Time for global action: An optimised cooperative approach towards effective climate change mitigation

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Supplementary Information

This document contains the supplemental materials for the article "Time for global action: An optimised cooperative approach towards effective climate change mitigation". The document is organised as follows. In section 1, the methods are explained including the description of (i) the Emissions Reduction Cooperation Model (ERCOM) (mathematical formulation, data and assumptions), (ii) the consumption-based allocation method and (iii) the sensitivity analysis applied to handle uncertainties. In section 2, some additional results are presented, while in section 3, the results of the sensitivity analysis are shown. Finally, the nomenclature and acronyms are described in section 4, while the list of references is provided in section 5.

Contents

1 Methods

1.1 Problem statement

We aim to quantify the benefits of tackling climate change by meeting a set of individual emissions reduction targets acting in cooperation. To do so, we consider as test bed the U.S. Clean Power Plan[1] which stablishes individual state emissions reduction targets to curb CO_2 emissions from the U.S. power sector by 35% from 2012 baseline levels.

Essentially, we are given a set of regions (i.e. U.S. states) that need to reduce their CO_2 emissions from electricity generation by acting either as isolated entities or in cooperation. Emissions reduction targets are provided for every state, which can be met individually in every region or in cooperation (i.e. stablishing partnerships so that the joint emissions fall below the summation of individual targets, while some regional targets might be exceeded as long as others compensate them). Each region is considered as a load area with a specific electricity demand. We are also given a set of potential technologies for electricity generation for which their carbon intensities and costs data in every region are known. The goal of the analysis is then to determine the optimal portfolio of technologies and electricity trades between regions that satisfy the electricity demand at minimum cost while not surpassing the emissions targets.

To carry out this analysis, we have developed a mixed-integer linear programming (MILP) model, referred to as ERCOM (Emission Reduction Cooperation Model) that will be described in detail in the ensuring section. ERCOM is capable of systematically identifying the most cost-effective ways of meeting the U.S electricity demand for different levels of cooperation among states.

1.2 ERCOM model

The model proposed herein minimises the U.S. electricity generation cost while satisfying the emissions targets imposed in the Clean Power Plan[1] (CPP) for different levels of cooperation among states. Specifically, the optimisation is performed for 2030, which is the policy horizon in the CPP. The model, referred to as ERCOM henceforth (as an acronym of Emissions Reduction Cooperation Model), takes the form of a mixed-integer linear program (MILP) where binary variables denote whether states meet their targets in partnerships or acting independently, while continuous ones represent technologies capacities, electricity generation, inter-state electricity flows and electricity trades with Canada. ERCOM considers U.S states as load demand areas which are interconnected among them by transmission lines. The set of potential options for power generation includes coal, natural gas, nuclear, hydropower, solar, wind, geothermal and biomass. Furthermore, ERCOM ensures the reliability of the system by enforcing the use of back-up generation based on firm technologies (which make up for power drops in power supply from intermittent renewable sources). The cost of both standard and back-up generation is assessed via the levelised cost of electricity (i.e. LCOE), which considers operating and capital costs, annualised over their expected lifetime.

The model provides a lower bound on the U.S. electricity generation cost for a given number of states cooperating in partnerships. For simplicity, we do not calculate the specific partnerships that could be formed (i.e. how many partnerships exist and which states cooperate within each one), but rather assume the existence of a global partnership encompassing all the states willing to cooperate. This assumption simplifies the combinatorial complexity of the problem. Further details on the model formulation and assumptions are provided in the ensuing sections.

1.2.1 Mathematical formulation

The ERCOM model comprises three main blocks of equations: those related to carbon emissions, load-meeting constraints and equations required to compute the cost of electricity generation. These blocks of equations are presented and described in detail next. Note that we use italic font to represent variables along the text.

1.2.1.1 Carbon emissions

The CPP imposes specific reduction targets on the territorial (i.e. production-based) CO_2 emissions of every state *j* (parameter $TARG_j$). Such targets must be met by every state either individually or by sharing them with those states belonging to the global partnership. To model this, we introduce binary variable Y_j, which takes a value of one if state *j* belongs to the global partnership and zero otherwise. This binary variable is then used in the following equation:

$$EM_j \leq TARG_j + Y_j M1 \quad \forall j \tag{S1}$$

Here, EM_j is a continuous variable that represents the CO_2 emissions of state *j* and M1 is a sufficiently large parameter. This equation works as follows: when state *j* addresses the CPP individually, the binary variable is zero and enforces the term Y_jM1 to be zero as well, so the corresponding target $TARG_j$ is imposed on the states' emissions. Conversely, when state *j* belongs to the global partnership, the binary variable is one and the term Y_jM1 takes a very big positive value (i.e. M1), thereby relaxing the constraint so that no bound is effectively imposed on its individual emissions. Furthermore, states belonging to the partnership share their targets in a way such that a global partnership emissions cap must be ultimately satisfied, as imposed via Eq. (S2).

$$\sum_j Y_j EM_j \leq \sum_j Y_j TARG_j \tag{S2}$$

That is, the summation of the emissions of those states belonging to the global partnership must not exceed the summation of targets of its individual members. Note that when a state acts independently, Y_j is zero and therefore its corresponding emissions and target disappear from both sides of the inequality. The product of Y_j and EM_j introduces a nonlinear term into the model. To keep it linear and simplify the calculations, we linearise the nonlinear term through the following equations:

$$\sum_j YEM_j \leq \sum_j Y_j TARG_j \tag{S3}$$

$$YEM_j \leq EM_j + M1(1 - Y_j) \quad \forall j \tag{S4}$$

$$YEM_j \geq EM_j - M1(1 - Y_j) \quad \forall j \tag{S5}$$

$$YEM_j \leq Y_j M1 \quad \forall j \tag{S6}$$

Following this approach, the product $Y_j EM_j$ in Eq. (S2) is replaced by continuous variable YEM_j, which is defined via constraints (4-6). These equations work as follows: when state *j* cooperates in the partnership (i.e. Y_j = 1), the term M1(1-Y_j) in Eqs. (S4-S5) vanishes, thus enforcing YEM_j to be equal to EM_j. Eq. (S6) is then relaxed and does not impose any additional bound on YEM_j. Conversely, when state *j* does not cooperate in the partnership, then $Y_j = 0$ and Eq. (S6) forces YEM_j to be zero, while Eqs. (S4-S5) are relaxed and do not impose any additional bound. Recall that when $Y_j = 0$, the production-based emissions of state *j* are bounded via Eq. (S1).

The number of states belonging to the global partnership (denoted by parameter CS) is controlled via Eq. (S7).

$$\sum_j Y_j = CS \tag{S7}$$

As will be later discussed, the model is solved for different values of CS, thereby reflecting different levels of cooperation.

State emissions are calculated from the electricity generated via technology *i* in each state *j* and the associated carbon intensity (parameter $CI_{i,j}$), as given by Eq. (S8). Note that the amount of electricity generated is modelled via continuous variables $GEN^{ST}_{i,j}$ and $GEN^{BU}_{i,j}$, which account for standard and backup generation, respectively.

$$EM_j = \sum_i GEN^{ST}_{i,j} CI_{i,j} + \sum_i GEN^{BU}_{i,j} CI_{i,j} \qquad \forall j \tag{S8}$$

Note that our model takes into account the need to resort to firm energy sources as ancillary systems so as to satisfy peaks in demand when facing unfavourable weather conditions. This will be explained in more detail later in this document.

1.2.1.2 Load-meeting constraints

The total amount of electricity generated in state *j* with technology *i* is bounded according to the availability of the associated resource in the state (which is denoted by parameter $GEN^{POT}_{i,j}$), as given by Eq. (S9).

$$GEN^{ST}_{i,j} + GEN^{BU}_{i,j} \le GEN^{POT}_{i,j} \qquad \forall j, i \ne coal, coal\ CCS, natural\ gas, natural\ gas\ CCS \tag{S9}$$

Eq. (S9) applies to all the technologies except for those competing for the same resources. Hence, coal-based technologies (i.e. coal and coal with carbon capture and storage (CCS)) compete for coal and are grouped into set *CT* (i.e. *CT = {coal, coal CCS}*), as illustrated in Eq. (S10).

$$\sum_{i \in CT} \left(GEN^{ST}_{i,j} + GEN^{BU}_{i,j} \right) \le GEN^{POT}_{i',j} \qquad \forall j, i' = coal \tag{S10}$$

Eq. (S11) is defined for natural gas-based technologies (i.e. natural gas and natural gas CCS), which form the set *NGT* (i.e. *NGT = {natural gas, natural gas CCS}*), and consume natural gas.

$$\sum_{i \in NGT} \left(GEN^{ST}_{i,j} + GEN^{BU}_{i,j} \right) \le GEN^{POT}_{i',j} \qquad \forall j, i' = natural\ gas \tag{S11}$$

Furthermore, country-wise bounds on generation are imposed via parameter GEN^{POTGLO}_{i} on those technologies which consume resources that can be traded between states (i.e. coal, natural gas, biomass, coal CCS and natural gas CCS). In these cases, besides inland potentials, it is necessary to enforce a global limit on the corresponding resource according to its availability in the whole country (Eqs. S12-S14).

$$\sum_{j}\left(GEN^{ST}_{i,j} + GEN^{BU}_{i,j}\right) \leq GEN^{POTGLO}_{i} \qquad \forall\ i = biomass \tag{S12}$$

$$\sum_{j}\sum_{i \in CT}\left(GEN^{ST}_{i,j} + GEN^{BU}_{i,j}\right) \leq GEN^{POTGLO}_{i'} \qquad \forall\ i' = coal \tag{S13}$$

$$\sum_{j}\sum_{i \in NGT}\left(GEN^{ST}_{i,j} + GEN^{BU}_{i,j}\right) \leq GEN^{POTGLO}_{i'} \qquad \forall\ i' = natural\ gas \tag{S14}$$

The amount of electricity generated (i.e. MWh) is constrained to be lower than the capacity installed (parameters $CAP^{ST}_{i,j}$ and $CAP^{BU}_{i,j}$, in MW). Capacity and generation are linked through the capacity factor (represented by parameter $CF_{i,j}$) and the annual hours (parameter H), as shown in Eqs. (S15) and (S16).

$$GEN^{ST}_{i,j} \leq CAP^{ST}_{i,j} CF_{i,j} H \qquad \forall i,j \tag{S15}$$

$$GEN^{BU}_{i,j} = CAP^{BU}_{i,j} CF_{i,j} H \quad \forall i,j \tag{S16}$$

he capacity factor is the ratio between the actual power output and the potential output at full nameplate capacity. This factor takes into account periods in which the plant is either out of service (e.g. due to plant maintenance or limited resources) or operated below its nominal capacity. Note that the bound on standard generation (Eq. (S15)) can be imposed as an inequality, even if the constraint will always be active in the optimal solution (i.e. satisfied as a strict equality). For back-up systems, the equation must be satisfied as a strict equality (Eq. S16), as these technologies must ensure the system reliability.

The CPP does not contemplate installing additional nuclear facilities as a compliance strategy to reduce CO_2 emissions. To model this, Eq. (S17) fixes the nuclear capacity, modelled by parameter $CAP^{CUR}_{i,j}$, to its present value.

$$CAP^{ST}_{i,j} + CAP^{BU}_{i,j} = CAP^{CUR}_{i,j} \quad \forall j, i = \ nuclear \tag{S17}$$

The model must ensure that power can be dispatched at any time. We therefore differentiate between dispatchable (i.e. coal w/o CCS, natural gas w/o CCS, nuclear, hydropower, biomass, geothermal and solar thermal) and non-dispatchable (i.e. solar PV rural and rooftop and wind onshore and offshore) technologies. The former can be dispatched according to the power demand, while the latter depend on the availability of intermittent resources. Hence, to ensure system reliability it is necessary to support intermittent renewable energies (IR) with ancillary systems such as back-up generation based on firm technologies (both renewable and non-renewable) or energy storage. Here, we consider the former option, which is modelled via Eq. (S18), where BUC is a parameter providing the capacity of dispatchable technologies that must be installed for every MW of non-dispatchable intermittent technologies, while *IR* is the set of non-dispatchable technologies requiring ancillary systems (i.e. *IR* = {*solar PV (rural), solar PV (rooftop), wind onshore, wind offshore*}).

$$\sum_{i \notin IR} CAP^{BU}_{i,j} = BUC \sum_{i \in IR} CAP^{ST}_{i,j} \quad \forall j \tag{S18}$$

The back-up capacity of intermittent renewables is set to zero, as imposed by Eq. (S19). Note, that we consider solar thermal CST as a dispatchable technology, since it incorporates thermal storage that allows maintaining a reliable electric power system with high shares of renewables[2–4].

$$CAP^{BU}_{i,j} = 0 \qquad \forall j, i \in IR \tag{S19}$$

Electricity transmission plays a key role in the electricity system optimisation, since it allows exploiting the region-specific abatement costs. Inter-state electricity trade is only allowed between neighbouring states (i.e. states *j'* included in set NU_j) participating in the global partnership (i.e. those for which Y_j = 1). Hence, two conditions must be enforced for two states to exchange electricity: that they are neighbours and that they both belong to the global partnership, as given by Eqs. (S20-S21).

$$TRD^{ORIG}_{j,j'} \leq Y_j M2 \quad \forall j, j' \in NU_j \tag{S20}$$

$$TRD^{ORIG}_{j,j'} \leq Y_{j'} M2 \quad \forall j, j' \in NU_j \tag{S21}$$

Here, $TRD^{ORIG}_{j,j'}$ is a continuous variable accounting for the amount of electricity that state *j* imports from state *j'*, and M2 is a sufficiently large parameter. As seen, when both states belong to the global partnership, then the corresponding binary variables are one (i.e. $Y_j = 1$ and $Y_{j'} = 1$), implying that electricity can be exchanged between both provided it does not surpass the allowable limit M2. When any (or both) of the states are not in the partnership, then the electricity flow is set to zero.

Additionally, the electricity is subject to losses during transmissions. We model this via Eq. (S22), which links the electricity transmitted at origin (continuous variable $TRD^{ORIG}_{j,j'}$) to that received at the final destination ($TRD^{DEST}_{j,j'}$) and the associated losses ($TRD^{LOSS}_{j,j'}$).

$$TRD^{ORIG}_{j,j'} = TRD^{DEST}_{j,j'} + TRD^{LOSS}_{j,j'} \qquad \forall j, j' \in NU_j \tag{S22}$$

That is, the final amount of electricity that reaches state *j* coming from state *j'* ($TRD^{DEST}_{j,j'}$) is equal to the initial amount sent from *j'* ($TRD^{ORIG}_{j,j'}$) minus the losses taking place in between ($TRD^{LOSS}_{j,j'}$). Here, the transmission losses are considered proportional (parameter TLF) to the distance between states *j* and *j'* (parameter $DIST_{j,j'}$) and the amount of electricity transmitted:

$$TRD^{LOSS}_{j,j'} = TRD^{ORIG}_{j,j'} DIST_{j,j'} TLF \qquad \forall j, j' \in NU_j \tag{S23}$$

Electricity imports from Canada represent a key compliance strategy to curb U.S. CO_2 emissions. We allow electricity trades between the southern Canadian provinces (i.e. British Columbia, Alberta, Saskatchewan, Manitoba, Ontario and Quebec) and neighbouring states, regardless of whether these U.S. states participate or not in the partnership. Electricity imports through these transmission lines suffer from energy losses, which are calculated via Eqs (S24-S25).

$$TRDCAN^{ORIG}_{j,k} = TRDCAN^{DEST}_{j,k} + TRDCAN^{LOSS}_{j,k} \qquad \forall j, k \in NC_j \tag{S24}$$

$$TRDCAN^{LOSS}_{j,k} = TRDCAN^{ORIG}_{j,k} DISTCAN_{j,k} TLF \qquad \forall j,k \in NC_j \tag{S25}$$

Here, $TRDCAN^{ORIG}_{j,k}$, represents the electricity sent from Canadian region *k* to U.S. state *j*, $TRDCAN^{DEST}_{j,k}$ denotes the electricity reaching the state and $TRDCAN^{LOSS}_{j,k}$ accounts for the electricity lost during transmission. $DISTCAN_{j,k}$ is a parameter providing the distance between state *j* and Canadian region *k* (note that trade is only allowed between neighbour *j*-*k* pairs), while TLF represents the transmission losses factor.

Total electricity imports from Canada cannot exceed a given percentage (denoted by parameter CTB) of the U.S. electricity demand (computed as the summation of the demand in each state DEM_j), as illustrated in Eq. (S26).

$$\sum_j \sum_{k \in NC_j} TRDCAN^{ORIG}_{j,k} \le CTB \sum_j DEM_j \tag{S26}$$

Where NC_j denotes the set of Canadian regions *k* which are neighbours to U.S. state *j*. Moreover, the amount of electricity imported by every state (i.e. imported from other U.S. states as well as from Canada) is bounded by the electricity demand in the state, as shown in Eq. (S27). This limits the capacity that a state has to act as a transmission node (i.e. a state is not allowed to import large amounts of electricity to later sell them to other states).

$$\sum_{j' \in NU_j} TRD^{DEST}_{j,j'} + \sum_{k \in NC_j} TRDCAN^{DEST}_{j,k} \le DEM_j \qquad \forall j \tag{S27}$$

The demand satisfaction constraint ensures that the electricity demand of each state *j*, denoted by parameter DEM_j, must equal the domestic electricity generation plus the input flows of electricity and minus the output flows, as illustrated in Eq. (S28).

$$\sum_i GEN^{ST}_{i,j} + \sum_{i \notin IR} GEN^{BU}_{i,j} + \sum_{j' \in NU_j} TRD^{DEST}_{j,j'} + \sum_{k \in NC_j} TRDCAN^{DEST}_{j,k} - \sum_{j' \in NU_j} TRD^{ORIG}_{j',j} = DEM_j DSF \tag{S28}$$

Here, DSF represents a demand satisfaction factor that is included to warrant the reliability of the system. That is, by forcing the system to cover the demand plus a reserve margin (i.e. DSF > 1), electricity supply is ensured even in case of outage. Note that demand and supply are matched annually rather than on an hour-per-hour basis. The hour-per-hour demand match is yet enforced by implementing back up generation systems in the supply.

