$p_{z,s,g,t} = vc_{g,t} \cdot (1+m) \tag{2}$$

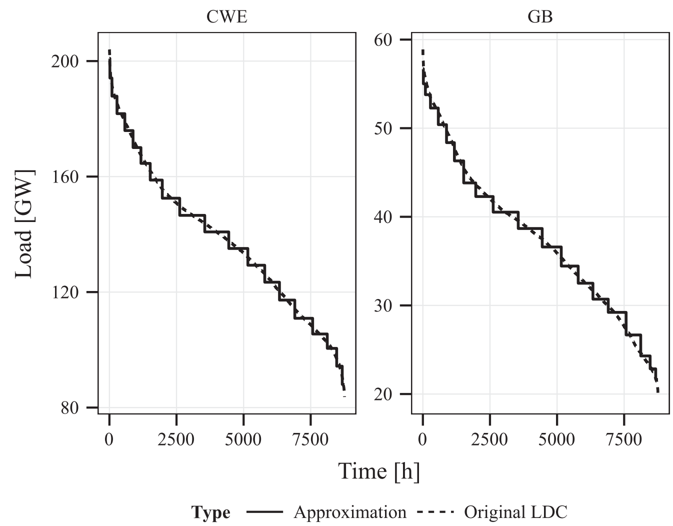

Fig. 1. Load duration curves of CWE and GB and their approximations.

2.3. Interlinked electricity and CO_2 markets

The electricity spot market is abstracted from an hourly power system model by representing demand in each zone as a step-wise approximation of the load duration curve. The load-duration curve has 20 segments (s) from base to peak load, with each segment having a fixed demand in each zone. Thus the hours in the year with a similar demand in both countries are grouped together in one segment (see Fig. 1). The duration of each segment can be varied in order to achieve a good approximation of the load duration curve. While this abstraction has its disadvantages,[8] it allows for significantly shorter model run times and thus enables us to make several hundred Monte-Carlo runs of the entire model in an acceptable amount of time. Interlinked with the electricity market is the CO_2 market including banking. It is implemented by an algorithm that finds a CO_2 price bringing the current electricity market and its emissions in equilibrium with forecasted CO_2 emissions, while abiding to the cap and the CO_2 hedging needs of power producers. This is achieved by simultaneously clearing the current electricity market and a forecasted electricity market in three years under a joint emission cap and a joint CO_2 price (which is compounded to the future). Thus emissions are banked at current time, if the compounded CO_2 price is expected to lead to an exceeding of the cap by the banked amount in the future time period (and vice versa).

[6] See the electronic appendix or https://github.com/EMLab/emlab-generation/tree/paper/co2PriceCaps.

[7] Agents are adaptable in a limited sense in that they remember past prices and perform a regression for estimating future prices. However, no more complicated learning techniques (such as reinforcement learning) are used in the model, since they require frequent repetition of behaviour. Since investment decisions occur rarely and are only made once under the same sort of condition, reinforcement learning methods do not appear to apply, as Banal-Estanol and Rupérez-Micola (2010) point out.

[8] By removing the temporal order between different hours of the year, technical constraints, such as start- and shutdown decisions, as well as power plant ramping constraints cannot be adequately represented in the model.

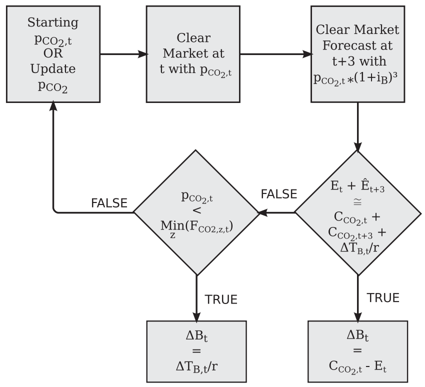

Fig. 2. Stylised electricity and CO_2 market clearing process.

In addition to that producers aim to hold around 1.5 years of their forecasted CO_2 emissions. The banking target and the hedging horizon of three years were chosen based on empirical data of hedging needs of European power producers, who hedge CO_2 permits according to their future power sales and, due to risk management procedures, rarely hedge further ahead than three years (Eurelectric, 2009; Neuhoff et al., 2012). Our banking model is influenced by two works: Schopp and Neuhoff (2013) present a partial-equilibrium model that explicitly jointly optimises CO_2 permit hedging and future power sales. Fagiani et al. (2014) use a fundamental price approach in a dynamic model, which; however, does not bring current banking and future price expectations into congruence. In our model the iterative market clearing process consists of the following steps, which are in part depicted in Fig. 2.

(1) Each generation company submits its electricity bids, one price-volume pair per power plant g for each segment s of the load-duration function according to Section 2.2. This also includes updating the fuel mix according to the CO_2 price of the current iteration. They only bid into the electricity market in which their power plant is located (zone z).

$$b_{z,s,g,t} = (p_{z,s,g,t}, V_{z,s,g,t}) \tag{3}$$

(2) The bids of the generation companies are adjusted for the CO_2 price $p_{CO_2,t}$ and, if applicable, the complementary CO_2 tax $T_{CO_2,z,t}$ (taking the emission intensity $e_{g,t}$ of the power plant into account).

$$b^{CO_2}_{z,s,g,t} = (p^{CO_2}_{z,s,g,t}, V_{z,s,g,t}) = (p_{z,s,g,t} + (p_{CO_2,t} + T_{CO_2,z,t}) \cdot e_{g,t}, V_{z,s,g,t}) \tag{4}$$

If a complementary tax is implemented, it is set to create a CO_2 price floor $F_{CO_2,z,t}$ in zone z:

$$T_{CO_2,z,t} = \max(0, F_{CO_2,z,t} - p_{CO_2,t}) \tag{5}$$

(3) The two electricity markets, which are physically coupled by an interconnector with a fixed capacity I_C of 3 GW,[9] are then cleared together (via market coupling) and the highest accepted bid $b^{CO_2,*}_{z,s,g,t} = (p^{CO_2,*}_{z,s,g,t}, V^{*}_{z,s,g,t})$ sets the market clearing price $p^{CO_2,*}_{z,s,g,t}$ in each zone z for each segment s of the load-duration function. In case demand $D_{z,s,t}$ in segment s cannot be satisfied, the clearing price is set to the value of lost load.

(4) The step described above is carried out for an electricity market forecast in three years (taking into account power plants under construction and dismantlement), except that the CO_2 price, used to clear the market, is compounded to $\hat{p}_{CO_2,t+3} = p_{CO_2,t} \cdot (1+i_B)^3$. The discount rate i_B is set to 5%, which lies in the reported range of interviews done by Neuhoff et al. (2012). As input data for the electricity market forecast, fuel price and demand trend forecasts for three years ahead are calculated. The applied regression methodology is described in Section 2.5. The past 5 years are used as input data for the regression.

(5) The market results lead to a certain (optimal) generation unit commitment, from which the resulting CO_2 emissions of the current market and the market forecast are determined.

$$E_t = \sum_{z,s,g} V_{z,s,g,t} \cdot e_{g,t}$$
$$\hat{E}_{t+3} = \sum_{z,s,g} \hat{V}_{z,s,g,t+3} \cdot e_{g,t+3} \tag{6}$$

(6) The clearing emission cap is given by the sum of the emission cap $C_{CO_2,t}$ of the current year, by the emission cap in three years time $C_{CO_2,t+3}$ and the difference to the banking target divided by a revision speed factor $\Delta T_{B,t}/r$. The banking target is determined by assuming that producers aim to hedge 80% of expected emissions in the coming, 50% in two and 20% in three years time. The expected emissions of E_{t+1} and E_{t+2} are determined by linear interpolation between E_t and E_{t+3}. This banking rule is based on a study done by Eurelectric (2009) and an interview series by Neuhoff et al. (2012). To allow some flexibility in returning to the banking target a revision speed factor r of $r=3$ is used.
If the CO_2 emissions exceed the clearing emissions cap, the CO_2 price $p_{CO_2,t}$ is raised, and vice versa if the emissions are below the cap, and steps (2) through (5) are repeated. The iteration stops and the market is considered to be cleared when the emissions are approximately equal to the CO_2 cap, when a price minimum (0 or global price floor) or price ceiling $C_{CO_2,t}$ is reached. In scenarios without a price ceiling, a constant maximum price of €500/ton is assumed.[10] Alternatively if the maximum number of iterations is reached, the last value of $p_{CO_2,t}$ is used. We apply a tolerance band of $\pm 3\%$ in order to finish the iteration in a timely fashion.

(7) Depending on whether the clearing emission cap is approximately reached, or if the lower of the national (or a common) price floor is sufficient to lead to emissions below the cap, the banked allowances are adjusted. In case the cap is approximately reached, the sum of banked allowances by all agents is adjusted by the difference between the emission cap of the current year and the emissions in the current year ($\Delta B_t = C_{CO_2,t} - E_t$). In case that the lower of the two emission floors is sufficient to lead to sub-cap emissions, the difference to the overall banked emissions is given by the difference to the banking target divided by the revision speed factor $\Delta T_{B,t}/r$. Thus, the lower of the price floors (or a common price floor) is simulated as a reserve price at which agents buy or sell[11] their credits to reach their hedging target. If more permits would be consumed than are banked, the target search algorithm is run for only the current period. The banked permits are assigned to agents according to their share in overall emissions. The difference to the previous years banked credits affects their cash position at the current year's permit prices. The agents start the simulation with 500 million CO_2 certificates already

[9] This corresponds to the current interconnection between GB and CWE. Larger values have not been investigated. See Section 3.7 for a discussion of this assumption.

[10] At that point the last fuel switching alternatives under most price scenarios are exhausted.

[11] Assuming that the reduction in banked allowances is not so large that it will depress secondary market prices below the reserve price.

Table 1
Notation.

Variable	Unit/Content	Description
t	a	Time step, in years
z	{CWE,GB}	Zone index
$S_{s,z}$	(D_s, l_s)	Segment is a tuple of demand and length
$D_{s,z}$	MW	Demand in Segment S
l_s	h	Length of Segment S (identical for both countries)
s	$\{1, \ldots, 20\}$	Segment index
$LDC_{z,t}$	$\{S_{z,1}, \ldots, S_{z,20}\}$	Load duration curve with 20 segments
$b_{z,s,g,t}$	$(p_{z,s,g,t}, V_{z,s,g,t})$	Bid into zone z, segment s, year t for power plant g, excluding CO_2 cost
$p_{z,s,g,t}$	€/MWh$_{el}$	Bidded price
$V_{z,s,g,t}$	ton/MWh$_{el}$	Bidded energy
$p^*_{z,s,t}$	€/MWh$_{el}$	Segment clearing price
$b^{CO_2}_{z,s,g,t}$	$(p^{CO_2}_{z,s,g,t}, V_{z,s,g,t})$	Bid adjusted by the iterative CO_2 target search.
g	$\{1, \ldots, G\}$	Power plant index
$e_{g,t}$	ton/MWh$_{el}$	Emission intensity of power plant g in year t
$p_{CO_2,t}$	€/ton	CO_2 permit price
$F_{CO_2,z,t}$	€/ton	CO_2 Price floor in zone z
$T_{CO_2,z,t}$	€/*ton*	Complementary CO_2 tax in zone z
$C_{CO_2,t}$	€/ton	Common price ceiling
$B_t, \Delta B_t$	ton	Banked emission permits, difference in banked emission permits
i_B		Interest rate for compounding the CO_2 price
$T_{B,t}, \Delta T_{B,t}$	ton	CO_2 permit banking target, and difference to it in year t
r		Revision speed factor towards the banking target
$vc_{g,t}$	€/MWh$_{el}$	Variable fuel costs of power plant g in t
$fc_{g,t}$	€	Fixed costs of power plant g in t
$p_{f,t}$	€/MWh$_{th}$	Price of fuel f in time step t
$s_{g,f,t}$	MWh$_{th}$	Amount of fuel f in fuel mix of power plant g in time step t
η_g		Efficiency of power plant g
$a_{s,g}$		Segment dependent availability of power plant g
m		Price mark-up of generators
$\hat{r}_{g,s,t}$	h	Expected running hours of power plan g, in segment s, in year t
$I_{g,t}$	€	Investment cost of power plant g in t
$WACC$		Weighted average cost of capital

Table 2
Fuel price and demand growth rate assumptions.