1.2.1.3 Cost of electricity generation

The objective function of the ERCOM model seeks to minimise the total cost of electricity generation in U.S., denoted by continuous variable $COST^{TOT}$, which is given by the summation of the individual costs in all of the states, as shown in Eq. (S29).

$$COST^{TOT} = \sum_j COST_j \tag{S29}$$

In turn, the cost of electricity generation in each state *j* (continuous variable $COST_j$) accounts for the state annualised capital costs (continuous variable $COST^{CAP}_j$), annual fixed and variable operating costs (continuous variables $COST^{FIX}_j$ and $COST^{VAR}_j$, respectively), as well as the costs derived from electricity imports from Canada ($COST^{CAN}_j$):

$$COST_j = COST^{CAP}_j + COST^{FIX}_j + COST^{VAR}_j + COST^{CAN}_j \qquad \forall j \tag{S30}$$

Note that the costs associated to inter-state trades are not considered in Eq. (S30), since they would cancel out in Eq. (S29) (i.e. the money paid by the states purchasing electricity is received by states selling it). State capital costs ($COST_j^{CAP}$) are determined from the installed capacity of both, standard and back-up technologies ($CAP_{i,j}^{ST}$ and $CAP_{i,j}^{BU}$), their unitary capital costs ($CO_{i,j}^{CAP}$), their capacity factor ($CF_{i,j}$) and the total annual hours (H), as given by Eq. (S31).

$$COST_j^{CAP} = \sum_i \left[\left(CAP_{i,j}^{ST} + CAP_{i,j}^{BU} \right) CO_{i,j}^{CAP} CF_{i,j} H \right] \quad \forall j \tag{S31}$$

The fixed operating costs of state *j*, denoted by continuous variable $COST_j^{FIX}$, are determined from the capacity of standard and back-up technologies *i* that are installed (represented by variables $CAP_{i,j}^{ST}$ and $CAP_{i,j}^{BU}$, respectively), their unitary annual fixed operating costs ($CO_{i,j}^{FIX}$), the capacity factor of each technology *i* in state *j* ($CF_{i,j}$) and the total annual hours (H):

$$COST_j^{FIX} = \sum_i \left[\left(CAP_{i,j}^{ST} + CAP_{i,j}^{BU} \right) CO_{i,j}^{FIX} CF_{i,j} H \right] \quad \forall j \tag{S32}$$

Furthermore, the variable operating costs in state *j* ($COST_j^{VAR}$) are estimated from the electricity generated by each technology *i* (both standard and back-up, that is, $GEN_{i,j}^{ST}$ and $GEN_{i,j}^{BU}$, respectively), and the unitary variable costs of those technologies in that state ($CO_{i,j}^{VAR}$), as shown in Eq. (S33).

$$COST_j^{VAR} = \sum_i \left[\left(GEN_{i,j}^{ST} + GEN_{i,j}^{BU} \right) CO_{i,j}^{VAR} \right] \quad \forall j \tag{S33}$$

The cost of electricity imports from neighbouring Canadian regions *k* (continuous variable $TRDCAN_{j,k}^{DEST}$) to state *j* are determined from the electricity flows imported and a unitary selling price (CO^{CAN}) via Eq. (S34):

$$COST_j^{CAN} = \sum_{k \in NC_j} TRDCAN_{j,k}^{DEST} CO^{CAN} \quad \forall j \tag{S34}$$

Finally model ERCOM can be written in compact form as follows:

$$\begin{aligned} (MCPP) \quad & \min \quad COST^{TOT} \\ & s.t. \quad Eqs.\ (1,3-34) \end{aligned}$$

The model is solved for different values of the parameter CS (i.e. varying the number of states in the global partnership), starting from the case where states act independently from each other (CS = 0) and ending in the solution where all of them cooperate in a global partnership (CS = 47).

ERCOM was implemented in the General Algebraic Modelling System[5] (GAMS) version 24.4.1. The model features 11,470 continuous variables, 47 binary variables and 8,167 constraints. The model was solved with CPLEX 24.4.6 on an AMD A8-5500 APU with Raedon 3.20 Ghz and 8.0 GB RAM. The solution time of each instance was below 1 CPU second in the aforementioned computer.

1.2.2 Data description and assumptions

This section describes the major assumptions made in ERCOM along with the data fed into the model. We first solved the model assuming deterministic values of the parameters and later on investigated the effects of various uncertainties via sensitivity analysis (see section 1.4 for the procedure followed and section 2.4 for the associated results).

1.2.2.1 Clean Power Plan: State targets

The CPP[1] was adopted by the U.S. Environmental Protection Agency (EPA) on the 3th August 2015, becoming the first and very big step in U.S. towards climate change mitigation. The overall goal of the CPP is to curb carbon emissions from the power sector by 32% (from 2005 levels) by 2030 (i.e. equivalent to 35% from 2012 baseline levels). To achieve this overall global target, the CPP establishes individual state-by-state targets. In addition, it provides states with enough flexibility to design strategic plans to meet their targets, either acting individually or cooperating with other states.

To set state-specific goals, EPA analysed affordable strategies for each state based on three building blocks: i) switching from coal-powered plants to natural-gas powered plants, ii) increasing low-carbon energy (i.e. increasing renewable energy generation), and, iii) improving the heat-rate of fossil-fuel fired plants to reduce their overall emissions rate. In practice, states have two compliance options, which translate into two types of CPP targets: (i) those imposed on the carbon intensities (rate-based approach) and (ii) those imposed over the total CO_2 emissions (mass-based approach). Without loss of generality, we use here targets on carbon intensities. These targets vary greatly across states (i.e. from 7% in Connecticut to 48% in South Dakota) owing to different electricity mixes, technological feasibilities and costs and emissions reduction potentials for each particular state.

Figure S1 displays the U.S. state specific CPP goals (i.e. parameter $TARG_j^{CI}$, represented as a reduction target in the figure) that should be accomplished in 2030. As observed, four states fall in the range 7-14% of emissions reduction level, five states in the range 14-21%, five states in the range 21-27%, eight states in the range 27-34%, 17 states in the range 34-41% and eight states in the range 41-47%. Further details on the calculation of the CPP emissions targets are provided by the U.S. Environmental Protection Agency (https://www.epa.gov/cleanpowerplan). These targets on carbon intensities ($TARG_j^{CI}$) are used to establish the state emissions target in ERCOM (i.e. $TARG_j$) via Eq. (S35).

$$TARG_j = \sum_i GEN_{i,j}^{CUR}\left(TARG_j^{CI} CI_{i,j}\right) \qquad \forall j \tag{S35}$$

Here, $GEN_{i,j}^{CUR}$ is the amount of electricity generated in 2012 with technology *i* in state *j* and $CI_{i,j}$ is the carbon intensity associated to that technology and state.

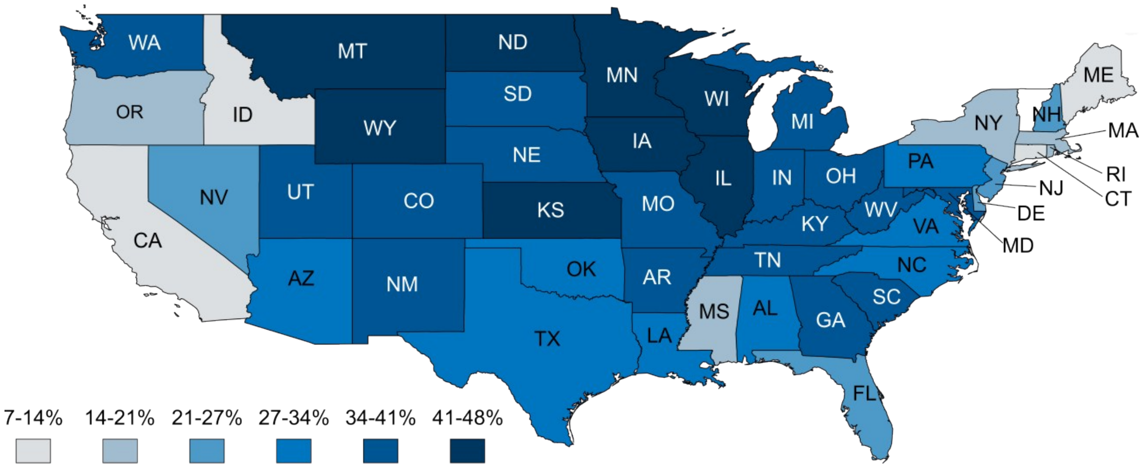


Figure S1. State specific emission reduction targets established by the CPP for 2030 referred to 2012 emissions levels. States are coloured according to the scale of emissions reduction targets imposed by the CPP. States labels are in compliance with ISO 3166-2 code.

1.2.2.2 Existing technologies capacity and generation

The existing capacities installed in the states along with the annual net generation rates (parameter $GEN_{i,j}^{CUR}$ in Eq. (S35)) for year 2012 were sourced from the Official Energy Statistics of the U.S. Energy Information Administration (EIA)[6]. Pie charts in Figure S2 depict the state electricity generation mixes (Subplot S2a) as well as the state installed electricity capacity (Subplot S2b). As seen, the electricity generation portfolios vary greatly from state to state. Most of the electricity mixes rely on coal, natural gas and nuclear, which are the dominant energy sources of electricity. However, in the Northwest, hydropower has the highest share in the electricity mixes of Washington, Orlando, Idaho, Montana and South Dakota. In addition, wind power (onshore) plays an important role in the northern and central states. Geothermal power is implemented mainly in California and Nevada, while Maine uses large amounts of biomass. Electricity production from Solar PV (both at rural and rooftop levels) is rather low in several states, and the same happens with concentrated solar thermal in Arizona, California and Nevada.

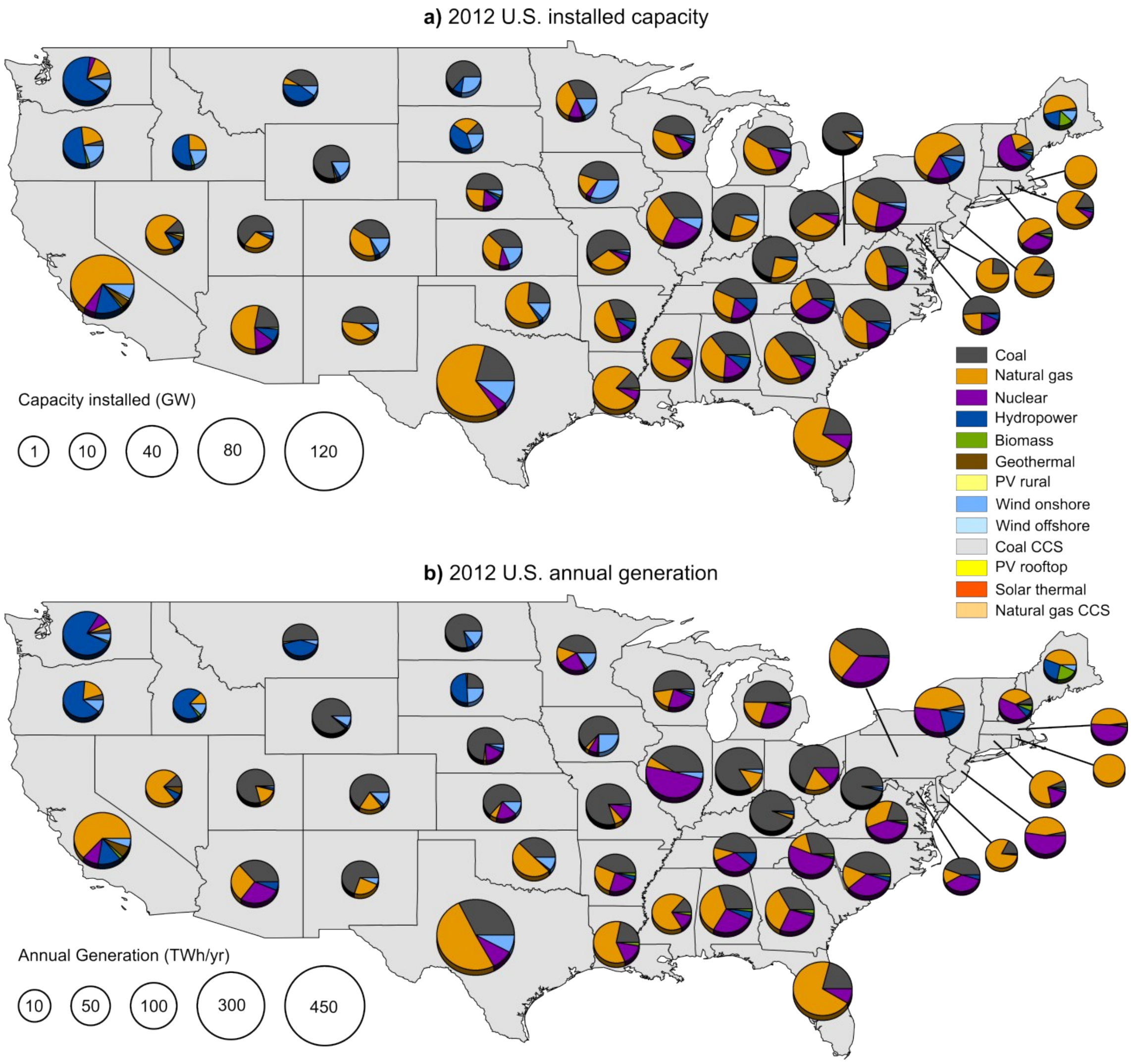


Figure S2. U.S. installed capacity and generation for 2012. Subplot S2a) depicts the installed capacity of each technology in each state in 2012 whereas subplot S2b) stands for the electricity generation. The size of the pie charts is proportional to the capacity installed and to the electricity generation of each state, respectively, whereas the slice colours denote the technology and the slice sizes represent the associated percentage share.

Figure S3 shows the global U.S. electricity generation portfolio and capacity for 2012. As can be observed, fossil fuels dominate the U.S. electricity portfolio. Almost 69% of the electricity in U.S. was generated from fossil coal and natural gas sources, while nuclear represents about 19%. The share of renewables was 11.8%, with hydro power accounting for 7%. As observed, the share of coal and nuclear in terms of power generation is above their share in terms of installed capacity. This is because coal and nuclear technologies provide base load, while natural gas typically covers peak loads and solar and wind renewables are intermittent due to their dependence on climatic conditions.

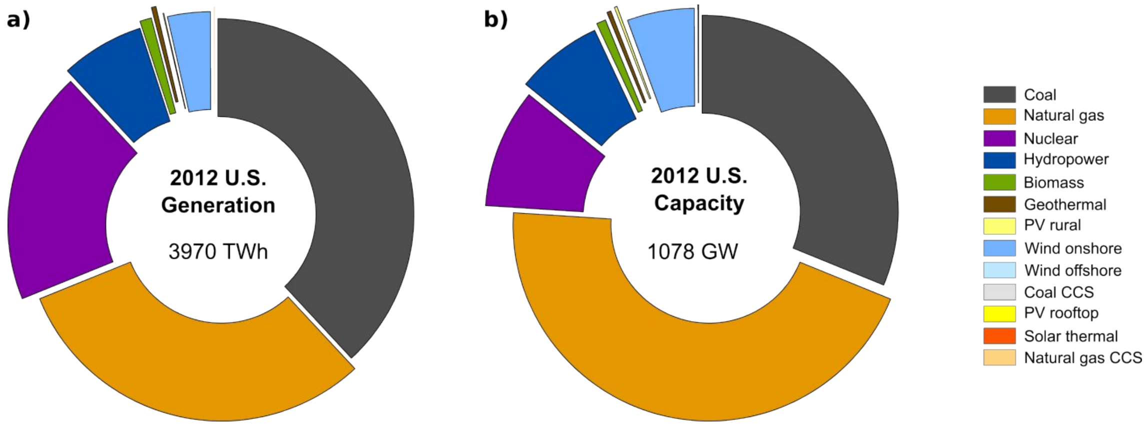


Figure S3. Global U.S. generation and installed capacity for 2012. Pie chart on the left (Subplot S3a) depicts the global U.S. power generation portfolio while pie chart on the right (Subplot S3b) depicts the global U.S. installed capacity. Slice colours represent the share of each technology according to the legend.

1.2.2.3 Geospatial and temporal definition: Load areas

The U.S. power electricity generation is optimised for 2030, which is the CPP policy horizon. ERCOM is defined at the state level and on an annual basis. Following this approach, the U.S. is divided into 47 load areas corresponding to the states boundaries included in the CPP. Furthermore, we match electricity supply and demand on an annual basis. We consider that the aforementioned geospatial and temporal resolutions are accurate enough for the purposes of our study. In the real operability of the electricity system, however, load and supply need to be balanced on a finer scale. To account for this, we enforce the model to back up the installation of intermittent renewables by means of ancillary systems based on dispatchable technologies, which ensures the reliability of the whole electricity system.

The electricity load (i.e. annual electricity demand) for each state was estimated using the data published by the U.S. Energy Information Administration (EIA) on electricity retail sales by state, which is a good proxy of consumption rates[6]. These data were sourced for the baseline year (i.e. 2012) and forecasted to 2030 by applying a 0.8% average annual growth rate, as projected by the EIA[7]. The electricity power demand varies greatly across states (Figure S4), being Texas, California and Florida the states showing the highest electricity demands. Furthermore, we consider a demand satisfaction factor (i.e. parameter DSF) that is set at 1.05 to ensure that the model can cover the electricity demand plus a reserve margin of 5%. This factor further reinforces the reliability of the system[8].

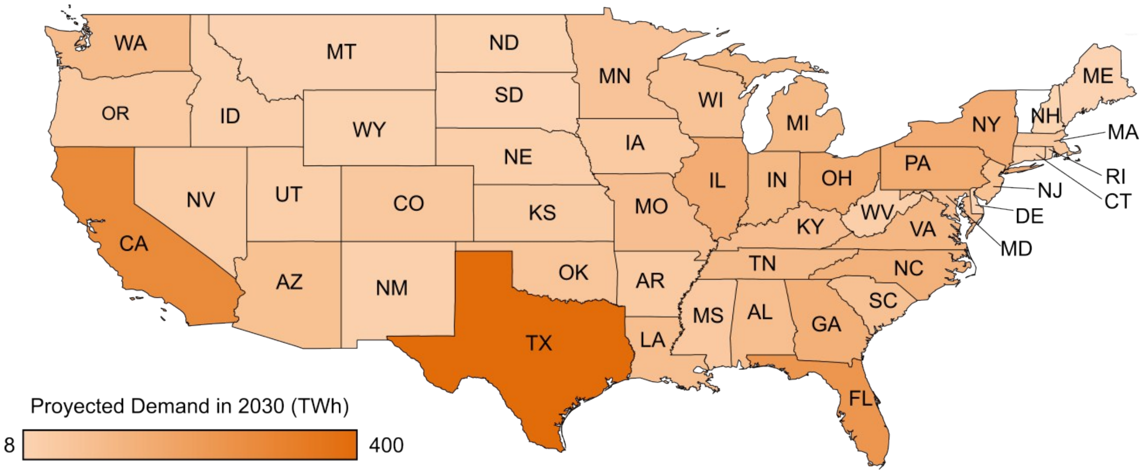


Figure S4. Projected annual electricity demands for each load area in 2030. States are coloured according to the scale of the projected electricity demand for 2030 expressed in TWh.

1.2.2.4 Transmissions lines

The U.S. electricity transmission network consists of approximately 200,000 miles of high voltage lines that connect generators to distributors in order to transport the electricity to the costumers. Unfortunately, data on the specific location and capacity of all U.S. power lines is missing, as EIA publishes interactive maps of only major electric transmissions lines (>345 kV) in the U.S. territory (see http://www.eia.gov/state/maps.cfm). Considering the state spatial resolution, the model assumes that the available U.S. electricity grid connects every U.S. state with its neighbouring states, that is, with those states with which it shares boundaries. Therefore, we model every state as a nodal area connected to neighbouring nodal areas by transmission lines, as depicted in Figure S5. Moreover, the CPP enables Canadian imports as a compliance strategy, so international transmission lines between U.S. states and the bordering Canadian provinces are also considered. Line arcs in the transmission network represent distances between states (parameter $DIST_{j,j'}$), as calculated with the great circle formula.

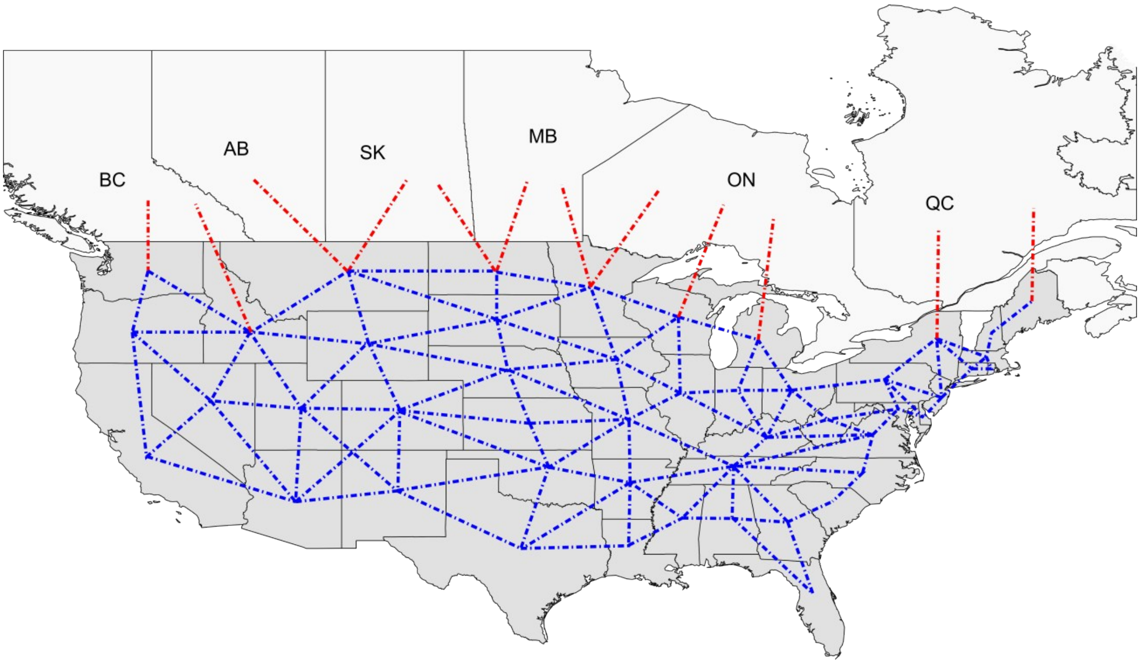


Figure S5. U.S. electricity potential transmission network considered in the study. Blue lines represent the transmissions lines whose ends are the nodes that correspond to the U.S. states. Red lines represent the international transmission lines with the Canadian provinces. Canadian provinces are labelled according to the ISO 3166-2 code.

1.2.2.5 Power losses during transmission and distribution

The EIA estimates that average annual transmission and distribution losses are roughly 6% of the total amount transmitted[6]. To capture such energy losses, we consider that 0.62% of the transmitted energy is lost every 100 km[9]. ERCOM models these losses via parameter TLF.

1.2.2.6 Capacity factors of the electricity generation technologies

Capacity factors (parameter $CF_{i,j}$) affect greatly the electricity generation and the LCOE. Differences in regional resources availability and plant operations lead to great variations of the capacity factor across the U.S. states. Average capacity factors for each technology in each state were calculated from historical data published by the EIA. These data cover the capacity installed and the electricity generated for period 1990-2013[6]. Data gaps in states not deploying a given technology in that time period where covered using the average capacity factor of the technology among all the states. There are two exceptions to this rule: (i) states not deploying nuclear power in the baseline year show a capacity factor of zero, since installing additional nuclear facilities is not a CPP compliance option; and (ii) a capacity factor of 0.36 was employed for wind offshore in coasting states, as recommended by the EIA[7], given that this technology is not deployed at all along U.S. in the baseline year. For biomass, we considered the categories “wood and derived fuel from wood” and “other biomass” available in the aforementioned source. Capacity factors for advanced coal and advanced combined cycle with carbon capture and storage (CCS) were assumed to be the same as those for conventional coal and natural gas, respectively. We also assumed that solar PV (both rural and rooftop scale) and solar thermal display the same capacity factor. Figure S6 shows the capacity factors. In general terms, we can observe that non-dispatchable technologies (i.e. those tied to an intermittent resource) show lower capacity factors than firm technologies (i.e. those whose output can be varied at will to meet a certain demand).

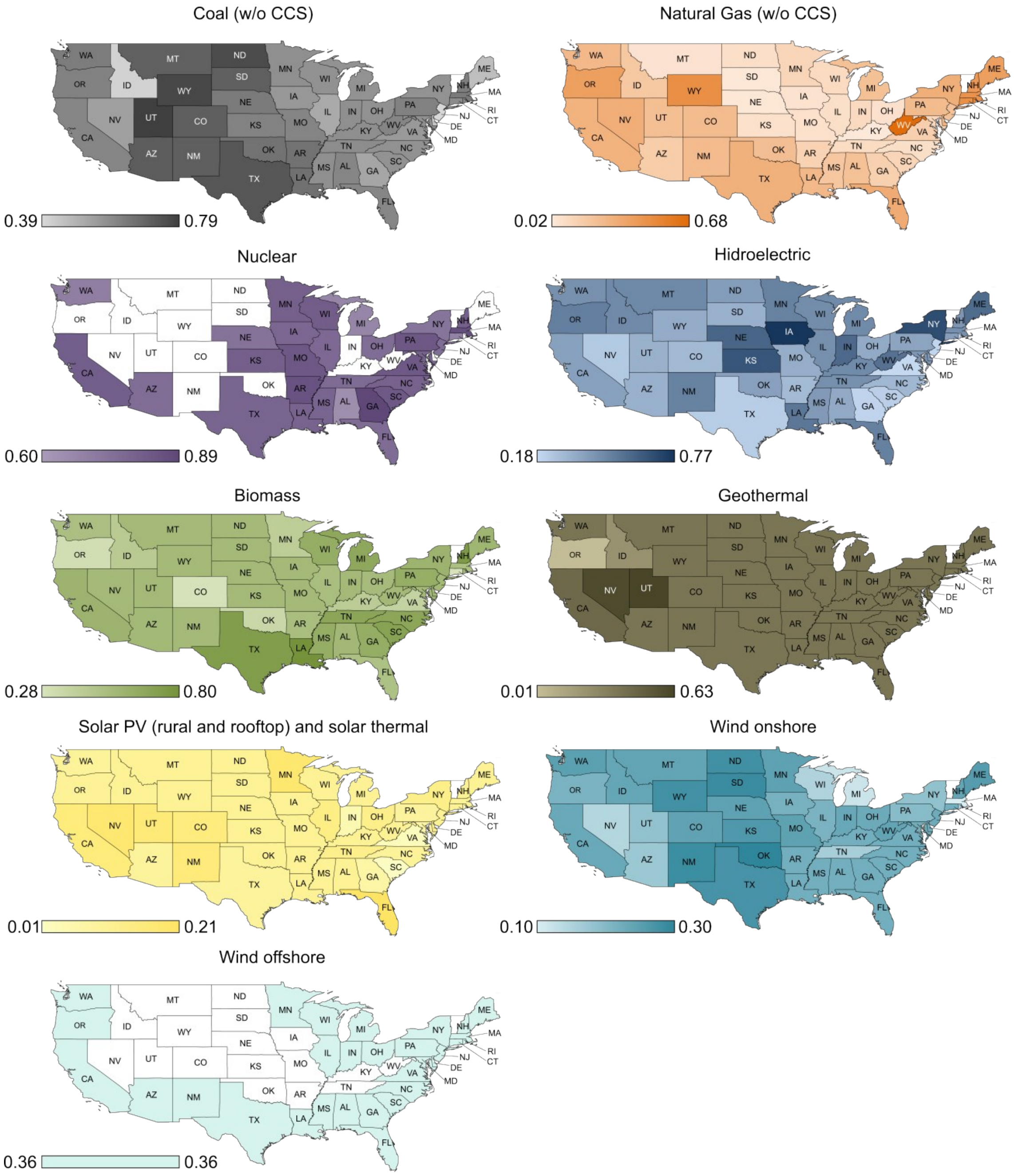


Figure S6. Capacity factor for each technology in each state. States are coloured according to the each specific scale so that the darker the shade of the state, the higher the capacity factor.

1.2.2.7 Cost of electricity generation technologies

The levelised cost of the electricity (LCOE) is (arguably) a convenient measure of the economic competiveness of the electricity generation technologies. Costs of electricity generation for each technology were determined from the average national LCOE for plants entering in service in 2020 following the Annual Energy Outlook 2015 developed by the EIA[7] (see Table S1). This report provides capital and transmission lines cost along with fixed and variable operations and maintenance (O&M) costs. The LCOE represents the cost per kWh of building and operating a plant over a given financial life (i.e. 30-year cost recovery period with a tax weighted average cost of capital of 6.1%). This parameter assumes a specific utilisation rate for each plant type (further details on specific assumptions are discussed in http://www.eia.gov/forecasts/aeo/index.cfm).

Table S1 Average capital and transmission lines costs, and fixed and variable operation and maintenance (O&M) costs for each electricity generation technology (2012 US$/MWh)[7].

	Capital and lines cost	Fixed O&M cost	Variable O&M cost
Coal	61.6	4.2	29.4
Natural Gas	15.6	1.7	57.8
Nuclear	71.2	11.8	12.2
Hydropower	72.7	3.9	7.0
Biomass	48.3	14.5	37.6
Geothermal	35.5	12.3	0
PV rural	113.9	11.4	0
Wind onshore	60.8	12.8	0
Wind offshore	174.4	22.5	0
Coal CCS	98.5	9.8	36.1
PV rooftop	113.9	11.4	0
Solar Thermal	196.6	42.1	0
Natural Gas CCS	31.3	4.2	64.7

These costs are region-specific due to local labour markets and differences in availability of energy sources. Hence, to capture such differences, costs were regionalised at the state level using Eqs. (S36-S38). These equations make use of the regional capacity factors (Figure S6) and state cost adjustment factors compiled by the U.S. Army Corps of Engineers[10].

$$CO^{CAP}_{i,j} = CO^{CAPAVE}_{i}\omega_j\left[\frac{47}{\sum_{j'} 1/CF_{i,j'}}\frac{1}{CF_{i,j}}\right] \quad \forall i,j \tag{S36}$$

$$CO^{FIX}_{i,j} = CO^{FIXAVE}_{i}\omega_j\left[\frac{47}{\sum_{j'} 1/CF_{i,j'}}\frac{1}{CF_{i,j}}\right] \quad \forall i,j \tag{S37}$$

$$CO^{VAR}_{i,j} = CO^{VARAVE}_{i}\omega_j\left[\frac{47}{\sum_{j'} 1/CF_{i,j'}}\frac{1}{CF_{i,j}}\right] \quad \forall i,j \tag{S38}$$

In these equations, $CO^{CAP}_{i,j}$, $CO^{FIX}_{i,j}$ and $CO^{VAR}_{i,j}$ are parameters denoting the regional capital/transmission lines cost, and fixed and variable O&M costs for each technology *i* in each state j (2012 US$/MWh), respectively; CO^{CAPAVE}_{i}, CO^{FIXAVE}_{i} and CO^{VARAVE}_{i} denote the average capital and transmission lines cost, and fixed and variable O&M costs for each electricity generation technology *i,* respectively (i.e. columns 2-4 in Table S1); and ω_j denotes the cost adjustment factor for each state *j*, where 47 is the number of elements used in the regionalisation (i.e. the number of states).

1.2.2.8 Electricity generation potential for each technology

The annual potential generation associated with every technology in each state (parameter $GEN_{i,j}^{POT}$ in ERCOM) is strongly related to the marginal abatement costs that ultimately drive the optimisation results (i.e. optimal electricity mixes and electricity trades). The model considers free trade of fossil fuels between states. We assume that the potential for fossil fuel-fired generation with coal and natural gas (both conventional and with CCS) is five times bigger than its generation in 2012. Regarding nuclear generation, potential levels are irrelevant, since the CPP does not consider new expansion as a compliance option. The potential for generation via renewables technologies is retrieved from the data published by the U.S. National Renewable Energy Laboratory (NREL)[11]. Furthermore, we assume that states can double their published biomass potential by trading resources between them. NREL estimates the technical renewable potential at the state-level based on renewable resources availability and quality, technical system performance, topographic limitations, and environmental, and land-use constraints (further details of the methodology and assumptions for estimating the renewables generation potential can be found in the report "U.S. Renewable Energy Technical Potentials: A GIS-Based Analysis"[11] available online at http://www.nrel.gov/gis/re_potential.html). Figure S7 shows the annual potential generation in TWh/yr for each technology and state considered in ERCOM.

Furthermore, global bounds (parameter GEN_{i}^{POTGLO} in ERCOM) are also imposed on the potential of technologies relying on energy sources that can be traded. Specifically, coal and coal CCS share a global upper bound given by coal-based generation limits in the baseline year. The same applies to natural gas w/o CCS. For biomass, we consider a global upper bound equal to the summation of all the states' potential, as published by NREL.

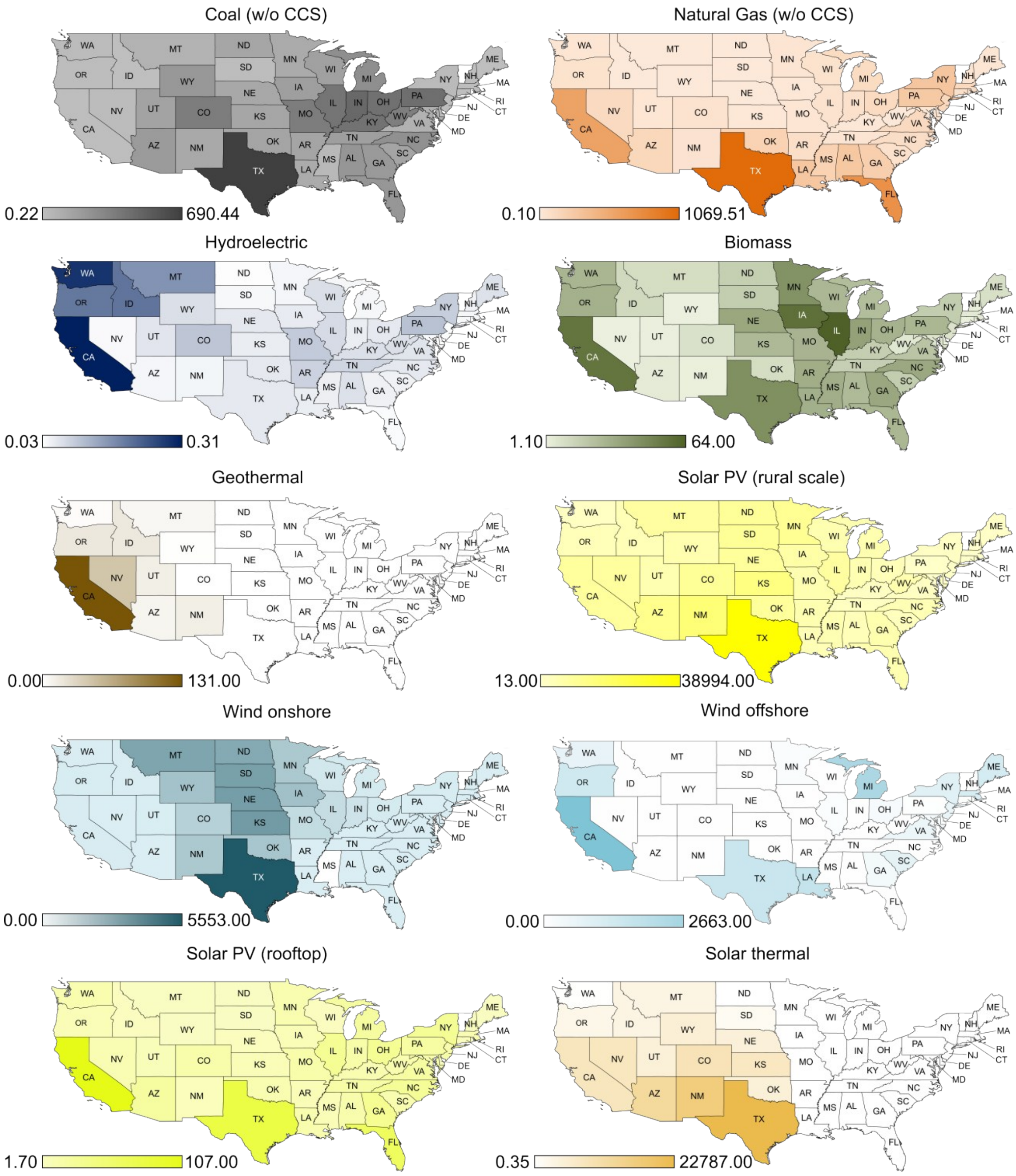


Figure S7. Annual electricity generation potential. States are coloured according to their annual electricity generation potential expressed in TWh/yr. The darker the shade, the higher the potential.