Type	Unit	Demand CWE	Demand GB	Lignite	Biomass	Uranium
Start	€/GJ	s.b.	s.b.	1.428	4.5	1.286
Average	[%]	1.30	1.00	0.00	1.00	0.00
Upper	[%]	5.40	4.00	1.0	7.00	1.00
Lower	[%]	−3.90	−2.00	−1.00	−5.00	−1.00

banked, which is at the upper limit of the estimation by Neuhoff et al. (2012).

2.4. Generation technologies and initial portfolio

Fifteen power generation technologies are implemented in the model (see Table A1). Investment costs, maintenance costs, operational costs, fuel efficiencies and technological learning (affecting fuel efficiencies and investment costs) are modelled after the IEA World Energy Outlook 2011 New Policies Scenario (IEA, 2011). Additional assumptions were made regarding power plant capacities, their technical life spans, CO_2 capture efficiency, depreciation times and co-firing (see A1). Due to the approximation of the load duration curve, model-specific assumptions needed to be made for some technologies. Minimum running hours serve as an investment decision approximation for plants with longer ramping times. The intermittency of renewable power plants is deterministically reflected in their availability during base and peak hours, i.e. a wind turbine only produces 5% of its nameplate capacity during peaks, whereas hydro power plants contribute more (60% of name plate capacity) to peak hours than to base hours (0%). The low contribution of wind to the peak is based on German empirical data. In between the base and peak segments, the segment-dependent availability $a_{g,s}$ is varied linearly. These assumptions are summarised in Table A1. The initial generation portfolios are modelled after the generation mix of CWE and GB in 2011 (data taken from Eurelectric, 2012), and the age structure of the power plants is modelled after the average age structure of power plants in the European Union (RWE, 2008). Since market power is not endogenously modelled, for simplicity an assumption was made with regard to the initial ownership and number of agents per zone: all technologies are evenly distributed between the 4 generation companies of each zone. Finally, for computational reasons, all capacities of power plants in the CWE zone are scaled by a factor of 4, as compared to Table A1.

2.5. Investment in generation capacity

Each generation company invests in only one zone, so market entry into the other zone is not considered. Investment decisions by generators are made in an iterative process in which the companies sequentially consider investing. A company's investment decision influences the decisions of the following companies. The investment process is stopped as soon as none of the companies invest any more. To prevent a continuous bias towards specific generation companies, the order in which they invest is determined randomly each year. Agents are assumed to finance 30% of the capital cost of a power plant from their cash flow (expecting a 12% return on equity), and pay this amount as down payments in equal instalments during the construction period of the plant. The remaining 70% are assumed to be debt-financed at an interest rate of 9%. The loan is assumed to be paid back in equal annuities during the depreciation period of the power plant (cf. Table A1). The agents take the following steps in each round (Table 1):

(1) The generation companies forecast fuel prices and electricity demand in n years time (n varies between 6 and 8 years for investors, which contributes to heterogeneity in the investment decisions) by applying a regression analysis, assuming future fuel prices and electricity demand to correspond to a linear trend. Similarly, they forecast CO_2 prices by taking the average of a linear regression forecast and the forecasted CO_2 clearing in 3 years time (cf. Section 2.3). The number of past years that are used for forecasting vary between 4 and 6 years for the various agents. This leads to heterogeneous forecasts and therefore to some heterogeneity in the investment behaviour.

(2) Based on the above assumptions and on the expected life spans of the existing power plants, a bottom-up estimation of future electricity prices $\hat{p^*}_{z,s,t}$ is made for each segment of the load-duration function by using the merit order of existing and announced new power plants and excluding power plants which are expected to be dismantled due to age.

(3) For each power generation technology type, it is verified that the necessary investment conditions, such as sufficient cash reserves and physical and social limit such as a maximum investment limit, are met in each zone.[12]

(4) The expected number of hours $\hat{r}_{s,g,t}$ that a plant is running are calculated from the estimated future energy prices in each segment. They are compared to the minimum running hours of the technology type (Table A1). Based on the expected running hours and prices, the expected cash flow during operation $CF_{Op,g}$ is calculated for the reference year $t+n$:

$$CF_{Op,g} = CF_{g,t+n} = \sum_{s}((\hat{p^*}_{z,s,t+n} - \hat{vc}_{g,t+n}) \cdot \hat{r}_{s,g,t+n} \cdot a_{g,s}) - fc_{g,t+n} \tag{7}$$

Generation companies compare power plants with different capacities κ_g with each other by calculating their specific net present values (NPV) per MW over the building period $(0..t_b)$ and the expected service period $(t_b+1...t_b+t_D)$. The weighted average cost of capital (WACC) is used as the interest rate:

$$\mathrm{NPV}_g = \left(\sum_{t=0...t_b} \frac{-I_{g,t}}{(1+\mathrm{WACC})^t} + \sum_{t=t_b+1...t_b+t_D} \frac{\mathrm{CF}_{Op,g}}{(1+\mathrm{WACC})^t} \right) / \kappa_g \tag{8}$$

(5) If any of the NPVs are positive, the technology type g with the highest specific NPV_g per megawatt is chosen.

2.6. Fuel price and demand trends

Electricity demand and lignite, biomass and uranium prices are modelled as stochastic trends, using a triangular distribution to determine the year-on-year growth rate. The assumptions for the average growth rate and the upper and lower bounds of the triangular functions are summarised in Table 2.

The costs of biomass are in the range estimated by Faaij (2006) for northern European biomass, lignite is based on Konstantin (2009), but inflation adjusted. Hard coal and natural gas prices are modelled as correlated stochastic Ornstein–Uhlenbeck processes. They are mean reverting to three different fossil fuel scenarios which we took from the UK Department of Energy and Climate Change (Department of Energy & Climate Change, 2012) and extended beyond 2035 (cf. Fig. B1). The variance around these trend lines was set to a long-term average between 1920 and 1996, and the mean reversion speed was set to 5 years as calculated by Pindyck (1999) (cf. Section Appendix B). The correlation between coal and gas prices was estimated from fuel prices in the UK between 1993 and 2011 (Department of Energy & Climate Change, 2013).

The load-duration function is based on ENTSO-E data from 2010 for the CWE and the UK. It is assumed that the growth rate of demand is the same in all segments of the load duration curve.

Table 3
Investigated CO_2 policies.

Policy	Price floor		Price ceiling
Country	GB	CWE	Both
PureETS	□	□	□
MinGB	■	□	□
MinCWE	□	■	□
BothMin	■	■	□
BMinMax	■	■	■

2.7. Renewable investment

Since European governments are subsidising renewables, renewable policy is implemented in the simulation by assuming that the governments in CWE and GB exogenously fulfil policy targets. These are implemented as national renewable target investors who only invest in renewable energy if private investment does not reach the government targets.

3. Model results and discussion

Because of the complexity of the model results, we integrate them with their discussion and analysis. This section starts with a description of the scenarios that we use in Section 3.1. Next, we present our model results regarding the effects of the different CO_2 policies on CO_2 prices and emissions in Section 3.2. In Section 3.3, we link this to the underlying changes in the generation portfolio and investment decisions. The impact on generation costs and consumer expenditures is analysed in Section 3.4. While Sections 3.2–3.4 discuss the model results on an exemplary base case, the analysis is extended to further fuel prices and renewable scenarios in Section 3.5. A sensitivity analysis regarding price floor levels is discussed in Section 3.6. In Section 3.7 we reflect on the results in light of our assumptions and the model's limitations. All statistical evaluations and graphs were done in GNU R (R Core Team, 2003).

3.1. Scenarios

We apply a combination of Monte-Carlo simulations and sensitivity analysis to investigate the dynamic development of investment decisions, CO_2 prices and electricity prices as a function of CO_2 policy choices. We model five different CO_2 policy options in a base case. For each of these policy scenarios, we vary

[12] Examples of such conditions are a limit on nuclear energy in CWE, due to political constraints in Germany and limits to the volume of new capacity that can be constructed simultaneously, e.g. due to labour force and equipment constraints, and geographic constraints to hydro power.

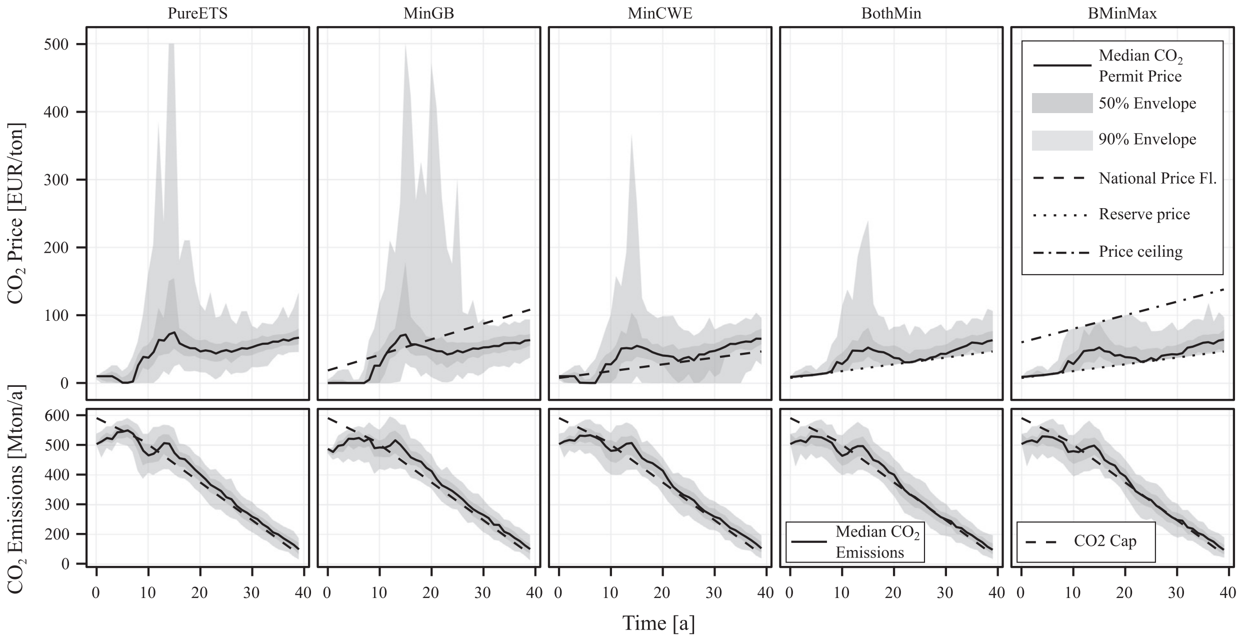

Fig. 3. CO_2 price and emissions development.

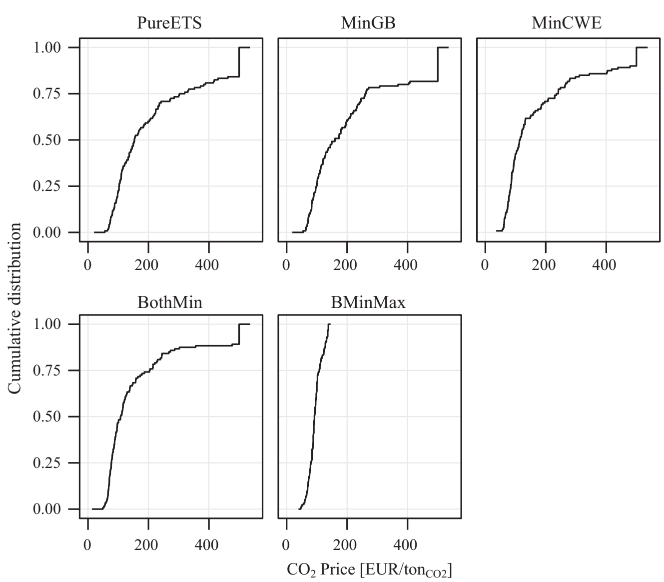

Fig. 4. Maximum CO_2 permit prices in different scenarios.