1.2.2.9 Electricity imports from Canada

We assume that electricity imports from Canadian regions are generated with hydropower and are therefore zero emitting and dispatchable. Electricity import prices (parameter CO^{CAN}) can fluctuate significantly (e.g. from as little as US$25/MWh to as much as US$70/MWh) [12], but for simplicity we set a price of US$39/MWh according to historical data[13].

In 2014, the electricity imported from Canada represented 1.8% of U.S. electricity retail sales, which was almost 10% of the total Canadian generation. In ERCOM, we assume that the electricity imports from Canada cannot exceed 5% of the demand of the U.S. (parameter CTB), which is in line with the expected growth estimated by the North American Electric Reliability Corporation (i.e. three times more compared to 2014 levels)[14].

1.2.2.10 Emission levels by technology: carbon intensity

The carbon intensity (parameter $CI_{i,j}$, expressed in CO_2 kg/MWh) for fossil fuel-fired power plants was sourced from the average regional performance rate included in Appendix 3 of the CPP final rule[1]. Such carbon intensities for coal and natural gas were calculated by the EPA as the average of the category-specific performance rates reported by unit levels or plant levels for 2012. Nuclear and renewables technologies are assumed to be zero emitting in the CPP. Regarding both coal and natural gas with CCS, we assume that they capture 90% of the flue gas CO_2, thereby reducing absolute emissions by 90%[15]. Figure S8 shows the carbon intensities of coal and natural gas in each state expressed in kg CO_2 per MWh. Note that carbon intensities from 2012 represent a conservative estimation that overlooks improvements in technology efficiency, which is one of the CPP building blocks.

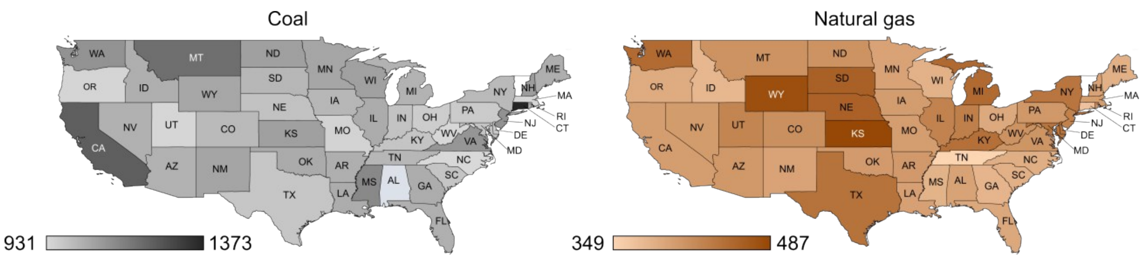


Figure S8. Emission performance rates of coal and natural gas by state. States are coloured according to their carbon intensity (CO_2 kg/MWh). The darker the shade, the higher carbon intensity.

1.2.2.11 System reliability: backup generation

High penetration of intermittent renewable power (i.e. wind and solar) can compromise the system reliability due to the variability and uncertainty of the sources (i.e. non dispatchable). To circumvent this issue, ancillary systems are installed to back-up the generation of intermittent renewable energies. However, the capacity of dispatchable technologies required to compensate their lack of firmness is still controversial, with very different values available in the literature (e.g. from as little as 15–20% of the intermittent capacity[16,17] to as much as 50–100%[18]). A value of 50% for the BUC parameter was therefore set in the ERCOM model. The physical interpretation for this is that each MW installed of an intermittent renewable technology requires the installation of additional 0.5 MW of firm technology to hedge supply in periods with unfavourable weather conditions.

1.3 Consumption-based allocation

Consumption-based carbon emissions and electricity generation costs are quantified by allocating emissions and costs to end users rather than to producers. At a global U.S. scale, the total consumption-based emissions (and cost) are equal to the production-based ones (recall that the imports from Canada are zero emitting). However, this does not happen on a regional basis due to the exchange of electricity between states. Allocation of emissions is still an open issue in the literature, where several methods were put forward to tackle this problem, particularly in the context of multi-product plants (i.e. how to allocate the total emissions of a plant among the products it manufactures[19]). As described in more detail next, here we allocate emissions and costs based on mass balances defined for every U.S. state. The allocation method is outlined in Figure S9 by means of a simplified example consisting of three states trading electricity. The waterfall plot bellow shows the breakdown of the consumption-based emissions calculation for state A. As seen, the consumption-based emissions corresponding to state A ($CBEM_A$) are calculated from its production-based emissions ($\bar{EM}_A$) plus the emissions embodied in the electricity imported from states B and C (red and green bars with blue contours respectively) minus the emissions embodied in the electricity exported from the state A to the neighbouring states (bars filled with blue colour); where the amount of emissions embodied in the trades are given by the product between the amount of electricity traded ($\bar{TRD}_{j,j'}^{ORIG}$) and the consumption-based carbon intensity (i.e. CO_2 kg/MWh) of the supplier state ($CBEM_{j'}(DEM_{j'}DSF)^{-1}$).

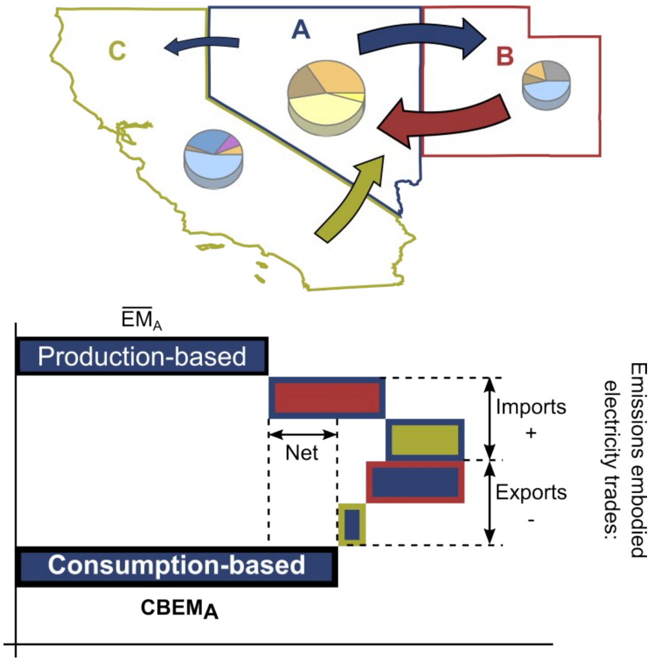


Figure S9. Illustration of the consumption-based allocation method. Three states (i.e. A, B and C) trading electricity are considered where arrows represent the emissions embodied in the electricity trades. The waterfall plot below denotes the breakdown of the consumption-based emissions calculation for state A. Length of the bars represents the amount of the emissions and each bar is filled according to the emitter state and contoured according to the receiver state.

1.3.1 Consumption-based emissions

To quantify the consumption-based emissions of a state in any optimal solution calculated by ERCOM, we derive the following balance on carbon emissions:

$$CBEM_j = \bar{EM}_j + \sum_{j' \in NU_j} \bar{TRD}_{j,j'}^{ORIG} \frac{CBEM_{j'}}{DEM_{j'}DSF} - \sum_{j' \in NU_j} \bar{TRD}_{j',j}^{ORIG} \frac{CBEM_j}{DEM_j DSF} \quad \forall j \qquad (S39)$$

Here, $CBEM_j$ are the consumption-based (footprint) emissions of state *j*, that is, the kg of CO_2 emitted to satisfy its electricity demand, while $\bar{EM}_j$ are the optimal production-based emissions of state *j* (the ones calculated by ERCOM), $\bar{TRD}_{j,j'}^{ORIG}$ represents the optimal trade between states *j* and *j'* (calculated also by ERCOM), DEM_j denotes the demand of state *j* and DSF is the demand satisfaction factor. Note that imports from Canada are zero-carbon and therefore are omitted from the balance. Hence, the equation states that the consumption-based emissions of a state equal its production-based emissions plus the emissions embodied in the electricity imported by the state minus the emissions embodied in the electricity exported from the state to other neighbouring states.

This equation is implicit in $CBEM_j$, as it requires the values of the consumption-based emissions of other states *j'* (i.e. $CBEM_{j'}$), which may in turn depend on the consumption-based emissions of the state for which the balance is defined. Therefore, Eq. (S39) leads to a system of linear equations that need to be solved simultaneously. After running ERCOM, the production-based emissions of every state ($\bar{EM}_j$) and the inter-state flows ($\bar{TRD}^{ORIG}_{j,j'}$) become available. With this information at hand, we next build the system of linear equations in Eq. (S39) and solve it to obtain the values of $CBEM_j$, which provide the consumption-based carbon emissions of every state.

1.3.2 Consumption-based costs

The cost of the electricity consumed by a state is calculated following a similar approach as before, as shown in Eq. (S40).

$$CBCOST_j = \bar{COST}_j + \sum_{j' \in NU_j} \bar{TRD}^{ORIG}_{j,j'} \frac{CBCOST_{j'}}{DEM_{j'}DSF} - \sum_{j' \in NU_j} \bar{TRD}^{ORIG}_{j',j} \frac{CBCOST_j}{DEM_j DSF} \quad \forall j \tag{S40}$$

This equation states that the cost of satisfying the electricity of a state is given by the cost of generating the electricity domestically plus the cost of the imports minus the cost of the exports. Here, $CBCOST_j$ is the cost of satisfying the electricity demand of state *j*, that is, the global cost of satisfying its electricity demand, while $\bar{COST}_j$ represents the optimal production-based costs of state *j*. $\bar{TRD}^{ORIG}_{j,j'}$ denotes the optimal electricity transmitted from state *j'* to *j*, DEM_j is the final demand of state *j* and DSF is the demand satisfaction factor. Costs associated to imports from Canada are not explicitly defined in Eq. (S40), but rather accounted for by the parameter $\bar{COST}_j$ (see Eq. (S30) in model ERCOM). Note that this allocation reflects the cost of generating electricity, but not the market price at which the electricity might be sold in the future (which will very likely lie above the former). Eq. (S40) defines also a system of linear equations that can be built once the optimal solution of ERCOM is identified (values of $\bar{COST}_j$ and $\bar{TRD}^{ORIG}_{j,j'}$). The solution of such system of equations therefore provides the value of $CBCOST_j$.

1.4 Sensitivity analysis

Some of the parameters in ERCOM are inherently uncertain. We perform a sensitivity analysis to understand how these uncertainties affect the outcome of the optimisation. To this end, the model is solved iteratively for different potential values of the uncertain parameters (i.e. scenarios), which are modelled using probability distributions. These values, each accounting for a different realisation of the uncertain parameter, are generated by applying sampling methods on the underlying probability distributions. After solving ERCOM for every scenario, we finally obtain a probability distribution of the model results (i.e. costs) that can be used to construct confidence intervals for the optimal U.S. electricity cost. In particular, we analyse the following cases:

- **Case 1**: to identify the most critical uncertainties, we first solve the model by varying one single parameter at a time (e.g. $D\tilde{E}M_j$ for all states *j*) while keeping the remaining parameters at their nominal (i.e. deterministic) values. We solve in total *9* NSC instances, where 9 refers to the number of uncertain parameters (see uncertain parameters in section 1.4.2; note that we explore the disaggregated LCOE parameters together, rather than separately) and NSC is the number of scenarios.
- **Case 2**: the model is solved considering all the uncertain parameters simultaneously (i.e. NSC times).

In the next section, we introduce the probability distributions used to model the uncertain parameters, whereas in section 1.4.2 we show how we fit each uncertain parameter to one of these distributions. Finally, in section 2.4 we discuss the results of the sensitivity analysis.

1.4.1 Probabilistic distributions

The probabilistic distributions used in the analysis are next discussed (a generic random variable *X* is used for simplicity).

1.4.1.1 Geometric Brownian Motion

Strictly speaking, Geometric Brownian Motion (GBM) is not a probabilistic distribution but rather a continuous-time stochastic process which is used to model unpredictable events occurring during "deterministic" trends[20]. Eq. (S41) describes the GBM differential equation applied to model a stochastic variable *X*:

$$dX_t = \mu X_t dt + \sigma X_t dW_t \tag{S41}$$

where X_t represents the value of stochastic variable *X* in time instant *t*, μ denotes the drift parameter, σ is the standard deviation (or volatility) and dW_t is the increment of the Wiener process, modelled as a stochastic variable that follows a standard normal distribution. Therefore, the first term of the equation represents the expected value of the stochastic variable *X* in time *t*, whereas the second term adds the stochastic component to the prediction.

Assuming that the natural logarithm of the future realisation of *X* is normally distributed (i.e. log-normally distributed), the solution to Eq. (S41) is given by Eq. (S42).

$$X_{t+\Delta t} = X_t \left[\left(\mu + \frac{\sigma^2}{2} \right) \Delta t + (\sigma \sqrt{\Delta t} (N(0,1))) \right] \tag{S42}$$

Here, Δt is the time step. Therefore, this equation allows forecasting future values of *X* (i.e. X_{t+T}) according to historical data (i.e. X_t), once the drift parameter μ and the volatility σ have been determined.

1.4.1.2 Triangular distribution

A random variable *X* following a triangular distribution (i.e. *X~T(a,b,c)*) can take values between a lower limit *a* and an upper limit *b*, with mode (i.e. peak) *c*. The probability density function is then given by:

$$f(x)=\begin{cases}\dfrac{2(x-a)}{(b-a)(c-a)} & a\le x\le c\\ \dfrac{2(b-x)}{(b-a)(b-c)} & c\le x\le b\end{cases}\tag{S43}$$

Triangular distributions can be used to approximate normal distributions when data is scarce but the minimum (*a*) and maximum (*b*) values of the random variable along with its modal (i.e. nominal) value (*c*) are available.

1.4.1.3 Uniform distribution

A random variable *X* following a uniform distribution (*X~U(a,b)*) has constant probability within the interval [*a*,*b*]:

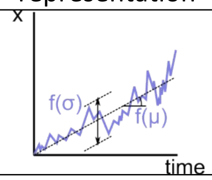
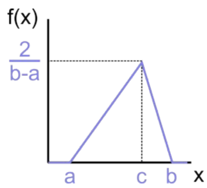
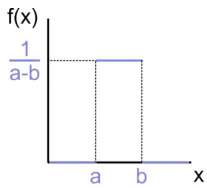
$$f(x)=\begin{cases}\dfrac{1}{(b-a)} & a\le x\le b\\ 0 & otherwise\end{cases}\tag{S44}$$

This is the simplest continuous probability distribution, since it only requires the extremes (*a*,*b*) of the support to be fully characterised.

1.4.2 Uncertain parameters

The uncertain parameters in ERCOM and the probabilistic distributions used to describe them are given in Table S2.

Table S2 Summary of probabilistic distributions used to describe uncertain parameters in ERCOM.

Uncertain parameter	Probabilistic distribution	Graphical representation	Characteristic parameters
$\widetilde{DEM}_j$	Geometric Brownian Motion		μ, σ
$\widetilde{BUC}$	Triangular		a, b, c
$\widetilde{CO}^{CAN}$			
$\widetilde{CO}^{CAP}_{i,j}$			
$\widetilde{CO}^{FIX}_{i,j}$			
$\widetilde{CO}^{VAR}_{i,j}$			
$\widetilde{CTB}$			
$\widetilde{CF}_{i,j}$	Uniform		a, b
$\widetilde{CI}_{i,j}$			
$\widetilde{GEN}^{POT}_{i,j}$			
$\widetilde{GEN}^{POTGLO}_{i,j}$			

Scenarios are generated from these distributions via Monte Carlo sampling, assuming in all the cases that the uncertain parameters are uncorrelated. More scenarios lead to better approximations but also to larger CPU times. In our case, 100 scenarios (i.e. NSC = 100) are enough to estimate the objective function for a confidence level γ = 95% (i.e. α = 0.05) according to Law and Kelton's test[21]. Specifically, for simplicity we apply this test to the results (i.e. total U.S. cost) of Case 2 (considering all uncertainties simultaneously) and use the same number of scenarios in Case 1 as well. The test is applied as follows:

1. We define a number of scenarios.
2. We solve model ERCOM for each of these scenarios, obtaining the electricity cost in each of them ($\bar{COST}^{TOT}_{s}$).
3. We calculate the confidence interval half length, δ(NSC,α), via Eq. (S45).

$$\delta(NSC,\alpha) = t_{NSC-1,\frac{1-\alpha}{2}}\sqrt{\frac{Var\left(\bar{COST}^{TOT}_{s}\right)}{NSC}} \tag{S45}$$

Here, $t_{NSC-1,\frac{1-\alpha}{2}}$ is the critical point of the t-distribution and $Var\left(\bar{COST}^{TOT}_{s}\right)$ is the variance of the total cost in the scenarios.

4. We finally check that Eq. (S46) holds:

$$\frac{\delta(NSC,\alpha)}{E\left(\bar{COST}^{TOT}_{s}\right)} \le \frac{\gamma}{1-\gamma} \tag{S46}$$

Here, $E\left(\bar{COST}^{TOT}_{s}\right)$ is the expected value of the optimal total U.S. cost.