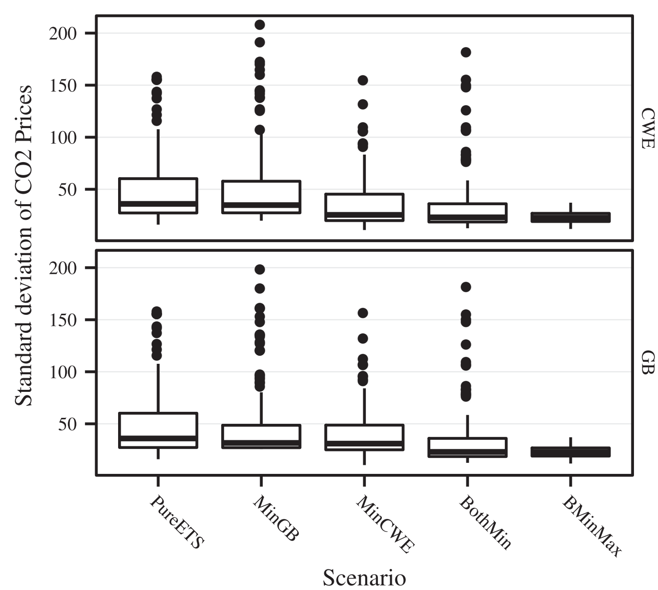

Fig. 5. Boxplot of the standard deviation of effective CO_2 prices in individual runs.

the fuel price development (around the scenario fuel price trends) and the electricity demand growth rate Monte-Carlo style. 120 Monte-Carlo runs are performed for each of the 5 scenarios. The same 120 realisations are used for all scenarios to avoid random differences between the scenario results.

The CO_2 policies under investigation are detailed in Table 3. For the MinGB case the price floor starts at €18.50/t_{CO_2} and rise with €2.30/t_{CO_2} per year. This corresponds approximately to the originally planned price floor in the GB (Department of Energy & Climate Change, 2011) which starts at about 16£/t_{CO_2} in 2013 and reaches 30£/t_{CO_2} by 2020 and 70£/t_{CO_2} by 2030.[13] For the MinCWE, BothMin and BothMinMax cases the price floor starts at €7.50/t_{CO_2} and rises with €1/t_{CO_2} per year.[14]

The national price floors are implemented as complementary taxes and do not (directly) affect the price of the CO_2 permits themselves, but only the total CO_2 price that is paid by affected generation companies.[15] We will also refer to this as the effective CO_2 price. The complementary carbon tax is defined as the difference between the CO_2 permit price and the desired price floor, if the CO_2 price is below the price floor (and otherwise it is zero). On the other

[13] In practice the UK government fixes the complementary tax two years ahead of its realisation, based on the future carbon price (UK Government HM Revenue & Customs, 2013). This results in a lower effective minimum price.

[14] The reason to choose a lower price floor for these scenarios is policy relevance: a price floor as a high the one in GB seems to be politically unrealistic for the whole EU ETS.

[15] While, strictly speaking, the sum of a price and a tax is not a price, we follow the nomenclature used by Wood and Jotzo (2011).

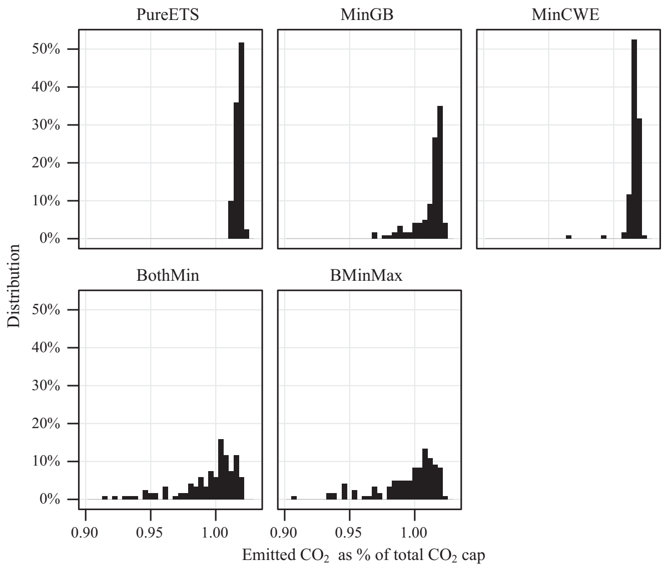

Fig. 6. Histogram of CO_2 emissions.

hand the price floors in the BothMin and BMinMax scenarios are implemented as a CO_2 auction reserve price.

The price ceiling in the BMinMax scenario starts at €$60/t_{CO_2}$ and rises by €$2/t_{CO_2}$ per year. It is implemented as a limit to the CO_2 permit price. If, at this price, demand for CO_2 permits is greater than the cap, additional emission permits are issued, so the CO_2 emissions cap is exceeded. The EU ETS is part of all our policy options. The emissions cap is calibrated using the 20% reduction target for 2020 (as compared to 1990 emissions) and an 80% reduction target for 2050 (compared to 2005 emissions).

In addition to the base case, we model two more renewable policy options. In the base-case scenario, we assume that the development of renewable until 2020 to follow the National Renewable Energy Action Plans (Beurskens et al., 2011) and between 2020 and 2050 to follow the 80% pathway of Roadmap 2050 by the European Climate Foundation (2010). In addition, we model a scenario with half this volume of renewable energy and a scenario without a renewable energy target. Regarding fuel prices, we use the medium scenario (cf. Section Appendix B) as a base case scenario, and a higher and a lower scenario for sensitivity analysis. Finally for all policy scenarios except the PureETS, we vary the price floor levels.

3.2. CO_2 prices and emissions

In order to show the effects of the different policy options on CO_2 permit prices and on effective CO_2 prices, Fig. 3 shows the development over time of CO_2 permit prices and CO_2 emissions. The CO_2 permit price is high in years 10–20, with a significant increase of volatility. This is due to an increase in the linear reduction factor of the CO_2 cap and the technical end of life of legacy nuclear power plants. As can be seen in the emission plot, agents bank CO_2 permits before, which they are using in the peaking period. After this period, the price drops in all scenarios and then rises again gradually towards the end of the simulation period. Emissions fluctuate around the cap, but are slightly above it, as agents reduce there banked emissions with their hedging needs.[16] MinCWE and BothMin reduce CO_2 permit prices, including the price peak, and naturally the price ceiling in BMinMax limits CO_2 price peaks.

[16] And are thus emitting more than is available under the yearly cap.

To provide an indication of the frequency of price peaks, Fig. 4 shows the cumulative distribution of the highest CO_2 permit prices that occur in the individual simulations. For a given CO_2 permit price on the *x*-axis, the intercept with the curve shows the percentage of runs in which the highest CO_2 price (in the entire run) is the same or lower. So while 30% of PureETS runs have a maximum permit price of 110 € /ton or less, the same quantile is 105 €/ton in the MinGB scenario. The frequency of maximum CO_2 permit prices is a measure of the likelihood that CO_2 permits become scarce in a given scenario. Fig. 4 shows that the PureETS and MinGB scenarios are most prone to CO_2 price peaks. The risk of price peaks is reduced by the introduction of a price floor in CWE and even more if both zones introduce a price floor. If we define price peaks as periods with prices greater than 150 €/ton CO_2, their duration also correlates with their height. Whereas there are two or fewer years with high price periods in 65% of the PureETS and MinGB simulations, this number falls to one year in the MinCWE scenario and there are no peak years in the BothMin and, by definition, the BMinMax scenario.

The overall volatility of effective CO_2 prices is, of course, affected by the occurrence of price peaks. This can be seen in Fig. 5, which shows a boxplot of the standard deviation of effective CO_2 prices in individual runs.[17] This figure sheds more light on how national CO_2 policies affect the volatility in the two zones, as it shows the volatility in each zone separately (by considering the national CO_2 price floors in addition to the CO_2 permit price). While the introduction of a price floor in GB reduces volatility slightly in GB (due to the prevention of a CO_2 price collapse in GB), effective CO_2 price volatility decreases only slightly in the CWE zone.

Last but not least, we review the degree to which the policy options achieve the CO_2 reduction target. Fig. 6 shows the relative frequency distribution of total emissions as a percentage of the emissions cap over the different runs for the investigated policy options. Emissions are close to the cap in the PureETS, the MinGB and the MinCWE scenario, which shows that when banking exists, a national price floor changes the total emission rate only by a small amount, even if CWE introduces that price floor. The fact that total emissions are slightly over the cap is due to the initial volume of banked permits. The situation is different in the BothMin and BMinMax scenarios, in which the minimum price for CO_2 is modelled as a reserve price at the auction. In this case, the volume of permits that is issued at the auction may drop below the cap if there is not enough demand at the reserve price, and therefore over abatement as compared to the cap can occur. In our scenarios, over abatement only occurs to a relatively small degree due to the relatively low level of the price floor. The differences between runs are mostly caused by the differences between the stochastic demand scenarios, as the price restrictions limit the system's responsiveness to extreme scenarios. The BMinMax case has slightly higher emissions, as compared to BothMin, which is caused by the additional CO_2 permits issued in the years when the CO_2 price ceiling is reached. An interesting and perhaps counter-intuitive outcome is that despite these price restrictions, this emission overshoot is limited. The reason is that while a price ceiling may allow emissions to exceed the cap in specific years, overall the price floor is high enough to induce sufficient abatement in the long run.

3.3. Generation portfolio

The differences in emissions and CO_2 prices between model runs are largely caused by different investment decisions. Fig. 7

[17] The standard deviation of prices, not logarithmic returns is used here as a measure for volatility, since zero prices occur.

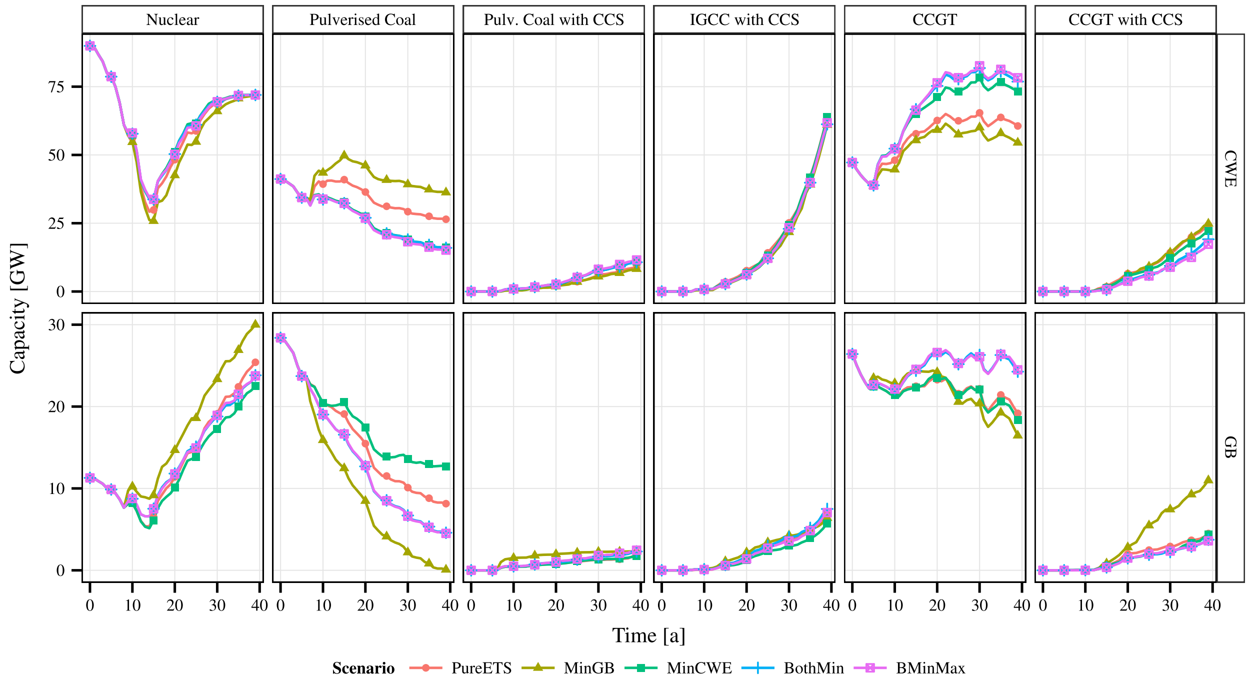

Fig. 7. Mean development of nuclear, pulverised coal, integrated gasification combined cycle (IGCC), combined cycle gas turbine (CCGT) and technologies with carbon capture and storage (CCS).