If this condition does not hold, we increase the number of scenarios and go to step 1 until the condition is satisfied.

The interested reader is referred to the original work by Law and Kelton[21] for further details. We next describe in detail how we fit each parameter to the corresponding distribution. Electricity demand

Electricity demand is subject to several unforeseen aspects such as market volatility, technology improvements (e.g. development of electric cars), population growth and new policies, among others. Unlike other uncertain parameters considered "constant" over time, we forecast future demands using the GBM approach based on historical data trends. Annual electricity demands for each state were sourced from electricity retail sales (reported to be a good proxy for electricity demand) published by the EIA. Specifically, we use historical retail sales from period 1990-2012[6], where 2012 was used as the baseline year.

An average annual growth rate of 0.8% projected by the EIA[7] was defined as drift parameter for each state (μ_j), while the volatility was determined using the historical data as follows Firstly, yearly returns for each state j ($r_{j,t}$) are calculated for each two consecutive time periods via Eq. (S47), by considering a time step of one year.

$$r_{j,t} = \frac{DEM_{j,t+1}}{DEM_{j,t}} \quad \forall t < T \tag{S47}$$

Then, the average of the yearly returns for each state ($\bar{r}_j$) is determined using Eq. (S48), whereas the standard deviation of the yearly returns provides the state volatility (σ_j), as given by Eq. (S49).

$$\bar{r}_j = \frac{\sum_t r_{j,t}}{2012-1990} \quad \forall j \tag{S48}$$

$$\sigma_j = \sqrt{\frac{1}{2012-1990}\sum_t \left(r_{j,t} - \bar{r}_j\right)^2} \quad \forall j \tag{S49}$$

Once drift and volatility have been determined, Eq. (S42) allows us to project demands from 2012 onwards up to 2030 (year-per-year) by applying Monte Carlo sampling on the *N(0,1)* (see Fig. S10).

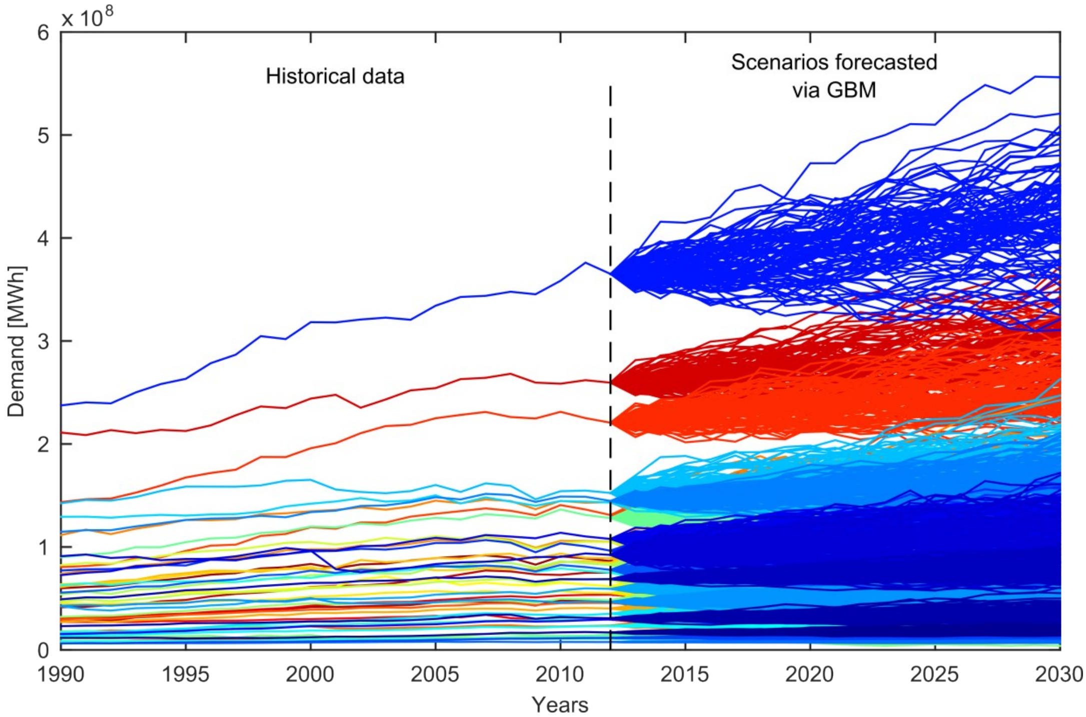


Figure S10. Scenarios for electricity demand in each state (MWh). States' demands are forecasted using GBM from 2012 onwards by using historical data from 1990-2012. Each projection represents one scenario with the same probability of occurrence.

1.4.2.1 Coefficient for back up generation

As previously discussed, firm capacity can range from as little as 15–20% of the intermittent capacity[16,17] to as much as 50–100%[18]. We use these values to fit a triangular distribution so that $\tilde{BUC} \sim T(0.15,1.00,0.50)$. Figure S11 provides a histogram based on the scenarios generated for this parameter.

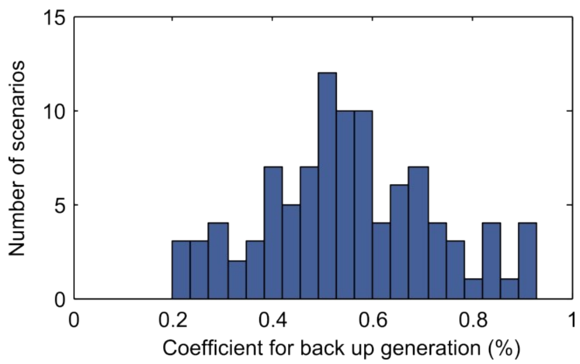


Figure S11. Scenarios for the coefficient for back up generation (%). Scenarios for the BUC parameter are generated based on a triangular distribution.

Note that a reliable representation of this parameter is of utmost importance, since it greatly influences the outcome of the optimisation. Higher values of this parameter will lead to mixes with less intermittent renewable technologies, whereas low values of BUC allow for larger shares of non-dispatchable resources.

1.4.2.2 Cost of electricity from Canada

The cost of the electricity purchased from Canada, $\tilde{CO}^{CAN}$, is subject to market fluctuations. We fit a triangular distribution where US$39/MWh is the nominal (i.e. peak) value[13], and with a minimum value a = US$25/MWh and a maximum value b = US$70/MWh, which are both defined considering historical electricity price flutuations[12]. Therefore, the final distribution is $\tilde{CO}^{CAN} \sim T(25{,}70{,}39)$ (see Figure S12).

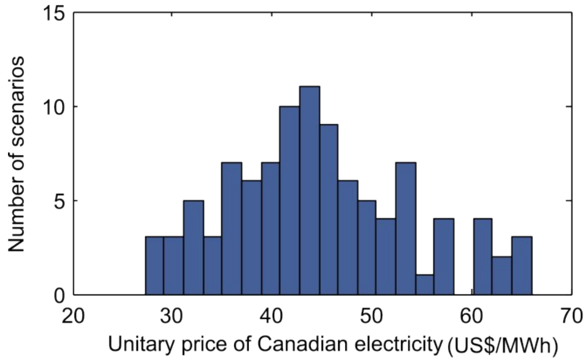


Figure S12. Scenarios for the cost of electricity imports from Canada (US$/MWh). Scenarios for the CO^{CAN} parameter are generated based on a triangular distribution.

1.4.2.3 Costs of electricity generation technologies

Capital and transmission lines cost as well as fixed and variable operations and maintenance (O&M) costs are influenced by several external factors:

- Annualised capital costs ($\tilde{CO}^{CAP}_{i,j}$) are uncertain because so are the equipment costs (which may be influenced by economies of scale) as well as investments in lines connecting new installations with the existing grid.
- Fixed operation and maintenance costs ($\tilde{CO}^{FIX}_{i,j}$) are uncertain due to volatile fuel prices and labour costs.
- Variable costs ($\tilde{CO}^{VAR}_{i,j}$) are subject to unpredictable maintenance tasks and fuel prices, among others.

Nominal values for these parameters were obtained by regionalising the average U.S. costs for each technology (i.e. CO^{CAPAVE}_{i}, CO^{FIXAVE}_{i} and CO^{VARAVE}_{i}) according to Eqs. (S36-S38), as described in section 1.2.2.7. In the case of the uncertain parameters, we follow a three-step approach by which we first fit triangular distributions considering the average parameters, then generate scenarios from them, and finally regionalise the value of each parameter in each scenario. Specifically, in the first step, the average parameters for each technology *i* (i.e. $\tilde{CO}^{CAPAVE}_{i}$, $\tilde{CO}^{FIXAVE}_{i}$ and $\tilde{CO}^{VARAVE}_{i}$) are fitted to three triangular distributions in which the peak values c correspond to the nominal values (Table S1) and the extremes of the distributions (i.e. a and b) are obtained by disaggregating the nominal values on the same proportion as the min-max bounds published[7] for the total LCOE. In the second step, the scenarios are generated via sampling on the distributions of the 39 parameters (i.e. three parameters for each of the 13 technologies considered). Finally, in step 3, we regionalise the values obtained for each parameter in each scenario by means of Eqs. (S36-S38). As an example, Figure S13 depicts histograms of the scenarios generated for the 13 technologies after applying the regionalisation step.

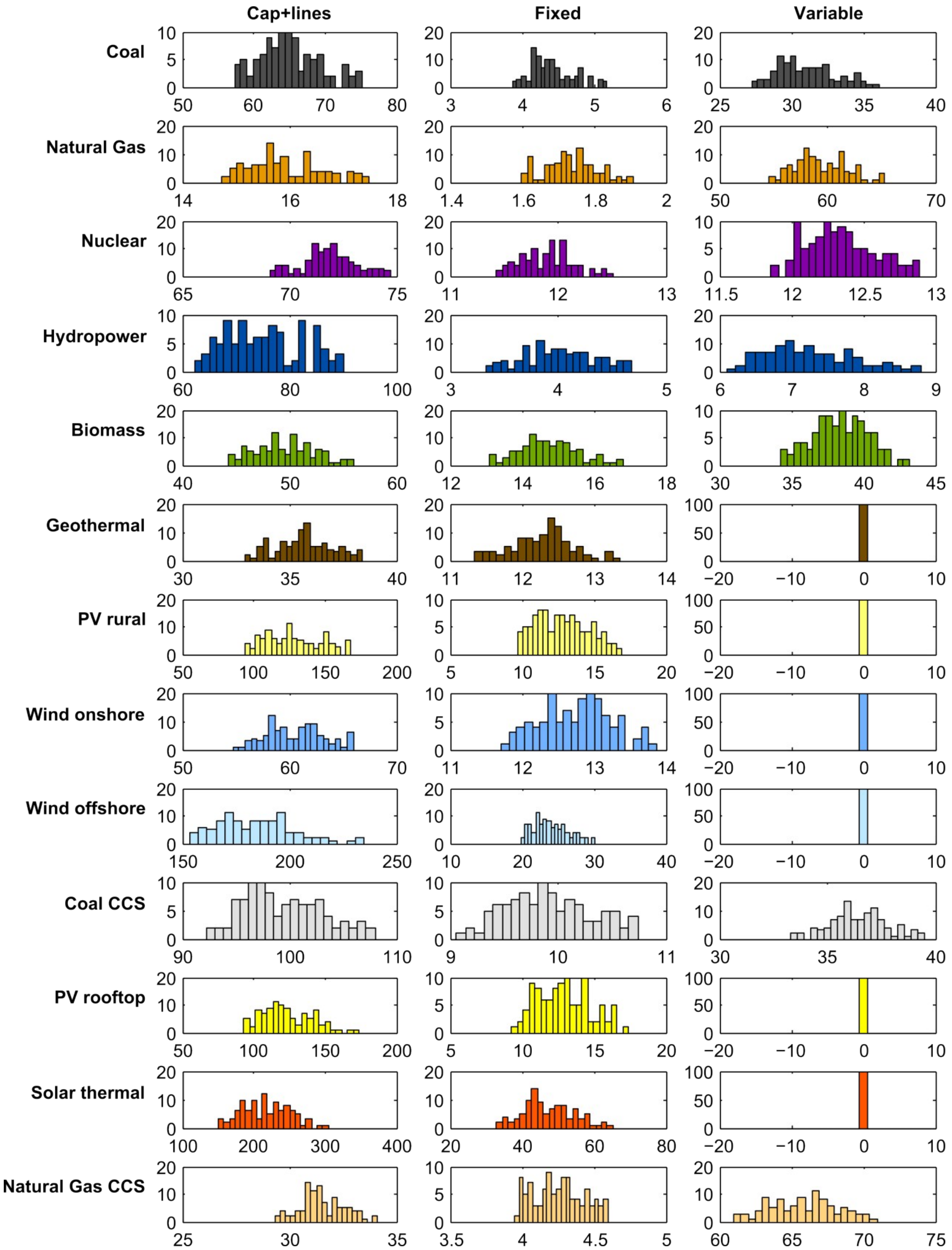


Figure S13. Scenarios for the disaggregated LCOE parameters (2012 US$/MWh). Scenarios for the LCOE parameter are generated based on a triangular distribution. Triangular distributions are first fit from minimum, maximum and average 2012 values for the corresponding technologies, then a set of scenarios are generated for each parameter via Monte Carlo sampling and finally the value of each parameter in each scenario are regionalised to account for local differences.

1.4.2.4 Bound on imports from Canada

Electricity imports from Canada must lie below 5% of the total U.S. demand, which is consistent with the three-fold growth estimate that is expected (with respect to the current share of 1.8%[14]). However, this value is subject to new hydropower developments, grid reliability and new agreements and policies, among others. Therefore, we explore the influence of such bound by resorting to the stochastic parameter $\tilde{CTB}$, which is assumed to follow a triangular distribution with a nominal value of 5% and with a support ranging from a minimum of 0% to a maximum of 7%. Figure S14 shows the scenarios generated for this parameter.

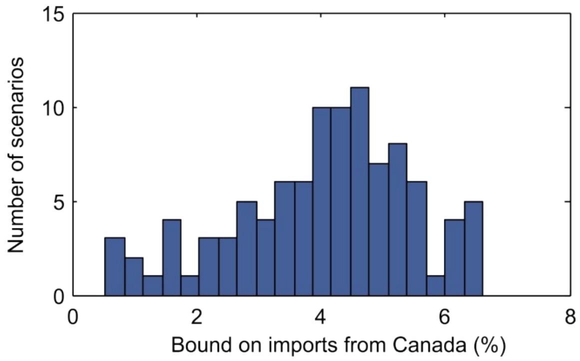


Figure S14. Scenarios for the upper bound on Canadian electricity imports (%). Scenarios for the CTB parameter is generated based on a triangular distribution.

1.4.2.5 Capacity factor

The capacity factor of a technology is subject to learning curves (in the case of immature technologies), efficiency improvements, unpredictable plant operation/maintenance as well as weather conditions (in the case of intermittent renewables), among others. We model this parameter as a stochastic ($\tilde{CF}_{i,j}$) variable following a uniform distribution for each *i-j* pair. Specifically, we centre the distributions to the deterministic values and define the support (i.e. a and b in the uniform distribution) according to the standard deviation of historical data[6]. For states lacking data on some technologies, we use the average standard deviation among the different states, similarly as we did with the deterministic value of $CF_{i,j}$ (see section 1.2.2.6).

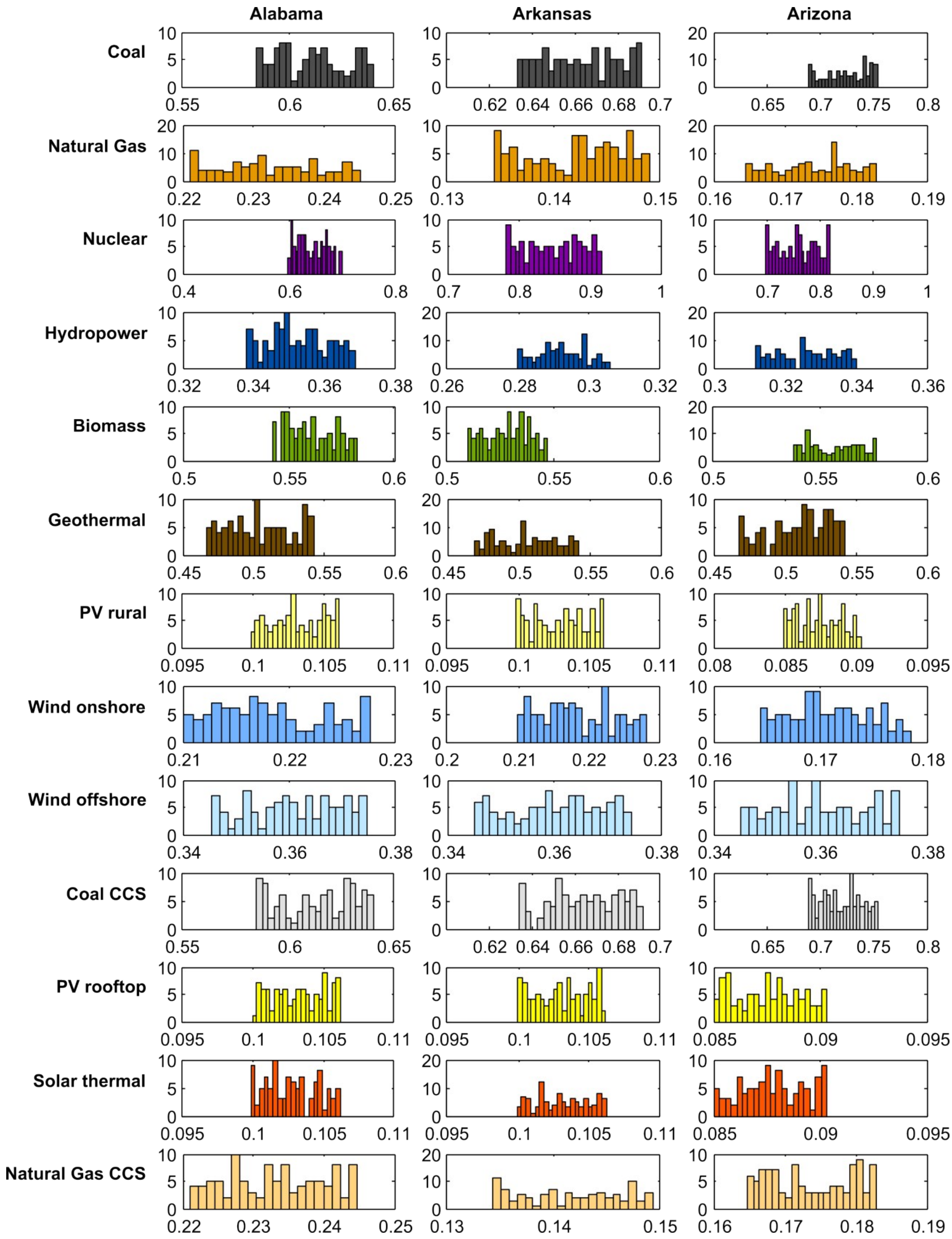


Figure S15. Scenarios for the capacity factor of electricity generation technologies. Sample of the scenarios for the $CF_{i,j}$ parameter in three states are generated by fitting to a uniform distribution centred at the deterministic value and with a variation as given by the standard deviation of historical data.