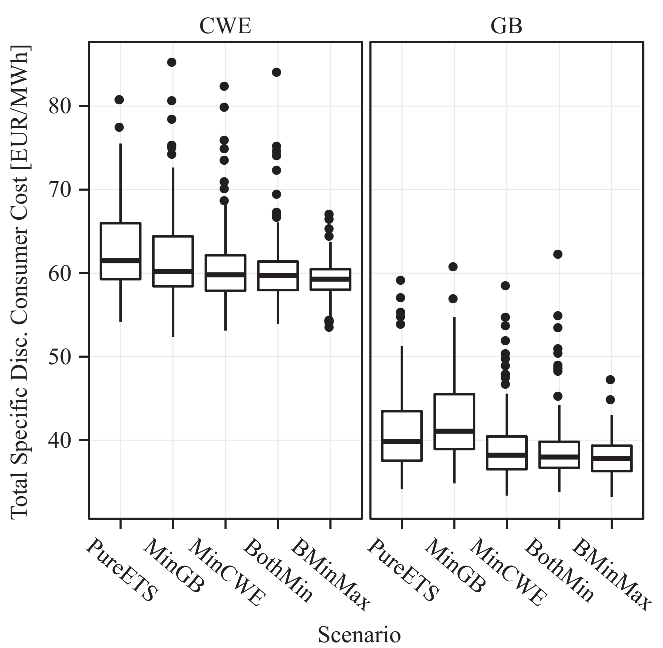

Fig. 8. Boxplot of specific consumer expenditures in CWE and GB (excluding RES subsidies).

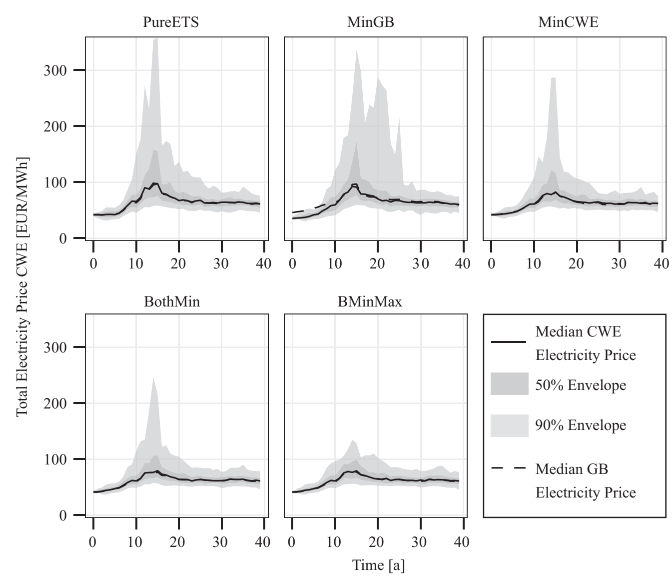

Fig. 9. Median electricity market price development in CWE (with 50% and 90% envelopes) and GB.

shows the mean development of selected technologies for the different policy options. The top series of graphs represent the CWE zone, the bottom series Great Britain. The lines represent the mean value of the different Monte-Carlo runs for each time step. The graph shows a selection of generation technologies in order to highlight the differences between the scenarios. (While there are considerable variations between the Monte-Carlo runs, we omitted the quantile envelopes so as to achieve a clearer representation of the scenario trends.)

Fig. 7 shows that price floors lead to a more continuous reduction of carbon intensive technologies such as pulverised coal (CoalPSC) and a faster build up of low-carbon technologies. This is especially true for medium term CO_2 abatement decisions such as substitution of coal by gas or nuclear power plants: whereas in the year 2025, on average, a total of 40.2 GW of CoalPSC, 57.4 GW of CCGT and 29.2 GW of Nuclear are installed in CWE in the PureETS scenario, this shifts to 32.4 GW of CoalPSC, 65.4 GW of CCGT and 34.1 GW of nuclear in the BothMin scenario.

Secondly, Fig. 7 confirms our earlier observation that national price floors lead to stronger decarbonisation locally, but that the resulting lower CO_2 permit prices lead to more investment in carbon-intensive technologies in the other zone. This is clearly

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Table 4
Price floor levels.

Price Floor	Start value [€]	Slope [€/year]
Very low	5	0.75
Low	7.5	1.00
Low slope	10	1.50
High	18.5	2.30

visible for CoalPSC for the MinCWE and MinGB policy options. From year 6 on, less CoalPSC is installed in the zone with the price floor, as compared to the PureETS scenario. This is followed by a prolonged period until year 11 with lower CO_2 prices as compared to the PureETS case (cf. Fig. 3), which in turn lead to more CoalPSC capacity in the zone without a price floor by the year 13 of the simulation, as compared to the PureETS scenario.

3.4. Total generation costs and consumer expenditure

Social welfare is equal to the total utility of electricity minus the total costs of generation. As the utility is difficult to estimate and electricity demand is assumed to be price-inelastic and our model does not include transmission, the goal of maximising social welfare can be approximated by minimising the discounted total costs of generation. We define the total cost of generation as payments that leave the group of generators, consumers and governments (who produce electricity via the renewable target investor). Therefore it is comprised by payments to power plant manufacturers, fuel suppliers and interest payments to banks. A second important indicator is consumer welfare, for which we use the total consumer expenditure as a proxy. For both indicators we use a social discount rate of 3% in order to discount future costs and expenditures to current costs.

Differences in total generation costs between the scenarios are relatively small. The average (of the Monte-Carlo runs) of the overall discounted total generation costs in the current scenario, PureETS, over the entire 39-year simulation period, is 3874 billion EUR. The MinGB case is on average 0.2% more expensive and the policy options of MinCWE, BothMin and BMinMax have on average 0.39%, 0.50% and 0.58% lower total generation costs than the PureETS. Although these differences are statistically significant[18] and can be explained by dynamically inefficient investments (early coal investments that are not used under high CO_2 prices), they are so small that consequently a policy choice should be made on other factors, such as social acceptability, costs to consumers or acceptability to risk averse investors.

The differences in consumer expenditures (for electricity) are more significant. Fig. 8 shows the specific discounted consumer costs (including renewable subsidies, which cause the higher cost in CWE due to the exogenous renewable scenario) over the simulation period. National carbon price floors lower the electricity prices in the other zone because they depress CO_2 permit prices. The effect of carbon price floors on the introducing zone differs between the MinGB and the MinCWE cases. In the MinCWE case, average electricity prices are lower and vary less around the median. This is due to the relatively low price floor, which does not push up the electricity price significantly but does reduce carbon price volatility. In GB, on the other hand, the national price floor is so high that it increases the cost of electricity to consumers, yet its impact on the entire system is not large enough to reduce carbon price volatility significantly. Both scenarios with a common reserve price reduce the cost of electricity to consumers further and also reduce the spread between the possible outcomes. The reduction in the cost of electricity to consumers is mainly due to the lower CO_2 prices and thus to a reduction in company profits and government income. A small share of around 10% is due to improvements in overall system efficiency.

On a yearly basis, differences in electricity prices are much more pronounced, as can be seen in Fig. 9. While the average price differences appear socially acceptable, in single years price differences can be much larger between PureETS and the reserve price scenarios (BothMin and BMinMax). In 25% of the cases, these price differences are €50/MWh or higher. Only the scenario with a price ceiling protects against the risk that high prices occur.

In practice, there are factors that dampen CO_2 prices, such as abatement opportunities in other ETS sectors. Moreover, if very high prices occurred, political intervention would likely take place, e.g. in the form of a temporary relaxation of the emissions cap. Therefore the high prices in the model should not be taken literally; instead, they indicate the risk that the carbon market does not induce abatement fast enough which could lead to economic and political tension. The presence of minimum and maximum prices removes this risk, while the abatement target is still achieved.

3.5. Sensitivity analysis: fuel and renewable energy scenarios

In the previous sections, the results for the base case scenarios were presented. Now we will discuss how different fuel and renewable energy scenarios affect the simulation outcomes. We chose these two parameters because of their high impact on decarbonisation: renewable energy directly affects CO_2 emissions and fuel prices and their relative difference affect decarbonisation costs. Differences in the renewable and fuel price scenarios have a significant effect upon CO_2 prices, but the model results mainly remain robust with respect to the fundamental nature of the differences between the CO_2 policy options.

The lower the renewable target in the simulation, the higher are the average CO_2 prices and the longer are the CO_2 price peaks. Especially in scenarios without renewable subsidies, model scenarios frequently show high prices (cf. Fig. C1). This is reasonable, since renewables displace conventional generation and its emissions. Total generation costs and consumer payments are significantly affected by renewable energy policy: the scenarios without renewable policy support consistently have around 40% lower total generation costs than the scenarios with a full renewable roll-out. This result is due to the high share of solar photovoltaic in the renewable scenarios and to the assumptions about renewable technology cost development.[19] With less renewable policy support, the consumer expenditure differences between the policy options become larger, since MinCWE, BothMin and especially BMinMax lower the frequency of scarcity prices for CO_2 (cf. Figs. C3 and C4). An interesting finding is that CO_2 price and consumer expenditure volatility increases more in the MinGB case when renewable subsidies are reduced, than in the other scenarios, up to the point that costs increase for consumers in CWE as compared to the PureETS case. A similar result is obtained for runs without CO_2 permit banking. Thus in absence of CO_2 price dampening factors,[20] and assuming short-sighted investors, a national CO_2 price floor in

[18] Kruskal–Wallis and pairwise Wilcox tests show that the MinGB, PureETS and MinCWE scenarios are significantly different from each other and from BothMin and BMinMax scenarios. Between the BothMin and BMinMax scenarios we did not find a statistically significant difference.

[19] A sensitivity analysis regarding these two parameters is out of the scope of this paper because we focus on CO_2 policy.

[20] Such as renewable subsidies, CO_2 banking by energy producers and speculators, abatement by other ETS sectors, as well as price elasticity on the demand sight.

small parts of the system might increase CO_2 price volatility. In practice, however, it is doubtful whether a sufficient high level of CO_2 price volatility that induces strong abatement swings would occur under existing dampening factors.

The sensitivity of the results to the fuel price does not provide unexpected results: higher coal and gas prices lead to higher CO_2 prices (since the CO_2 price is often determined by the gas/coal price spread which rises in absolute terms) and longer periods with scarcity prices for CO_2. However, the higher the fuel prices, the higher are the total generation costs and the consumer expenditures. The order between the policy options is robust over the different fuel price scenarios (cf. Figs. D2 and D3), but the differences between the policy options decrease with lower fuel prices, due to the decrease of CO_2 scarcity prices and the effect of MinCWE, BothMin and especially BMinMax on dampening them.

3.6. Sensitivity analysis: the level of the price floor

Another important assumption concerns the level of the price floor. We tested the sensitivity to this assumption by varying the price floor level compared to the base scenario:

The high scenario (cf. Table 4) is the closest to the actual minimum price floor introduced in GB (and used in the MinGB base case scenario), and we see it as an upper bound to a European compromise on a common price floor. The very low floor scenario on the other hand presents a lower bound, with a starting level close to 2013 prices. Together the discussed floor prices cover a broad range of dynamic results, as can be seen in Fig. E1.

Not surprisingly, the higher the price floor and the bigger the introducing zone, the stronger are the effects on the CO_2 permit price, as was also discussed in Section 3.2. The effects of different price floors on CO_2 permit prices are shown in Fig. E1. The higher the price floor, the more often it is applied. Already the price floor starting at €10/ton and rising by €1.50/ton per year is active in a majority of years. However, high price floors cause a policy overshoot in that carbon emissions may drop below the emissions cap (cf. Fig. E2). Very high price floors thus achieve very low volatility (since they basically act as a tax), however also lead to higher costs to consumers due to the greater carbon abatement efforts (cf. Figs. E3 and E4). A lower price floor in combination with a price ceiling achieves at least the same level of low volatility at lower prices for consumers.

3.7. Reflection on the assumptions

As with any model, there are several underlying assumptions and limitations to our analysis, which need to be taken into account before coming to an evaluation of its results. First of all, it should be kept in mind that due to the long-term nature and the many assumptions that are necessary, the results of this model do not constitute exact market forecasts, but are rather an investigation of the investment dynamics in the power sector and there interaction with CO_2 policies. We will discuss here the main assumptions underlying the model (other than the ones that were discussed in the sensitivity analysis) and how we expect them to influence our results.

The investors in our analysis have a rather short-term horizon for making decisions and only a limited capacity to forecast demand, and the prices of fuels, CO_2 and electricity. If investors were more clairvoyant, we would expect less pronounced investment and abatement swings. This would reduce the difference in overall total generation costs and consumer expenditures (due to a lower occurrence of price peaks) between the policy options. However, investment decisions leading to over capacity and as well as erroneous CO_2 price forecasts have been observed in Europe, giving support to our assumptions.

The scope of the model is limited to the electricity sectors of Great Britain and Central-Western Europe, with a fixed interconnection capacity. Electricity demand is assumed to be price-inelastic and banking of CO_2 permits is only done by power producers for the next three years. These assumptions have as a consequence that the model may exaggerate CO_2 price swings, because some inter-temporal and inter-sectoral flexibility is ignored. A larger system, like the EU-ETS, would dampen price swings. As a result, in practice we would expect the differences in consumer expenditures between the policy options to be smaller, since they are driven by price peaks. A larger interconnection capacity between zones will negatively impact the dispatch of generators in periods in the zone where a national price floor is active. For this reason we see the introduction of national carbon price floors in well-interconnected electricity systems as politically unviable. This view is supported by the fact that Great Britain excluded Northern Ireland from their price floor, since it is well connected to Ireland (UK Government HM Revenue & Customs, 2013).

4. Conclusions and policy implications

We present an agent-based model of investment by profit-oriented electricity generation companies in two interconnected electricity markets (based on Great Britain and Central Western Europe) and including an endogenous CO_2 market with banking. In this setting, we analysed five different CO_2 policy options with national and pan-national price floors, as well as a price ceiling, under the stochastic input parameters of electricity demand and fuel prices.

We found that in an unaltered EU ETS, or one with a minimum price floor in Great Britain, there is a significant chance of CO_2 price shocks and CO_2 price volatility, which may lead to socially in-acceptable electricity prices in single years. In comparison a common, moderate CO_2 auction reserve price of 7.50€/ton$_{CO_2}$, increasing by 1€/ton$_{CO_2}$ per year, results in a more continuous decarbonisation pathway. This reduces CO_2 price volatility and the occurrence of carbon scarcity price periods and electricity price shocks. It also reduces the spread of possible consumer expenditures. A price floor that is set too high causes inefficiencies, but also reduces emissions to a level significantly below the cap. An additional, moderate price ceiling of 60€/ton$_{CO_2}$, increasing by 2€/ton$_{CO_2}$ per year, would effectively shield consumers from the remaining risk of price shocks. Importantly, these price restrictions were not found to cause a large risk: no overall emission overshoots in the long run nor large long-lasting temporal overshoots occur. The volatility of CO_2 prices is lower in scenarios with larger volumes of subsidised renewable energy and with a lower absolute coal to gas price spread.

A national price floor, like in the GB, leads to a faster decarbonisation in the introducing country and lowers the cost to consumers in the other zone; the larger the price floor, the stronger the effect. Especially a price floor in the larger zone lets the consumers in the small zone free ride on significantly lower electricity prices. National price floors do not lead to significantly less emissions overall; even a small zone can cancel out the over-abatement induced by the national price floor in a large part of the ETS.

Our work is complementary to the previous work by Burtraw et al. (2010) and Wood and Jotzo (2011). In contrast to Burtraw et al. (2010) we simulate agents with less perfect foresight and we discuss both common and national price floors. In comparison our findings highlight the risk of consumer price shocks due to non-continuous decarbonisation pathways. Wood and Jotzo (2011) analyse a great variety of price floors and caps

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theoretically. We investigate some of these in a simulation model and confirm their hypothesis regarding the reduction of CO_2 price, and that national price floors will commensurately reduce effort elsewhere.

We recommend to introduce a moderate price floor and price ceiling when designing or improving emission trading systems. This lowers the cost of abatement by reducing policy uncertainty for investors and shields consumers and industry from carbon price peaks. While other policy methods, such as backloading, exist, price caps provide better predictability (see also Fankhauser and Hepburn, 2010), since politically unsustainable price levels (both on the upper and lower end) are prevented and implicit price caps are made explicit. A national price floor is necessarily implemented as a supplementary tax, but if it is expanded into a system-wide price-floor we recommend shifting to a reserve price in the allowance auction to prevent banking of high volumes of emission allowances.

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Appendix A. Technologies

See Table A1. Used acronyms: steam cycle (SC), pulverised steam cycle (PSC), integrated gasification combined cycle (IGCC), open cycle gas turbine (OCGT), combined cycle gas turbine (CCGT) and carbon capture and storage (CCS).

Appendix B. Gas and coal price model

As introduced in Section 2.6, coal and gas prices in the simulation are modelled as mean reverting stochastic processes following trend lines (cf. Fig. B1). For this the Ornstein–Uhlenbeck process have been used, where $\boldsymbol{\mu}_t$ are the log trend value in each time step, $\mathbf{X}$ the log fuel price vector of gas and coal prices, dW_t two correlated Wiener process, and $\boldsymbol{\sigma}$ the volatility vector and λ

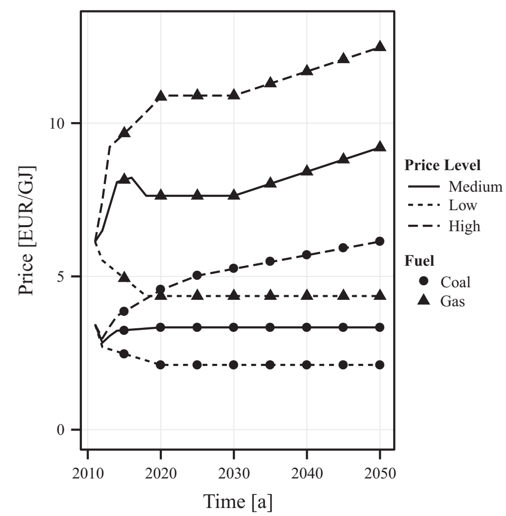

Fig. B1. Fuel price trends for coal and gas.

Table A1
Power generation technology assumptions.

Generation technology	Capacity κ_p [MW]	Construction time t_b [a]	Permit time t_{Pe} [a]	Technical lifetime [a]	Depreciation time t_D [a]	CO_2 capture eff. [%]	Min. Running hours r_h [h]	Base Availability $a_{20,p}$	Peak Availability $a_{1,p}$	Fuels (max. %)
Nuclear	1000	7	2	40	25	n.a.	5000	1	1	Uranium
Coal Pulverised SC	758	4	1	50	20	0	5000	1	1	Coal, Biomass (10%)
Lignite	1000	5	1	50	20	0	5000	1	1	Lignite
CoalPSC with CCS	600	4	1	50	20	87.5	5000	1	1	Coal, Biomass (10%)
IGCC	758	4	1	50	20	0	0	1	1	Coal, Biomass (10%)
IGCC with CSS	600	4	1	50	20	87.5	0	1	1	Coal, Biomass (10%)
Biomass combustion	500	3	1	40	15	0	5000	1	1	Biomass
Biogas	500	3	1	40	15	0	0	1	1	Biomass
CCGT	776	2	1	40	15	0	0	1	1	Gas
CCGT with CCS	600	3	1	40	15	85	0	1	1	Gas
OCGT	150	0.5	0.5	30	15	0	0	1	1	Gas
Hydropower	1000	5	2	100	30	n.a.	0	0	0.60	n.a.
Wind	600	1	1	25	15	n.a.	0	0.40	0.05	n.a.
Wind offshore	600	2	1	25	15	n.a.	0	0.60	0.07	n.a.
Photovoltaic	100	2	1	25	15	n.a.	0	0.20	0.04	n.a.

the speed of mean reversion:

$$d\mathbf{X} = \lambda(\boldsymbol{\mu_t} - \mathbf{X}) + \boldsymbol{\sigma} d\mathbf{W_t} \quad \text{(B.1)}$$

The Wiener processes $\mathbf{dW_t}$ were obtained using the Cholesky decomposition of the correlation of log fuel price returns. The mean reversion speed is set to 1/5 (approximately 5 years of mean reversion), which is in line with an estimation made by Pindyck (1999), which, however, could not be substantiated by root unit tests, since these need an even longer period to be applied. The implementation for discrete time steps was done using the exact approach by Gillespie (1996).

Appendix C. Sensitivity analysis: renewable subsidies

See Figs. C1–C3. The renewable scenarios are shortened to FRES (Full RES), HRES (Half RES) and ZRES (Zero RES).

Appendix D. Sensitivity analysis: fuel prices

The fuel price scenarios are simply named medium, high and low in the different figures. The expenditure boxplots (Figs. D2 and D3) show total consumer expenditures, including renewable subsidies.