1.4.2.6 Carbon intensity

Carbon intensities depend on how plants are operated as well as on the composition of fuels, among other factors. An uncertain parameter, $\tilde{CI}_{i,j}$, is thus defined which follows a uniform distribution centred around the deterministic value and with a support providing a variation of ±30%. Note that by generating independent scenarios for coal with and without CCS, we are indeed modifying the % of CO_2 captured in CCS (i.e. it will not always be 90%, as assumed for the deterministic case, but rather depend on the scenario). The same happens for natural gas w/o CCS. Figure S16 illustrates the scenarios generated for the carbon intensity for emitting technologies in some of the states. Non-emitting technologies are excluded from the sensitivity analysis, that is, we consider that $CI_{i,j} = 0$ for all of them in any scenario.

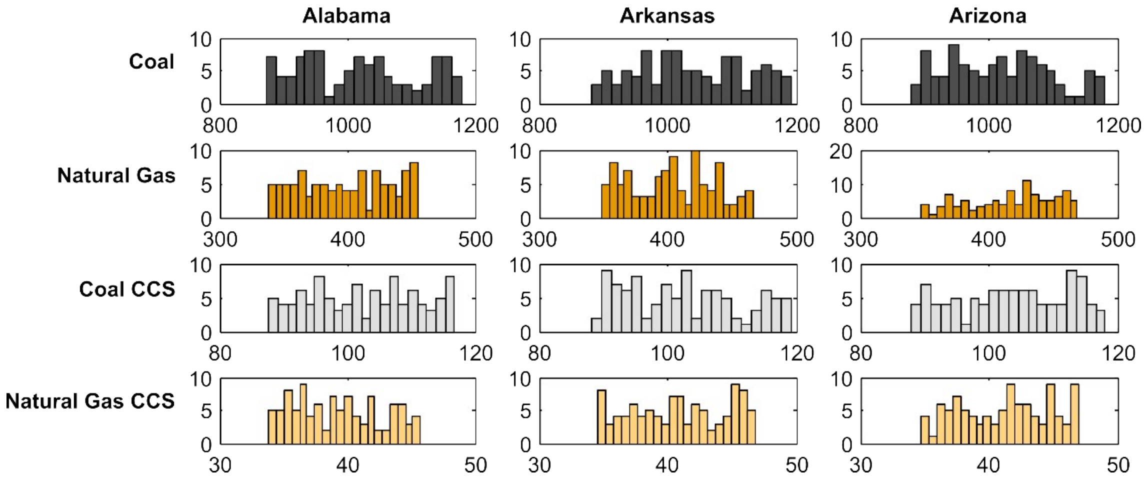


Figure S16. Scenarios for the carbon intensity (CO_2 kg/MWh). Sample of scenarios for the $CI_{i,j}$ parameter in three states generated based on a uniform distribution.

1.4.2.7 Generation potential

Uncertainty in the generation potential, $\tilde{GEN}_{i,j}^{POT}$, stems mainly from poor weather forecasting (in the case of non-dispatchable renewables), discovering/depletion of fuel sources and technological development, among others. We approximate this stochastic parameter by fitting a uniform distribution assuming a support centred on the deterministic value with a variation of ±30%. Therefore, $\tilde{GEN}_{i,j}^{POT} \sim U(0.7GEN_{i,j}^{POT}, 1.3GEN_{i,j}^{POT})$, which can be discretised in scenarios as depicted in Figure S17.

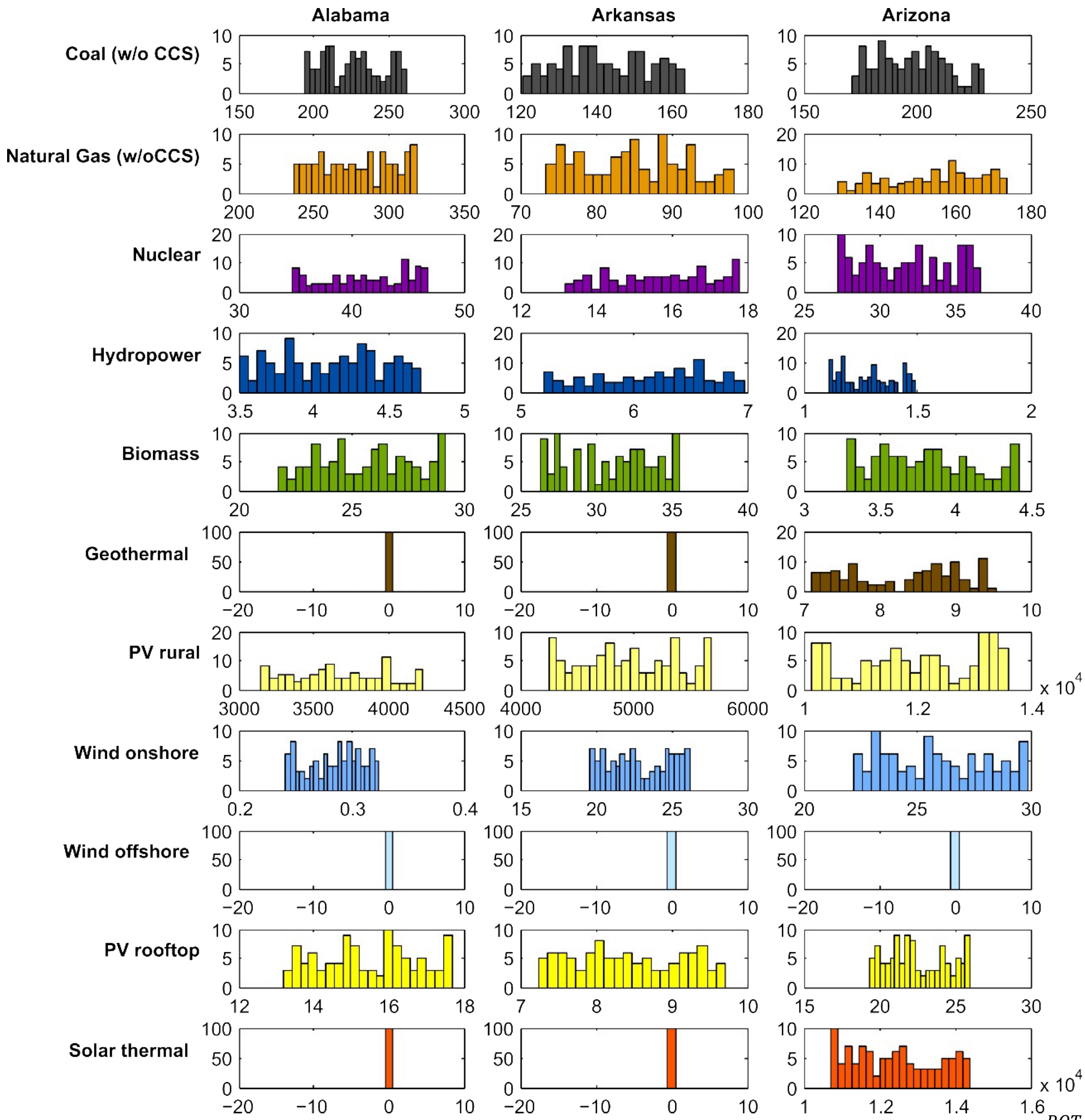


Figure S17. Scenarios for the generation potential (TWh/yr). Sample of scenarios for the $GEN_{i,j}^{POT}$ parameter in three states generated based on a uniform distribution.

1.4.2.8 Global generation potential

Natural gas is expected to play a key role in the close future. Proved reserves and technically recoverable resources (for shale gas, tight gas and offshore natural gas) described in the Reference case of the Annual Energy Outlook 2016 published by the EIA[22] suggest that current generation with natural gas could be doubled in oncoming years. In light of this, we model the global bound on the generation potential of natural gas as an uncertain parameter following a uniform distribution with a support between the baseline year generation and twice this amount (i.e. $\tilde{GEN}_{natural\ gas}^{POTGLO} \sim U\left(GEN_{natural\ gas}^{POTGLO}, 2GEN_{natural\ gas}^{POTGLO}\right)$). Figure S18 illustrates the scenarios generated for this parameter. Note that we only consider as uncertain the global potential for technology *i = natural gas*. The other potentials are kept at their deterministic values throughout the study.

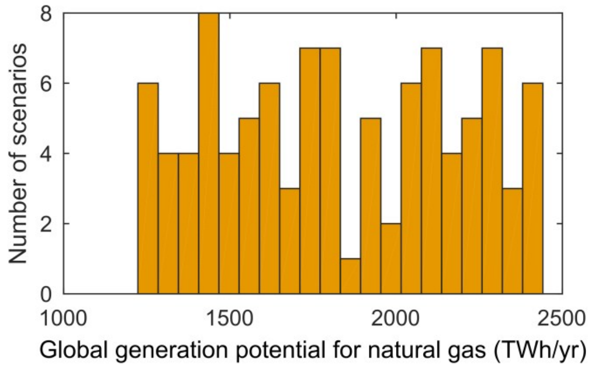


Figure S18. Scenarios for the global bound on the generation potential of natural gas (TWh/yr). Scenarios for the $GEN_{natural\ gas}^{POTGLO}$ parameter are generated based on a uniform distribution.

2 Supplementary results

We next provide some results omitted from the main manuscript due to space limitations. First, in section 2.1 we provide the U.S. geographical breakdown of the non-cooperative optimal solution (A). Then, in section 2.2, we further describe consumption and production-based emissions/costs results. In section 2.2.1, we assess the emissions and costs embodied in the trade in the global U.S. partnership; while finally in section 2.2.2 we show the breakdown by state of emissions and costs (totals, carbon intensities and specific costs) according to both the production and consumption-based accountings.

2.1 Optimal non-cooperative solution (Solution A)

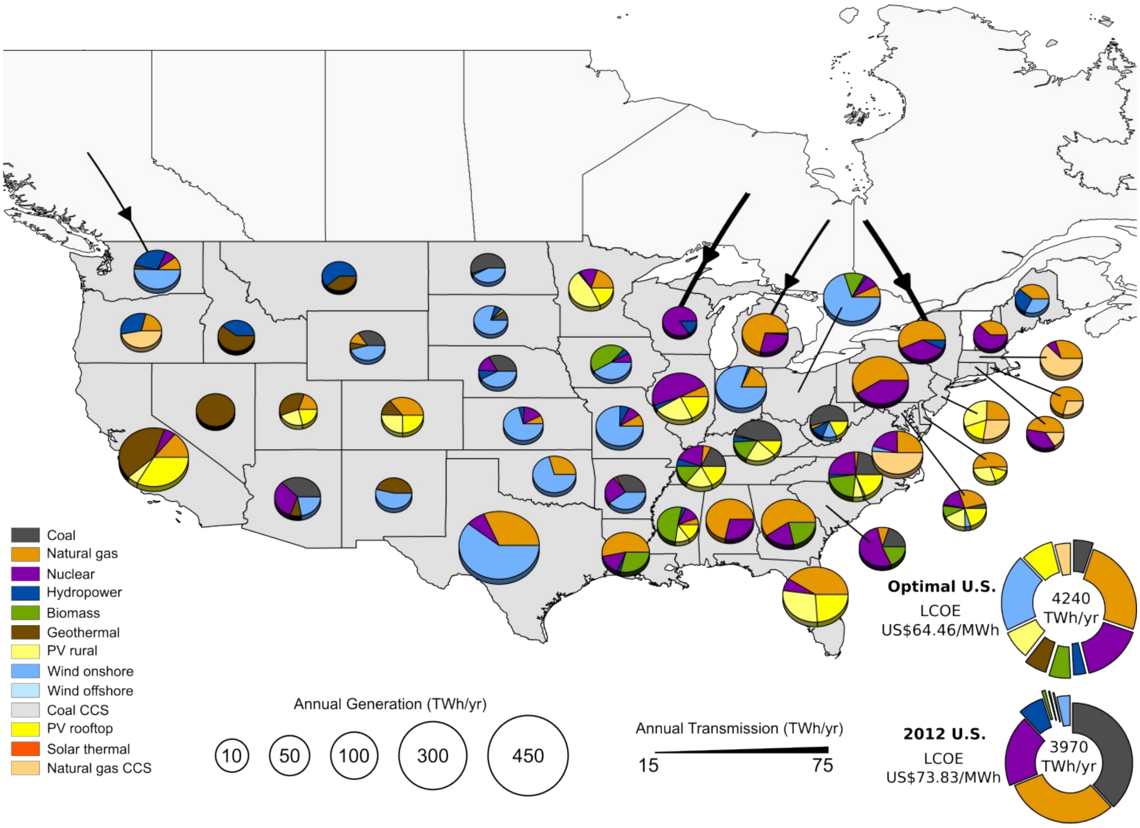


Figure S19. Geographical breakdown of the U.S. cost-optimal electricity system in solution A. The size of the pie charts is proportional to the electricity generation of each state (TWh/yr) whereas the slice colours represent the share of each technology. The global U.S. electricity generation portfolio for 2012 and for solution A are depicted (bottom right) together with the associated LCOE.

Solution A is obtained by minimising the total cost of electricity generation and forcing states to comply with their CPP target individually (i.e. parameter CS is set to zero, so all binary variables are zero as well). Note that this solution covers the demand in 2030, but its cost is expressed in 2012 dollars. In this solution no cooperation (i.e. target sharing or electricity trade) is allowed, and therefore states can only reduce their emissions by switching to cleaner energy mixes. Solution A leads to a total U.S. cost of electricity generation 4% below the base line (i.e. 2012) while simultaneously the CO_2 emissions are reduced almost double the CPP target (67% compared with the 35% required). Figure S19 shows the optimal electricity portfolio in each state without any form of cooperation among them. As can be observed, CPP targets can be met individually without increasing the U.S. LCOE, which is slightly lower than in

2012 (i.e. US$64.4/MWh compared to US$73.8/MWh). Broadly speaking, in solution A, coal-fired power plants are almost phased out, while natural gas generation declines slightly and nuclear power is kept constant (as specified in the CPP). The share of renewables increases until representing a 47% of the total electricity demand. Economically competitive renewable technologies are deployed in many states. Namely, wind onshore increases substantially (from 3% to 20% of the total power needs), while solar PV (both at rural and rooftop scale) reaches almost 16% (from almost zero levels in 2012). States deploying these technologies complete their portfolios with back-up firm technologies based on coal, natural gas, geothermal and natural gas with CCS. These technologies ensure the system reliability under intermittency of sources. Geothermal and biomass resources are exploited until accounting for almost 6% (each) of the total electricity generation. Geothermal is largely implemented in western states (e.g. California, Nevada, Idaho, Utah and Montana), while biomass is employed in south eastern states (e.g. Louisiana, Mississippi and Georgia) as well as in Iowa and Ohio, among others. Besides deploying renewable resources, some states reduce their emissions by replacing coal by natural gas (e.g. Pennsylvania, Michigan, New York, Alabama and New Hampshire), while others implement carbon capture and storage technologies in natural gas-fired plants (e.g. Connecticut, Massachusetts, New Jersey, Oregon, Rhode Island and Virginia).

2.2 Further assessment of individual efforts: production vs consumption-based perspectives

2.2.1 Emissions and cost embodied in trade

Assessing the efforts every state makes in the cooperation only from a production-based perspective is arguably unfair since all the responsibility and the burden is allocated to electricity producers, which may be the states required to increase their generation for the sake of the overall gain (e.g. Oklahoma). Conversely, states displacing their facilities to other regions avoid the burden attributed to the generation of their electricity demand, leading to 'carbon leakage'. To shed further light on this, we consider the implications of adopting a consumption-based approach, which, unlike the territorial approach followed by CPP, assigns the responsibilities to consumer states, i.e. those that use rather than generate electricity. To this end, we quantify the CO_2 emissions and costs embodied in the electricity flows between the states in solution B (Figure S20) following the allocation method explained in Section 1.3 in Supplementary Information. Note that the amount of carbon (or costs) embodied in the flows is driven not only by the volume of the trade but also by the carbon intensity (or LCOE in the case of costs) of the electricity sources (Figures S21 and S22).

Allocation of emissions (Figure S20a) allows classifying states as net importers or net exporters of carbon emissions. The former release domestically less emissions than the amount emitted elsewhere in the U.S. to generate the electricity they consume. For the net exporters, this balance results in more emissions released locally than those associated with satisfying their own demand. Twenty nine states are net importers of emissions and 13 are net exporters, with four states not participating in electricity trade and one state importing only zero-carbon electricity from Canada. Within the first group, examples include Pennsylvania, Texas and New Jersey, while the exporters include Oklahoma, Florida, New York and Nevada. For most states that trade electricity, using the production and consumption perspectives results in a different level of emissions. In some cases, the mismatch between production and consumption emissions is marginal (Figure S20a and Figure S21a), as in Wyoming (0.4 more in the consumption-based approach). In others, it can be significantly higher, as in Pennsylvania (45.5 CO_2 Mt/yr more) and in Oklahoma (70.7 CO_2 Mt/yr less), evidencing that in some cases substantial emissions are traded between the states. Under the consumption-based approach, Oklahoma would be now released from any liability about the carbon embodied in its exports to the neighbouring states (i.e. final consumers), which would be held responsible for the emissions attributed to such trades. Therefore, the consumption-based perspective provides a different picture of the efforts made by each state. However, it still fails to capture the behaviour of the state as a producer, thereby neglecting the potential efforts undertaken to reduce its carbon intensity. For instance, Colorado would be attributed the responsibility for the emissions embodied in its imports from Oklahoma, but it would not be credited for switching to a lower carbon mix (from a coal-intensive mix to a mix based on geothermal and solar).