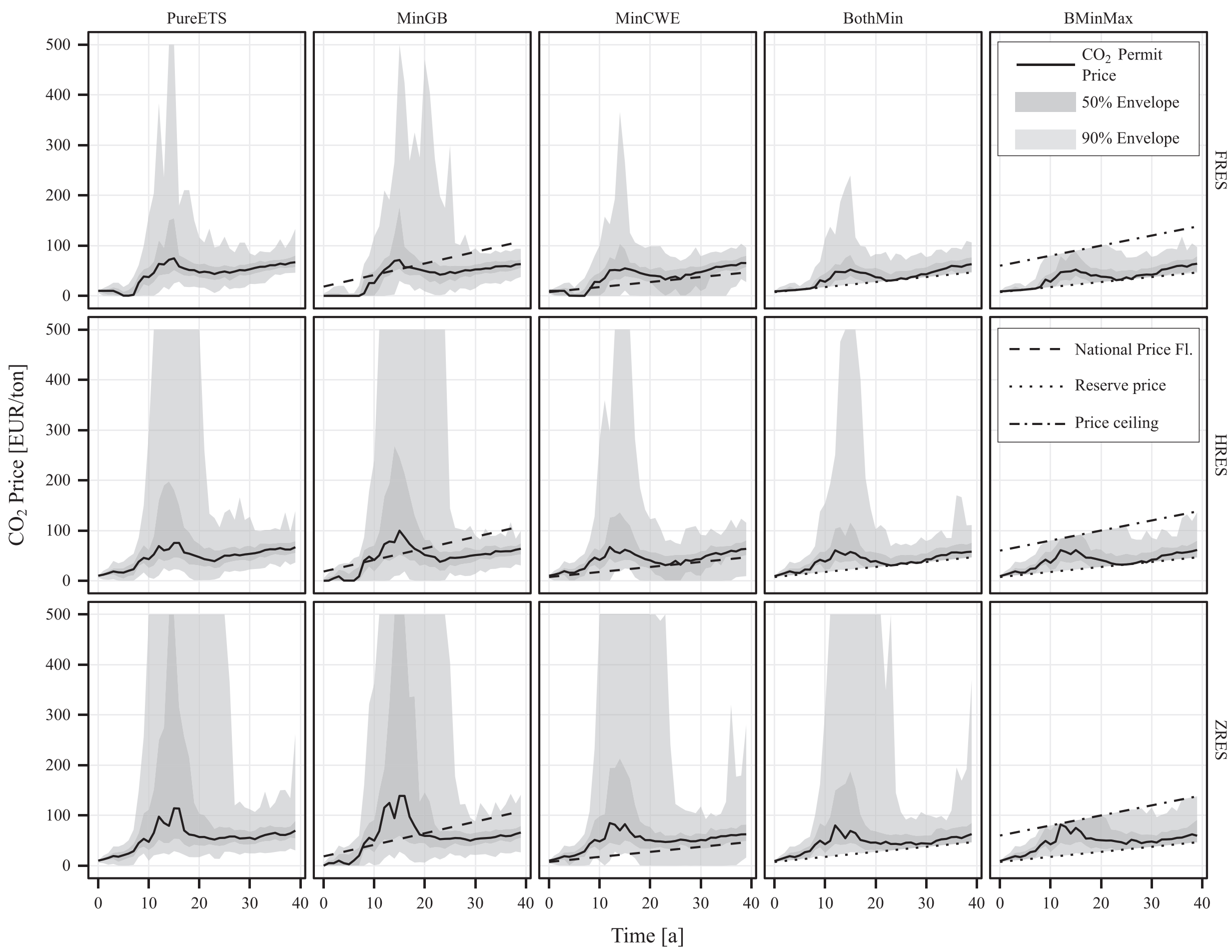

Fig. C1. CO_2 price development for RES sensitivity.

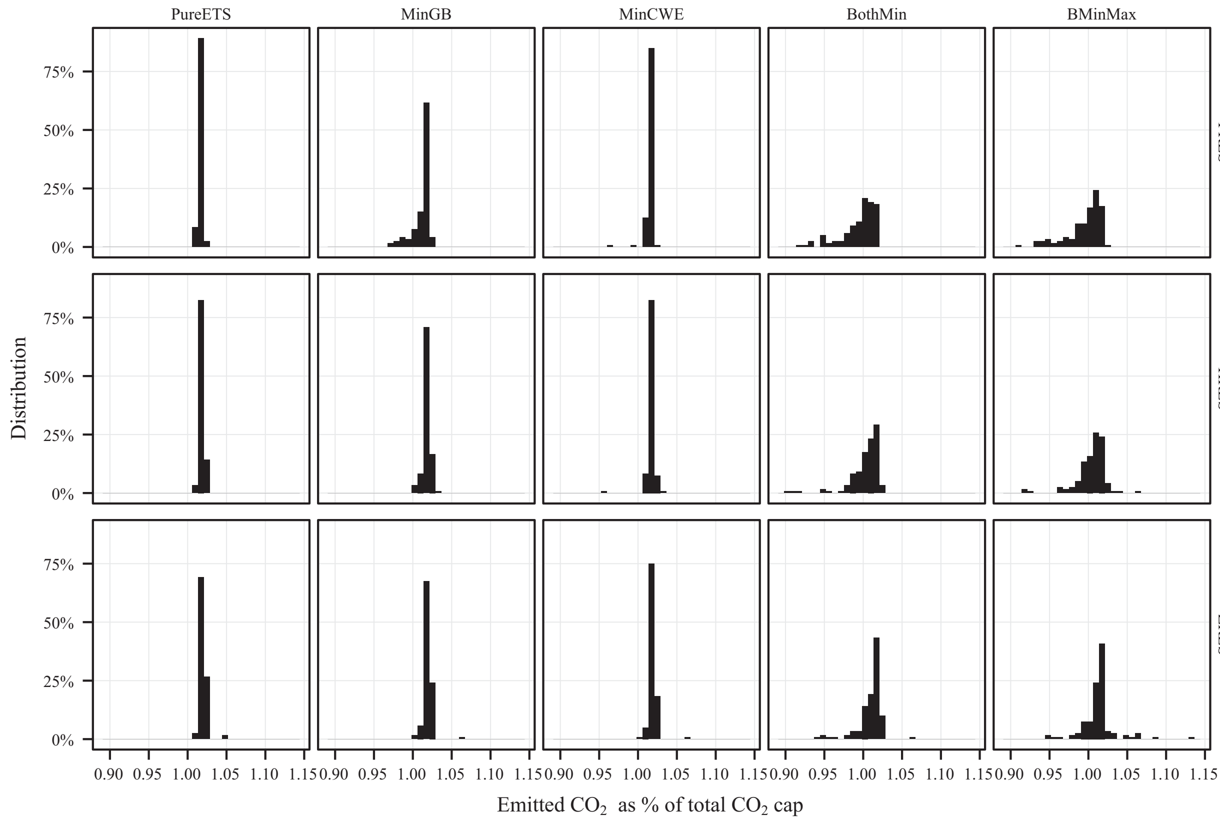

Fig. C2. Histograms of CO_2 emissions for RES sensitivity.

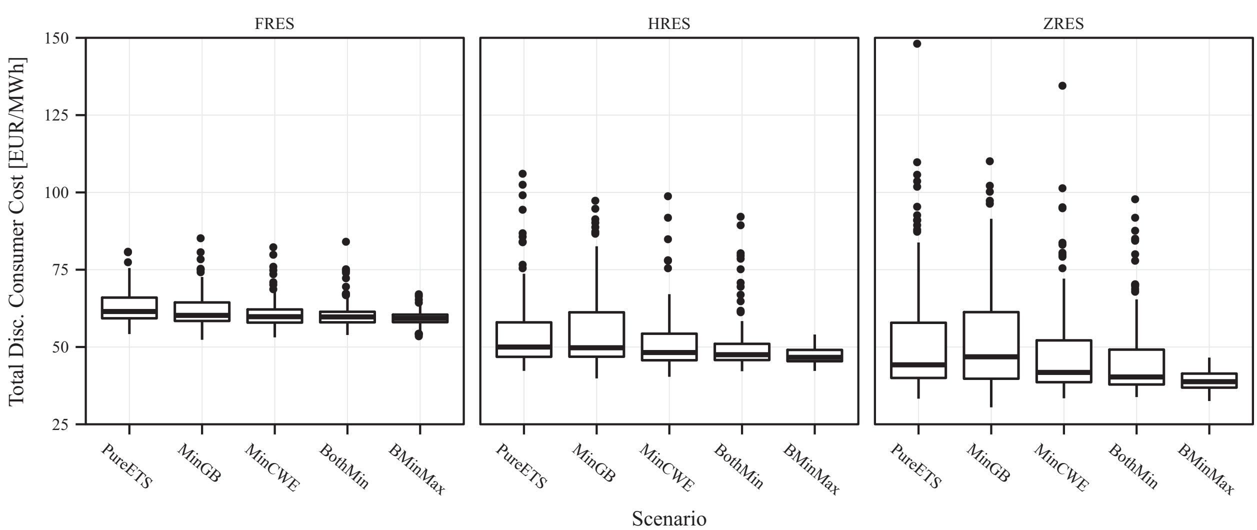

Fig. C3. Boxplots of consumer expenditures in CWE in different RES scenarios.

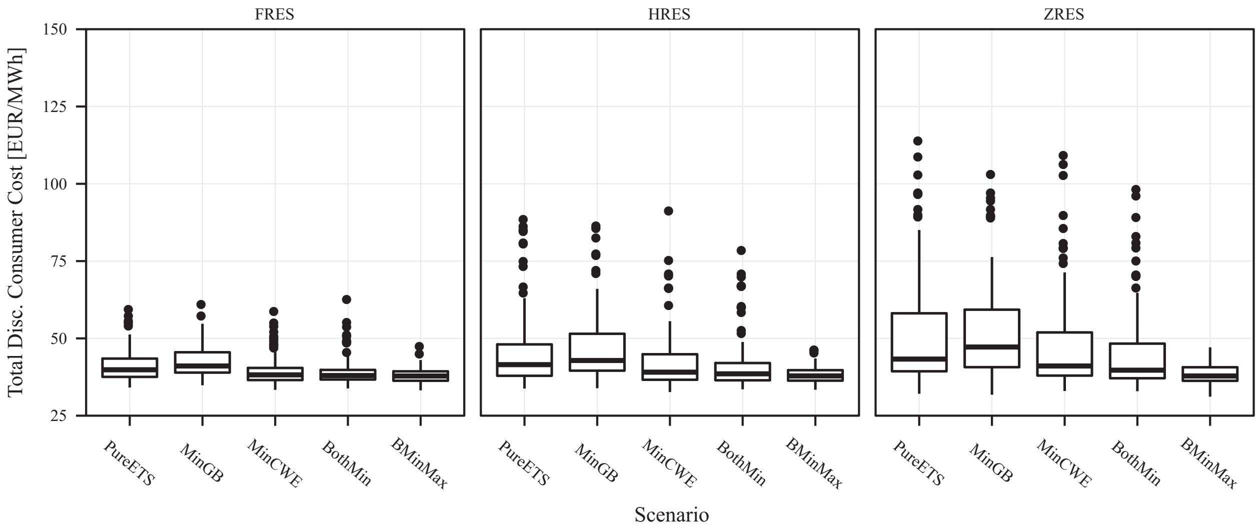

Fig. C4. Boxplots of consumer expenditures in GB in different RES scenarios.