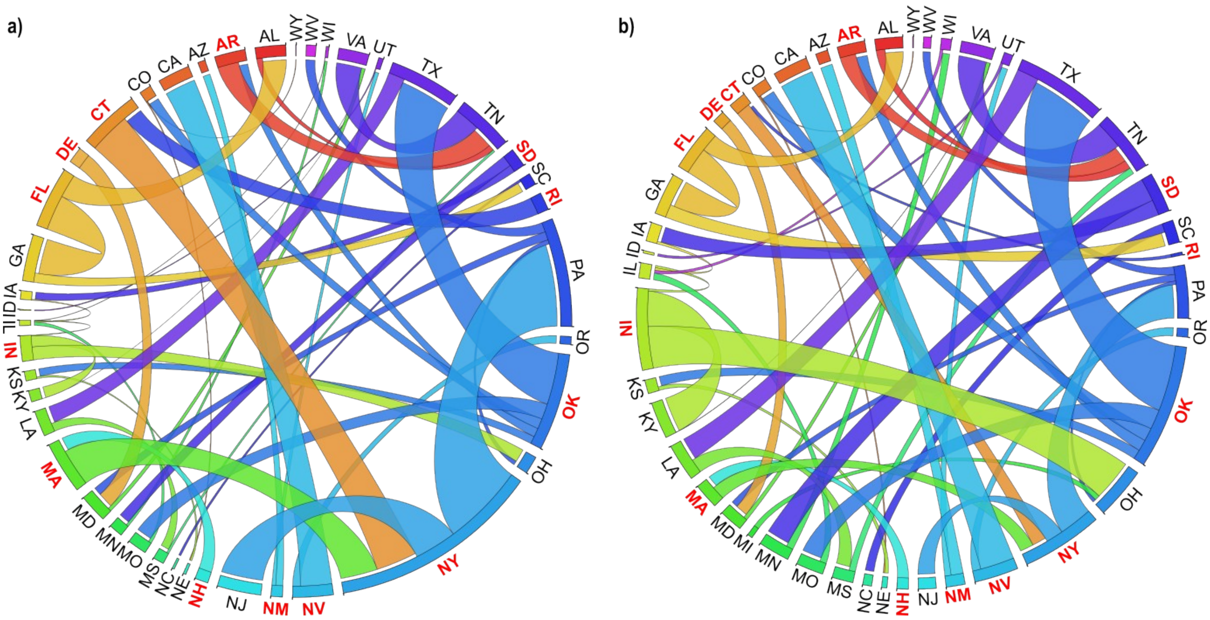


Figure S20. Emissions and costs embodied in the electricity trade under full cooperation (solution B in Figure 1). Subplot S20a illustrates CO_2 emissions and subplot S20b the costs embodied in trade. In the chord diagrams, the states are denoted by coloured circle arcs, where the arc length measures the total emissions (subplot S20a) and costs (subplot S20b) of imports and exports traded. Each trade is represented by a chord whose thickness is proportional to the magnitude of the trade (in CO2 Mt/yr in subplot S20a and in billion US$/yr in S20b). Chords are coloured according to the origin of the trade (i.e. according to exporter state). States whose aggregated export chords take up less than 50% of their arc length, are net importers of emissions (subplot S20a) or of costs (subplot S20b), whereas the opposite holds for net exporters (which are depicted with red labels).

Similar to the emissions, next we allocate the total cost of electricity among the U.S. states (Figure S20b) to find out if monetary flows could compensate for the efforts made when cooperating. This allocation is equivalent to assuming that the importer state purchases electricity at generation cost (i.e. LCOE) rather than at market price, which will arguably be higher. We use the LCOE because predicting future market electricity prices with accuracy is rather challenging due to their inherent volatility. This hampers the assessment of the future true economic contribution of each state in the cooperative solution.

The results show that in 32 states the cost of meeting their electricity demand is above the cost of their domestically generated electricity, while the opposite applies in 15 states. The mismatch in costs can be as low as in Wyoming (billion US$0.2/yr higher in the consumption perspective) or as high as in Ohio (billion US$10.5/yr more) and Oklahoma (billion US$25.1/yr less). Therefore, allocation of costs from a consumption-based perspective reveals a totally different situation from that shown in Figure 4. For instance, Oklahoma, previously a penalised state because its production-based electricity cost increased through cooperation, would now receive a revenue for its electricity exports (see Figure S20b) that would place the state slightly above the diagonal in Figure 4. Conversely, Ohio, which gained from the cooperation, would incur extra costs through electricity imported from Michigan, Indiana and Pennsylvania. The same rationale can explain the different compensatory movements arising in other states, yet under this accounting we are still disregarding the individual contribution that each state makes as a producer to reduce the overall U.S. cost of electricity.

As seen, the production and the consumption-based accountings are complementary[23–25] and provide different insights into the contributions made by different states, to the extent that a single state may either benefit or be penalised, depending on the approach followed. At the U.S. level, the total amount of emissions embodied in the electricity trade represents 78% of the total electricity emissions released in the U.S., while the costs embodied in such trade reach 53% of the total cost of electricity generation in the country. Such large volumes of electricity flows emerge as a natural consequence of cooperation as trade favours the states with the most cost-effective resources.

2.2.2 Production and consumption-based accountings: breakdown by state

Cooperation among all U.S. states allows achieving the most cost-effectiveness mitigation; however, it entails an uneven distribution of efforts (both in terms of contribution to curb emissions and to reduce costs) which cannot be simply neglected. The exploitation of regions (i.e. states) with better abatement costs leads to two groups of states playing different roles: states acting as suppliers of electricity and states acting as recipients of electricity. The former increase the electricity generation by means of their low-cost and/or low-emitting technologies therefore suffering more from local burdens (but at the same time benefitting from the increase in the number of jobs, the associated tax share and enhanced energy security). The opposite holds for the latter group, whose members displace facilities abroad thereby avoiding the responsibility attributed to their electricity demand generation.

Due to the asymmetric distribution of efforts, some states can be either harmed or benefitted when moving from an individualist strategy to the cooperative one, which compromises the engagement of all states into the cooperation. Therefore, quantifying the contribution each state makes for attaining mutual gains provides valuable insight on how to credit/penalise them. However, each individual contribution changes greatly depending on whether the responsibilities are allocated to producers or to consumers which makes it necessary to assess the efforts considering both perspectives.

Thus, we quantify both production and consumption-based emissions and costs following the allocation method explained in Section 1.3 in the Supplementary Information. The comparison between the traditional production-based approach and the consumption-based one provides further insight and better understanding on how responsibilities should be allocated among the parties involved. To shed further transparency on this issue, Figure S21 displays the breakdown by state of total emissions and carbon intensities according to the production and consumption-based accountings, while Figure S22 shows the same comparison for the total and specific costs.

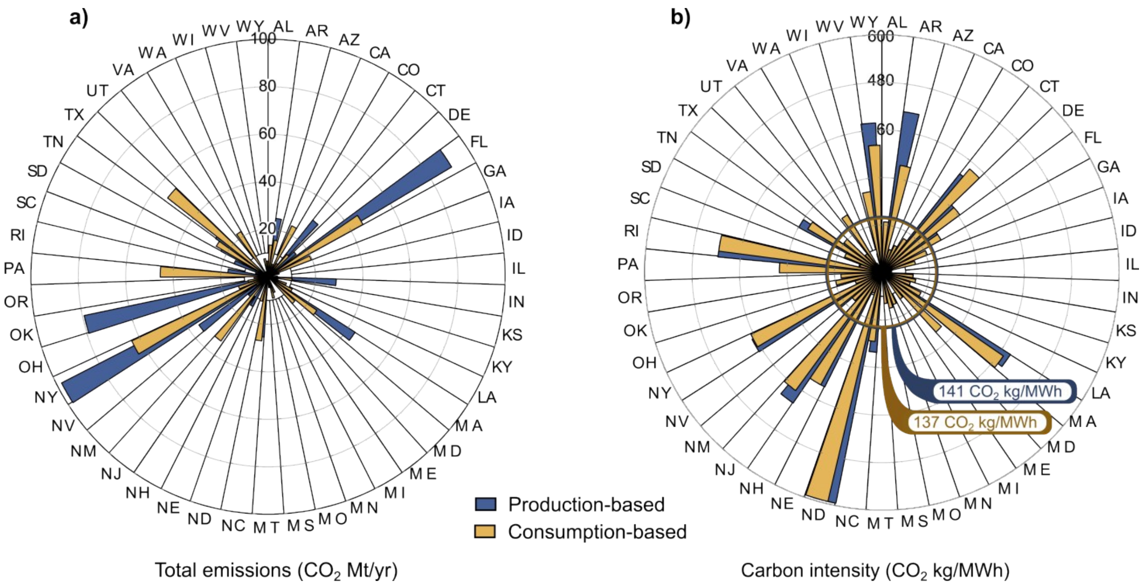


Figure S21. Comparison between production and consumption-based emissions in solution B by state. Subplot S21a displays the total emissions by state (in Mt CO_2) while subplot S21b displays the carbon intensity by state (expressed in CO_2 kg/MWh). Blue bars correspond to the production-based accounting while yellow bars correspond to the consumption-based one. Circumferences in subplot B depict average U.S. specific emissions following the same colour pattern as bars.

Total emissions (expressed in Mt CO_2) from the electricity generation vary greatly among U.S. states, regardless of the accounting system. This significant spatial heterogeneity is not only observed in the electricity generation (i.e. suppliers and recipient states) but also in the composition of the electricity mixes (i.e. lower and higher carbon intensities). As seen, there is a clear mismatch between the traditional production-based accounting and the consumption-based one at the state level, which evidences that substantial emissions are embodied in the electricity trades. The existence of this large discrepancy justifies the need of considering both perspectives in order to provide a more transparent picture of the “true” contributions made. Our results show that there are more states which are net importers of emissions (29) than net exporters of emissions (13). On a production basis, most of the U.S. emissions in solution B correspond to a few states, with only eight states (i.e. New York, Florida, Oklahoma, Massachusetts, Nevada, Connecticut, Indiana and Arkansas) accounting for more than 70% of the total U.S. emissions. However, under the consumption-based perspective, those states are held responsible for only 30% of the total U.S. emissions evidencing the need to analyse the results following both accounting systems. For instance, Oklahoma acts as a supplier state in the partnership due to its lower abatement cost, producing 79.2 Mt CO_2 (third larger emitter in the U.S. partnership), while only 8.5 Mt CO_2 corresponds to its consumption (ranked as 21st larger emitter). Conversely, Texas, which does not appear as a top emitter in the production-based accounting, almost doubles its emissions from a consumption-based perspective (i.e. 27.4 Mt CO_2 according to the production-based and up to 53.8 Mt CO_2 in the consumption-based), thus becoming the second largest emitter (according to the consumption-based accounting). Even in the case of New York, which is by far the larger emitter from both perspectives, production and consumption-based emissions differ significantly, evidencing that both approaches complement each other and together provide a deeper understanding of the real contribution made by states towards curbing CO_2 emissions.

In subplot B we can see that carbon intensities (i.e. CO_2 kg/MWh) also show great variations among states (regardless of the accounting system). These are due to the differences in carbon intensities among the states' optimal electricity mixes. On a production basis, the largest carbon intensity corresponds to North Dakota, with a 55% coal-based electricity mix, followed by states deploying either coal-rich (e.g. Arkansas) or natural gas-rich (e.g. New Jersey, New York, Rhode Island or Massachusetts) portfolios. While most of these states are also among the top emitters on a consumption basis, some of them present significant differences between both accountings due to the emissions embodied in electricity trades. Production-based carbon intensities are above consumption-based ones in eight states, while 26 states show higher carbon intensities in the consumption-based accounting and 13 states show the same carbon intensities in both accountings. Within the first group, we find states such as Arkansas, where the higher production-based emissions result from the combination of being a net exporter of electricity and deploying a high emitting electricity mix. Some other states within this group, like Wyoming, show lower carbon intensities as consumers because they import cleaner electricity with low embodied emissions. Within the second group (higher consumption-based carbon intensities), we find states such as Pennsylvania, which increase its consumption-based carbon intensity by importing electricity with high embodied emissions (e.g. importing large amount of electricity from the natural gas rich portfolio of New York). Finally in the last group (i.e. showing the same carbon intensities in both accountings), we find states which do not trade electricity at all (i.e. Maine, Montana and North Dakota); states which only export electricity (e.g. Florida, Indiana or Oklahoma); and states that import electricity with the same carbon intensity that the electricity they produce (e.g. Michigan only imports zero-emitting electricity from Canada and its mix is based on zero-emitting nuclear and hydropower).

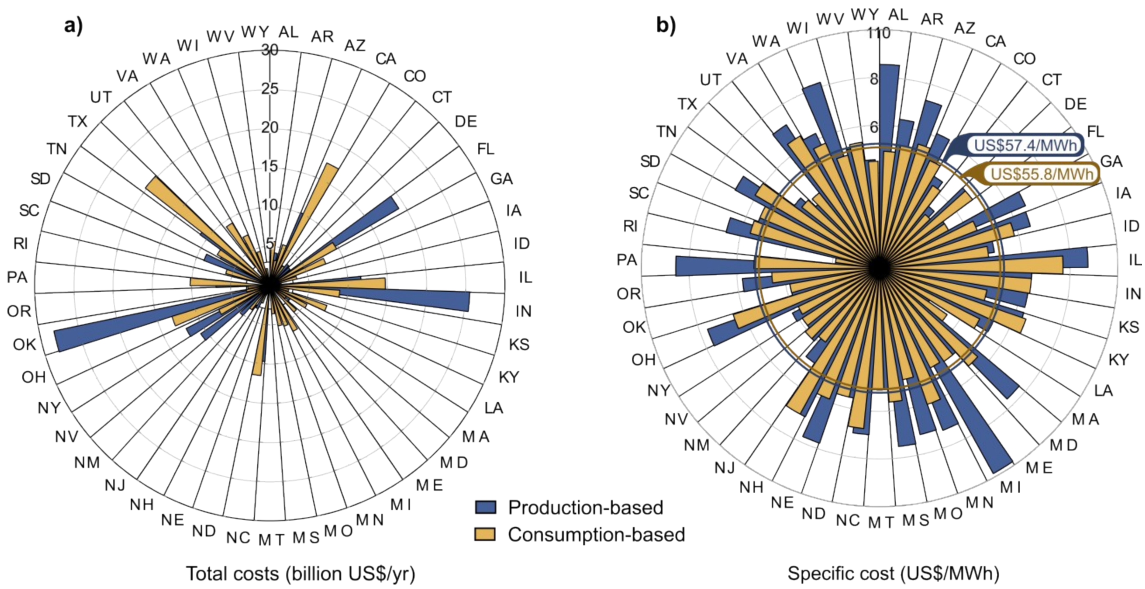


Figure S22. Comparison between production and consumption-based costs in solution B by state. Subplot S22a displays the total cost by state (in billion US$) while subplot S22b displays the specific cost by state (expressed in US$/MWh). Blue bars correspond to the production-based accountings while yellow bars correspond to the consumption-based accounting. Circumferences in subplot B depict average U.S. specific costs following the same colour pattern as bars.

Allocation of costs by state (Figure S22a) shows that, regardless of whether a production or consumption-based accounting system is considered, there is a significant variability among states. This is due to the different volumes of net generation among states and also to the spatial heterogeneity of the electricity cost. Production-based and consumption-based total costs differ greatly due to the large volume of electricity traded which in turn is translated in large monetary flows between suppliers and consumers of electricity (note that we allocate the cost of producing the electricity, which will presumably be lower than the market price of the electricity transferred). Results in subplot S22a show that in 13 states, the cost of electricity generation is above the cost of covering their electricity demand, while in 31 states the opposite situation occurs. On a production basis, more than 53% of the total U.S. generation cost in solution B is assumed by only 8 states (i.e. Florida, Indiana, Illinois, Oklahoma, California, Nevada, New York and Texas). However, under a consumption-based perspective, this figure is reduced down to 33% which again evidences the need of considering both perspectives. Furthermore, for a single state, the mismatch between the total costs as a producer and as a consumer can be large, as for example in Oklahoma which presents production costs of US$28.2 billion while its consumption costs are US$3.0 billion (89.4% lower).

The specific costs (i.e. US$/MWh) are more equally distributed than carbon intensities (Figure S21b). Carbon intensities vary greatly among states since emissions are far below the target and therefore they play no significant role in shaping the optimal solution. In contrast, specific costs are more similar across de U.S. territory. This happens because technologies are selected mainly according to their economic competiveness. Hence, the worst technologies (cost wise) are ruled out, with the ones being installed displaying similar average costs.

Results in subplot S22b show that the production-based specific costs lie above the consumption-based ones in 31 states (e.g. Michigan, Pennsylvania, Wisconsin, Alabama and Maryland), whereas the opposite holds in only four (e.g. specially Massachusetts and Rhode Island). Notably, most U.S. states reduce their specific costs in the consumption-based accounting, since the electricity they import is mainly produced in a few states with much lower specific costs. On the other hand, states where production-based unitary costs exceed consumption-based ones are not necessarily net exporters of electricity, because the monetary flows embodied in the electricity traded depend on both, the unitary costs and the volume of electricity exchanged (and the same applies to the net importers of electricity). For instance, Alabama is net importer of electricity (purchasing more electricity from the cost-effective portfolio of Florida than it sells to Tennessee). Besides, its production-based costs exceed the consumption-based ones, a mismatch that stems from the large difference in specific generation costs between Alabama and Florida (i.e. US$94.0/MWh compared to US$36.3/MWh, respectively; a 61.2% lower in Florida). Furthermore, we can identify 12 states in which the production and the consumption-based specific costs are the same. These are states which either trade no electricity at all or only export it. Note that, unlike what happened with the emissions, here Michigan presents lower costs from a consumption-based accounting than from a production-based one, because its imports from Canada are cheaper than its domestic generation.