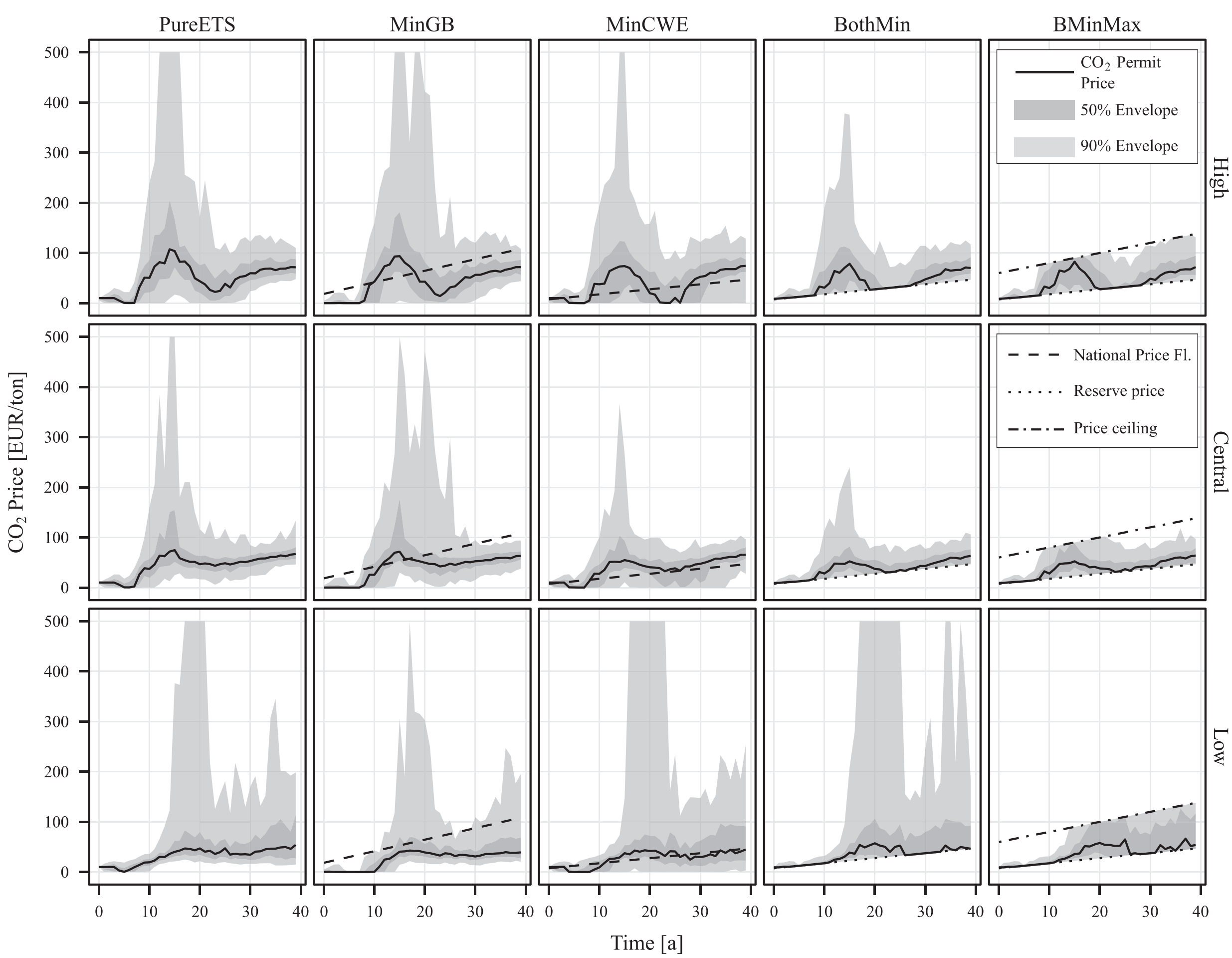

Fig. D1. Histograms of CO_2 emissions for fuel price sensitivity.

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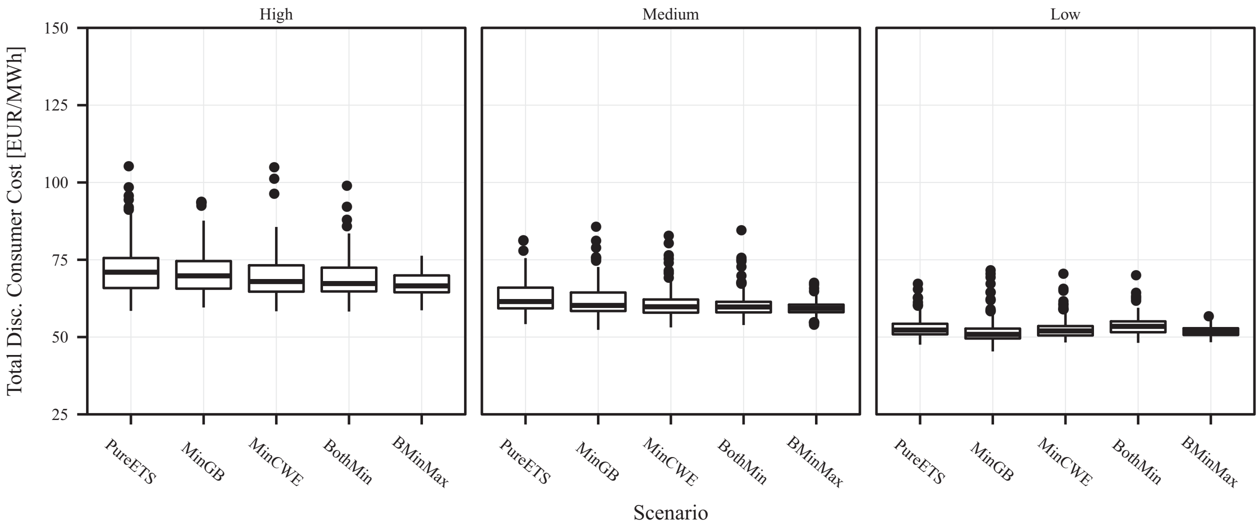

Fig. D2. Boxplots of specific total consumer expenditures in CWE in different fuel price trend scenarios.

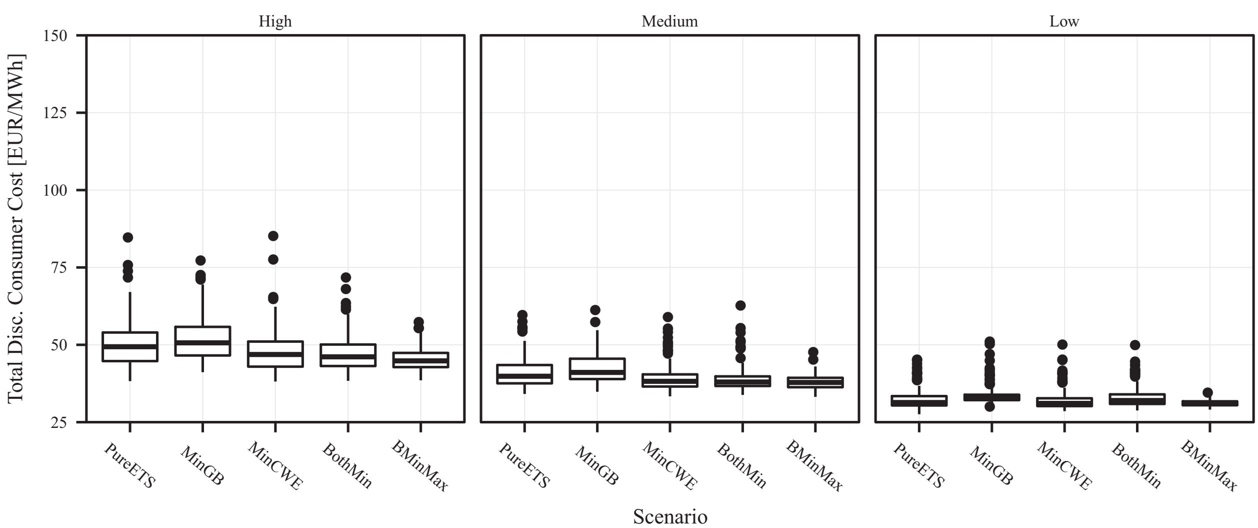

Fig. D3. Boxplots of specific total consumer expenditures in GB in different fuel price trend scenarios.

Please cite this article as: Richstein, J.C., et al., Cross-border electricity market effects due to price caps in an emission trading system: An agent-based approach. Energy Policy (2014), http://dx.doi.org/10.1016/j.enpol.2014.03.037

Appendix E. Sensitivity: floor price level

See Figs. E1, E2, E3 and E4 and Table E1.

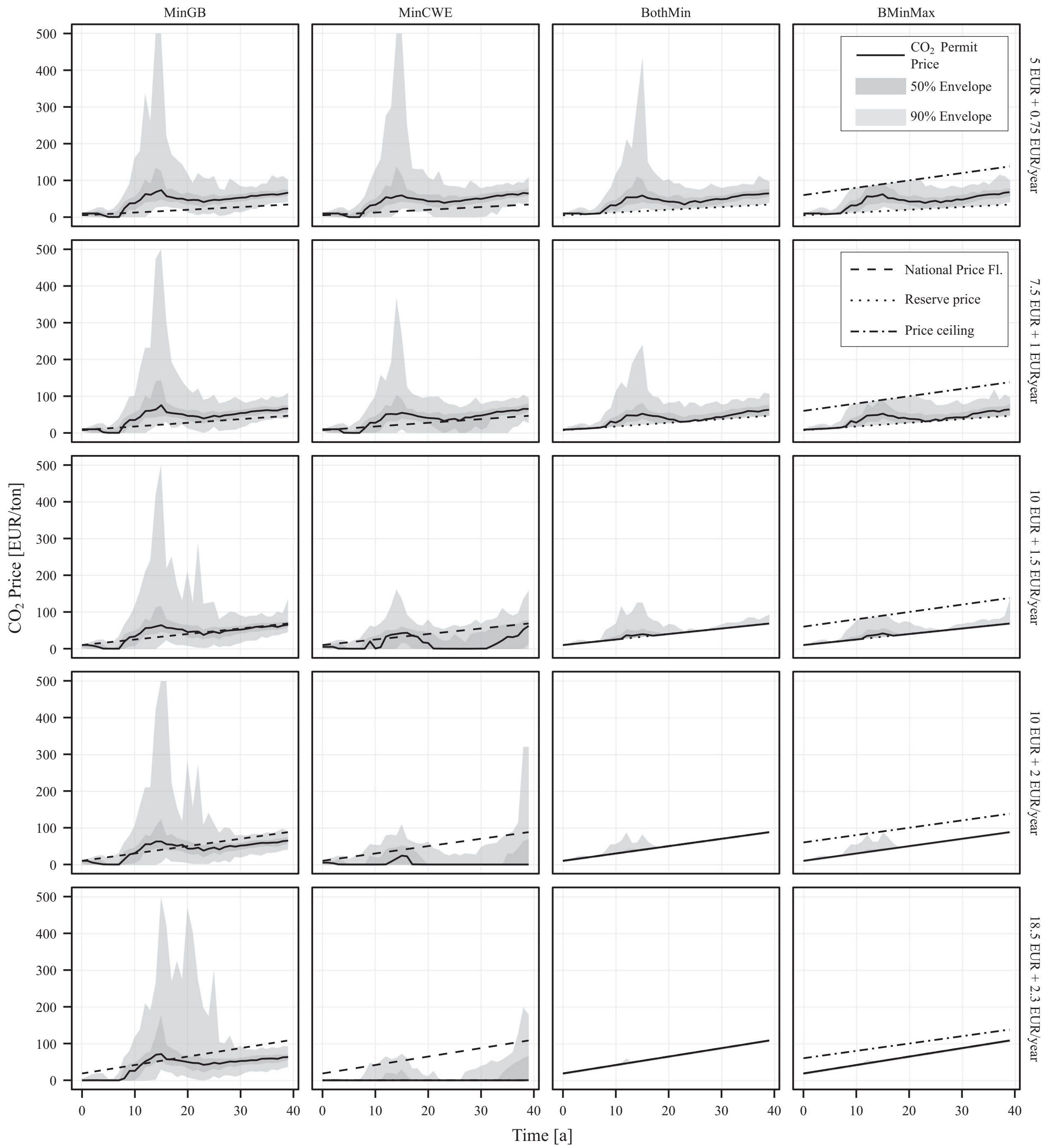

Fig. E1. The impact of different price floor and caps on CO_2 prices. The levels of the price floors are indicated to the right of the graphs.

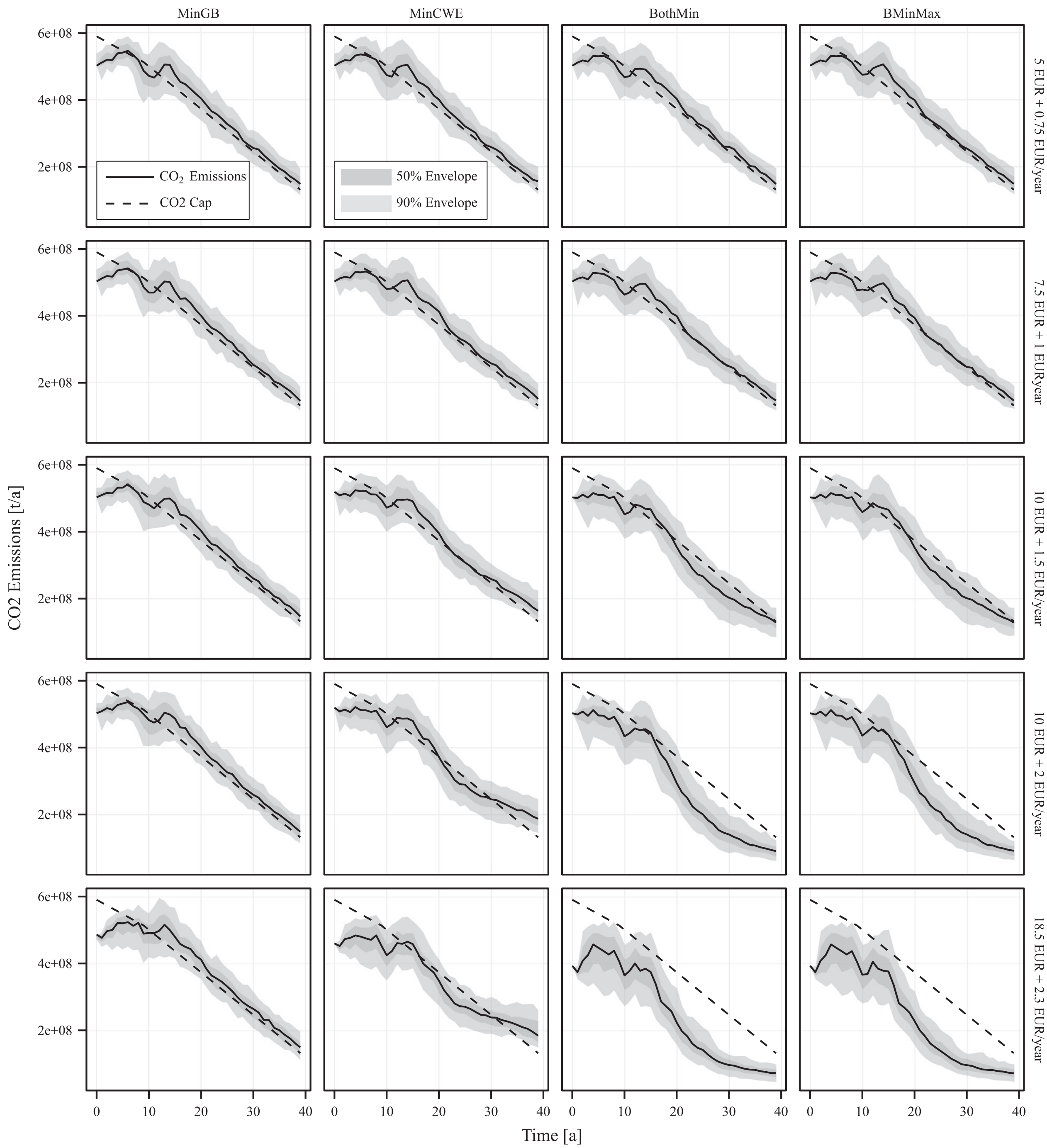

Fig. E2. The impact of different price floor and caps on CO_2 emissions. The levels of the price floors are indicated to the right of the graphs.

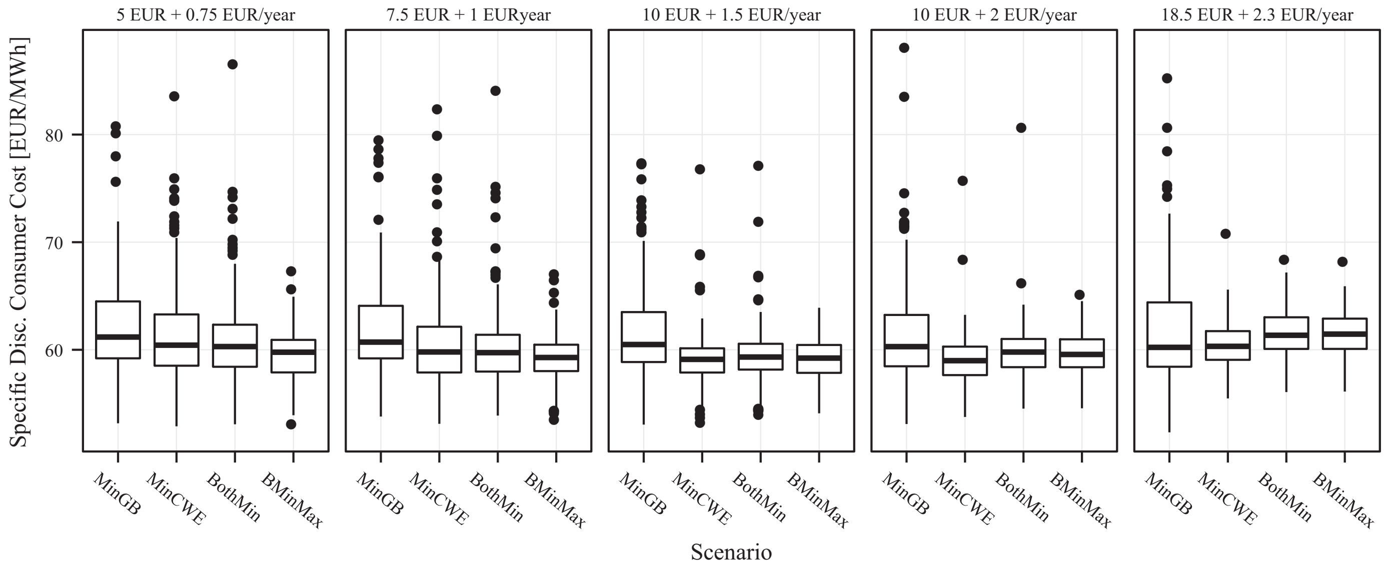

Fig. E3. The impact of different price floor and caps on total cost to consumers in CWE.

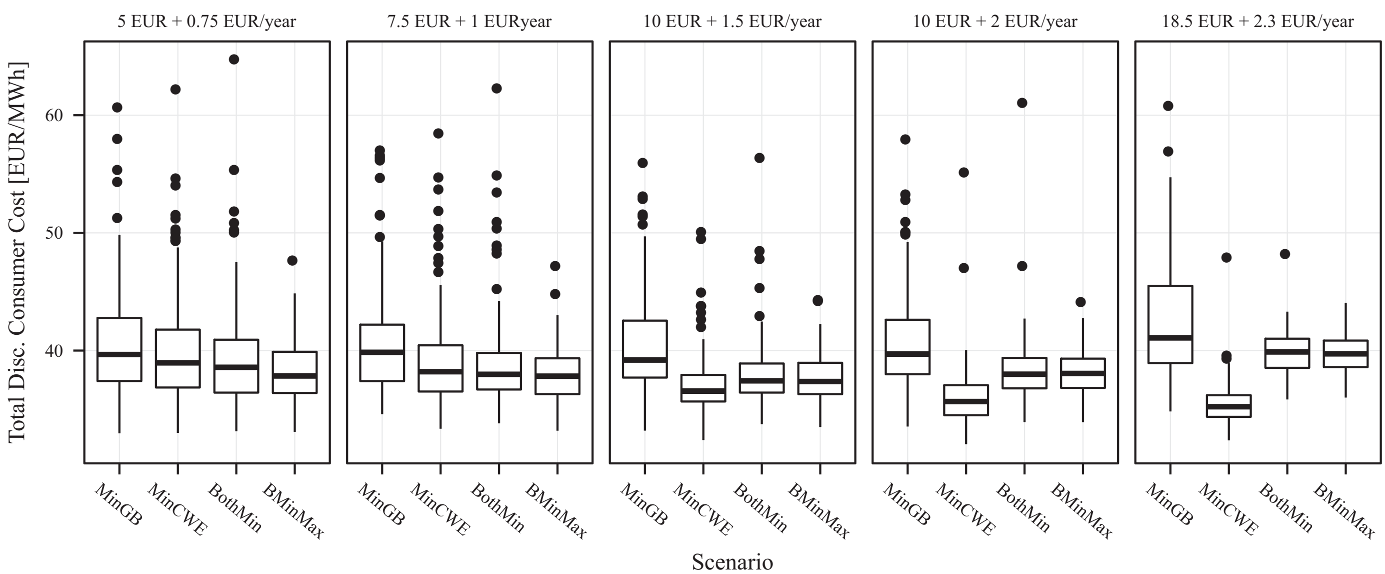

Fig. E4. The impact of different price floor and caps on total cost to consumers in GB.

Table E1
Total generation costs regarding price floors [EUR].

CO_2 Policy	Price floor	0%	25%	50%	75%	100%
MinGB	5 EUR + 0.75 EUR/year	3.51e+12	3.79e+12	3.86e+12	3.97e+12	4.31e+12
MinGB	7.5 EUR + 1 EURyear	3.49e+12	3.78e+12	3.85e+12	3.96e+12	4.32e+12
MinGB	10 EUR + 1.5 EUR/year	3.49e+12	3.78e+12	3.85e+12	3.96e+12	4.33e+12
MinGB	10 EUR + 2 EUR/year	3.48e+12	3.78e+12	3.86e+12	3.96e+12	4.33e+12
MinGB	18.5 EUR + 2.3 EUR/year	3.49e+12	3.79e+12	3.85e+12	3.99e+12	4.34e+12
MinCWE	5 EUR + 0.75 EUR/year	3.47e+12	3.77e+12	3.84e+12	3.96e+12	4.32e+12
MinCWE	7.5 EUR + 1 EURyear	3.46e+12	3.76e+12	3.83e+12	3.95e+12	4.31e+12
MinCWE	10 EUR + 1.5 EUR/year	3.45e+12	3.75e+12	3.83e+12	3.94e+12	4.32e+12
MinCWE	10 EUR + 2 EUR/year	3.47e+12	3.76e+12	3.84e+12	3.95e+12	4.32e+12
MinCWE	18.5 EUR + 2.3 EUR/year	3.51e+12	3.78e+12	3.86e+12	3.96e+12	4.34e+12
BothMin	5 EUR + 0.75 EUR/year	3.45e+12	3.77e+12	3.84e+12	3.96e+12	4.32e+12
BothMin	7.5 EUR + 1 EURyear	3.46e+12	3.75e+12	3.83e+12	3.95e+12	4.30e+12
BothMin	10 EUR + 1.5 EUR/year	3.47e+12	3.77e+12	3.84e+12	3.95e+12	4.31e+12
BothMin	10 EUR + 2 EUR/year	3.51e+12	3.80e+12	3.86e+12	3.97e+12	4.34e+12
BothMin	18.5 EUR + 2.3 EUR/year	3.55e+12	3.83e+12	3.91e+12	4.01e+12	4.37e+12

Table E1 (*continued*)

CO_2 Policy	Price floor	0%	25%	50%	75%	100%
BMinMax	5 EUR + 0.75 EUR/year	3.45e+12	3.77e+12	3.84e+12	3.96e+12	4.31e+12
BMinMax	7.5 EUR + 1 EURyear	3.46e+12	3.75e+12	3.83e+12	3.95e+12	4.31e+12
BMinMax	10 EUR + 1.5 EUR/year	3.47e+12	3.76e+12	3.84e+12	3.95e+12	4.32e+12
BMinMax	10 EUR + 2 EUR/year	3.50e+12	3.80e+12	3.86e+12	3.97e+12	4.34e+12
BMinMax	18.5 EUR + 2.3 EUR/year	3.55e+12	3.83e+12	3.91e+12	4.00e+12	4.36e+12

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