3 Sensitivity analysis

In this section we present the results of the sensitivity analysis providing confidence intervals for the benefits from cooperation and analysing the behaviour of the optimal cooperative solution B when uncertainties are considered into the ERCOM.

3.1 Sensitivity of the benefits from cooperation

In the main manuscript, we showed that the total U.S. cost of electricity generation can be reduced by 12% when all the states cooperate to curb CO_2 emissions. In order to provide confidence intervals for such benefits, we next explore how this figure varies when considering uncertainties. To this end, we recalculate solutions A and B following the procedure described in section 1.4. For each of the uncertain parameters, we provide the probability distribution of the model results (Figure S23) and identify the worst and best case scenarios (i.e. minimum and maximum benefits, respectively), which define the interval where the real benefits should fall.

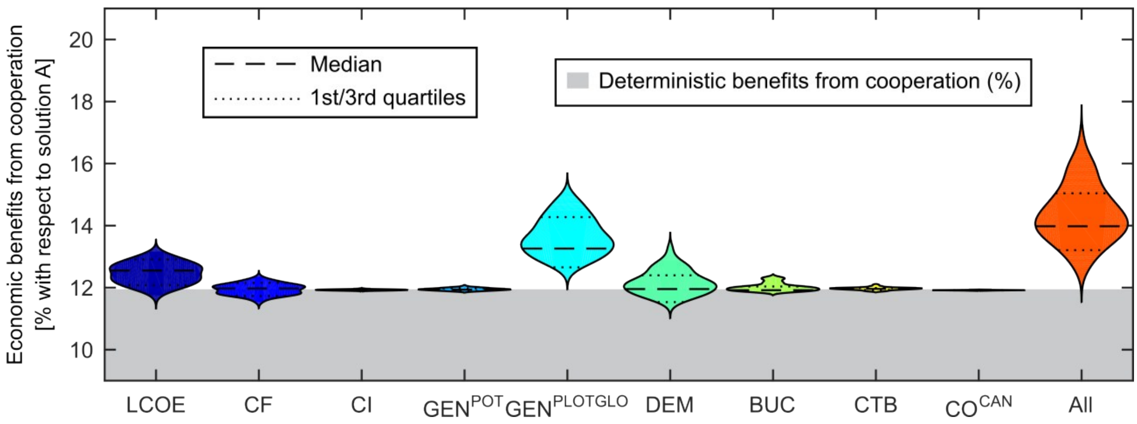


Figure S23. Sensitivity of the benefits derived from cooperation to the uncertain parameters. Each violin depicts the probability distribution of the difference between the U.S. cost in solutions B and A (expressed as a percentage) when uncertainty is considered in a given parameter(s) (indicated in the x axis). The width of the violin reflects the frequency (i.e. number of scenarios) of the solutions. Additionally, the benefit derived from cooperation in the deterministic case is also depicted for the sake of comparison.

We start by analysing the effects of single uncertainties (first nine violins in Figure S23), finding that there are four parameters whose uncertainty has little effect on the benefits of cooperation (i.e. similar savings as in the deterministic case are obtained regardless of the realisation of uncertainties). These are: (i) the carbon intensities (CI); (ii) the regional potential for electricity generation with each technology (GEN^{POT}); (iii) the amount of electricity traded with Canada (CTB); and (iv) the unitary cost of this electricity (CO^{CAN}). These results can be explained as follows. Carbon intensities show little influence on savings because emissions fall below the CPP targets in the optimal solution. Hence, technologies are mostly implemented according to their relative economic competitiveness. On the other hand, changes in the state bounds on electricity generation impact very little on the results because these are in general high enough to not limit the installation of economically appealing technologies. Finally, parameters related to Canadian imports (i.e. bound on electricity imports and their unitary price) affect both solutions A and B in a similar manner, so the difference between both is always low. This is not surprising given that, firstly, deterministic solutions A and B already showed very similar Canadian imports (i.e. 197 vs 201 MWh) and, secondly, because Canadian imports represent a little share of the total U.S. cost (around 3% in both cases).

There are two parameters, namely the capacity factor (CF) and the coefficient for back up generation requirements (BUC), which show slightly higher influence on the benefits derived from cooperation, yet these are still small (i.e. between 11.3% and 12.6%, for the changes in the CF, and between 11.7% and 12.5% for variations in the BUC). Therefore, while they affect more the individual solutions A and B, the difference between both solutions remains very much alike since they are changed in similar proportions.

Conversely, the following parameters have stronger impact on the benefits that can be achieved when cooperating: (i) the LCOE of each technology; (ii) the electricity demand; and (iii) the global potential generation bound. For instance, when uncertainties are realised on the LCOE, savings can vary from as little as 11.3% to as much as 13.6%. Although these numbers are close to the deterministic 12%, they entail significant variations in benefits: from US$1.8 billion less savings to US$4.6 billion more. Note that scenarios for LCOE are not correlated, which means that costs for one technology can increase in one state but decrease in others. This penalises solution A more severely than B, since the latter can still resort to the most cost-effective technologies/states and use trade to supply electricity to less favourable regions.

Moreover, the DEM also shows a high influence on the savings that can be achieved, which range from 11.0% to 13.8% (i.e. from US$2.6 less to US$5.3 billion more than in the deterministic case). This is because the individualist strategy of solution A forces states with poor abatement costs to increase their generation to respond to a higher demand, thus severely worsening the U.S. costs. Conversely, in the cooperative solution B, regional advantages can still be exploited to supply economically appealing electricity thus cushioning the increase in the costs. Finally, the GEN^{POTGLO} parameter shows the biggest influence among individual uncertainties, leading to benefits from cooperation lying always above those in the deterministic case (i.e. from 12% to a maximum value of 15.7%). This happens because in all the scenarios the global bound imposed on natural gas resources is relaxed (see section 1.4.2.9). This allows supplying the resource even to states where it is scarcer, thus increasing the share of the low-cost gas technology throughout the U.S. territory.

Finally, we analyse the effect of all the uncertainties simultaneously (case All in Figure S23). We find that benefits from cooperation can range from as little as 11.5% to as much as 17.9%, that is, from US$1.2 billion less to US$16.8 billion more than in the deterministic case. The sensitivity analysis therefore shows that cooperation can bring significant benefits even when uncertainties are considered, that is, uncertainties do not change the main insight obtained from the analysis. The median of the results is significantly shifted (i.e. from 12% in the deterministic case to 14% when uncertainties are considered). This mismatch might be caused by the uncertainty level of the global bound on natural gas, for which a more conservative value was established in the deterministic case.

3.2 Sensitivity of the full cooperative solution (Solution B)

Cooperation (i.e. solution B) allows bringing the U.S. electricity cost down to US$248 billion and CO_2 emissions down to 607 Mt CO_2 when considering nominal parameters. In order to explore how these figures change in light of uncertainties, we next solve model B for the different scenarios and depict the resulting distributions of costs (subplot S24a) and emissions (subplot S24b) in Figure S24.

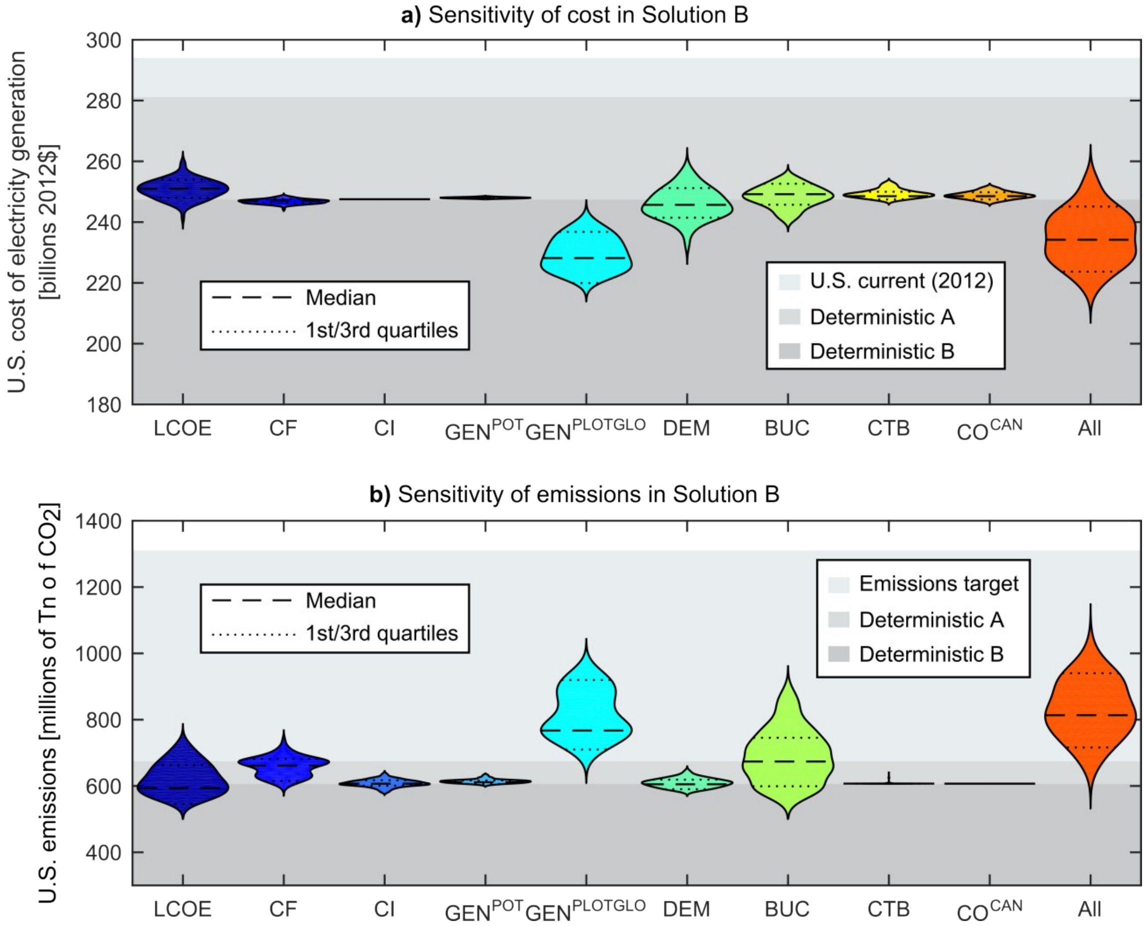


Figure S24. Results from the sensitivity analysis of solution B. Violin plots depict the distribution of the U.S. cost (subplot S24a) and emissions (subplot S24b) obtained when uncertainty is considered in the parameter indicated in the x axis (recall that only the cost is optimised). The width of the violin reflects the frequency (i.e. number of scenarios) of the solutions. The figure shows also the cost and emissions obtained for the deterministic parameters in solutions A and B, along with the U.S. cost in the baseline year (2012) and the CPP emissions target.

We first analyse how individual uncertainties affect the cost and emissions under full cooperation (i.e. solution B). As can be observed in Figure S24, the parameters with the strongest impact on the model outcome (both in cost and emissions) are LCOE, GEN^{POTGLO}, DEM and BUC. Particularly, GEN^{POTGLO} shows the biggest influence among the individual uncertainties, revealing that the total U.S. cost could be reduced by 13.7% comparing to the determinist case (i.e. US$33.7 billion less). Furthermore, global emissions could increase by 72.4%, as a result of enlarging the share of natural gas in the overall electricity mix (recall that scenarios on GEN^{POTGLO} relax the global bound on natural gas-based resources). The total U.S. cost varies similarly when uncertainties in LCOE or DEM are considered (between -4.0% and +6.4%, and between -8.7% and +6.84%, respectively), yet the total emissions reflect a higher variation for the former (i.e. between -17.7% and +30.5%, compared to -6.5% and +9.1%). This can be explained as follows. In the deterministic solution B, emissions fall well below the CPP target (i.e. 70% reduction vs the 35% required). This occurs because the model decides to install technologies based only on their economic competitiveness, and some of the most competitive ones happen to show in turn lower carbon intensities. In such context, the order of the economic competitiveness of two technologies showing similar costs but very different CO_2 emissions can be switched when uncertainties are considered in the LCOE, thus significantly affecting the overall figure regarding the emissions. This does not happen when the uncertain parameter is the demand, since the economic competitiveness of the technologies remains the same. Finally, the uncertainty on the BUC affects more the emissions than the costs. Hence, the cost in solution B can vary ±4.5%, while the emissions can either be reduced or increased significantly (i.e. from almost 17.7% reduction to a 58.8% increase). Recall that this parameter provides the amount of firm technologies required as back up for each MWh of intermittent renewables installed. Taking into account that the carbon intensity of firm technologies is in average higher than that of intermittent resources (which are all zero-emitting), it is not surprising that different values of BUC have a strong impact on the overall cleanness of the U.S. portfolio.

We then analyse all the uncertainties simultaneously (case All in Figure S24), noting that both costs and emissions show the most significant sensitivity among all the cases. As can be observed, the cost is lower than in the deterministic case in most scenarios (between -16.5% and +7.3%) while the opposite holds for the emissions (-12.6% and +89.6%), evidencing the high influence of GEN^{POTGLO} in these results. Besides, in this case, as well as in general terms, the uncertainties affect more the distribution of emissions than that of the cost. This is due to the margin existing between emissions in the deterministic solution B and the target imposed by the CPP.

4 Nomenclature

4.1.1 Indexes

i	Technologies.
j	U.S. states.
k	Canadian regions.

4.1.2 Sets

CT	Set of coal-based technologies *i*.
IR	Set of intermittent (i.e. non-dispatchable) technologies *i*.
NGT	Set of natural gas-based technologies *i*.
NC_j	Set of Canadian regions *k* which are neighbours of state *j*.
NU_j	Set of states *j'* which are neighbours of state *j*.

4.1.3 Parameters

BUC	Backup capacity of dispatchable technologies required for every MW of non-dispatchable intermittent technologies.
$CAP_{i,j}^{CUR}$	Capacity installed with technology *i* in state *j* in the baseline year (i.e. 2012).
$CF_{i,j}$	Capacity factor of technology *i* in state *j*.
$CI_{i,j}$	Carbon intensity of technology *i* in state *j*.
CO^{CAN}	Unitary annual cost of electricity imports from Canada.
$CO_{i,j}^{CAP}$	Unitary annualised capital cost of technology *i* in state *j*.
CO_i^{CAPAVE}	U.S. average unitary annualised capital cost of technology *i*.

$CO_{i,j}^{FIX}$	Unitary annual fixed operating costs of technology *i* in state *j*.
CO_{i}^{FIXAVE}	U.S. average annual fixed operating costs of technology *i* in state *j*.
$CO_{i,j}^{VAR}$	Unitary annual variable operating costs of technology *i* in state *j*.
CO_{i}^{VARAVE}	U.S. average annual variable operating costs of technology *i* in state *j*.
$\bar{COST}_j$	Annualised cost of electricity generation in state *j* in the optimal solution.
CS	Number of states belonging to the partnership.
CTB	Upper bound on total electricity imports from Canada.
DEM_j	Electricity demand of state *j*.
$DIST_{j,j'}$	Distance between states *j* and *j'*.
$DISTCAN_{j,k}$	Distance between state *j* and Canadian region *k*.
DSF	Demand satisfaction factor.
$\bar{EM}_j$	Optimal production-based emissions of state *j*.
$GEN_{i,j}^{CUR}$	Electricity generation with technology *i* in state *j* in the baseline year (i.e. 2012).
$GEN_{i,j}^{POT}$	Potential generation with technology *i* in state *j*.
GEN_{i}^{POTGLO}	Potential generation with technology *i* in U.S.
H	Annual hours (i.e. 8760).
M1	Sufficiently large positive parameter.
M2	Sufficiently large positive parameter.
$TARG_j$	Target imposed by the CPP on the CO_2 emissions of state *j*.
$TARG_j^{CI}$	Target imposed by the CPP on the carbon intensity of state *j*.
TLF	Trade losses factor (equivalent to 0.62% per 100 km).
$\bar{TRD}_{j,j'}^{ORIG}$	Electricity exported from state *j'* to state *j* in the optimal solution.
ω_j	Cost adjustment factor for state *j*.

4.1.4 Continuous variables

$CAP_{i,j}^{BU}$	Standard capacity installed of technology *i* in state *j*.
$CAP_{i,j}^{ST}$	Backup capacity installed of technology *i* in state *j*.
$CBCOST_j$	Consumption-based annualised cost of electricity consumed in state *j*.
$CBEM_j$	Consumption-based CO_2 emissions of state *j*.
$COST_j$	Production-based annualised cost of electricity generation in state *j*.
$COST_j^{CAN}$	Annual cost of electricity imports from Canada.
$COST_j^{CAP}$	Annualised capital costs of electricity generation in state *j*.
$COST_j^{FIX}$	Annual fixed operating costs of electricity generation in state *j*.
$COST^{TOT}$	Total annualised cost of electricity generation in U.S.
$COST_j^{VAR}$	Annual variable operating costs of electricity generation in state *j*.
EM_j	Production-based CO_2 emissions of state *j*.
$GEN_{i,j}^{BU}$	Backup electricity generation with technology *i* in state *j*.
$GEN_{i,j}^{ST}$	Standard electricity generation with technology *i* in state *j*.
$TRD_{j,j'}^{DEST}$	Electricity that state *j* imports from state *j'* (after losses).
$TRD_{j,j'}^{LOSS}$	Electricity losses in electricity trade between states *j* and *j'*.
$TRD_{j,j'}^{ORIG}$	Electricity exported from state *j'* to state *j*.
$TRDCAN_{j,k}^{DEST}$	Electricity that state *j* imports from Canadian region *k* (after losses).
$TRDCAN_{j,k}^{LOSS}$	Electricity losses in electricity trade between Canadian region *k* and state *j*.
$TRDCAN_{j,k}^{ORIG}$	Electricity exported from Canadian region *k* to states *j*.
YEM_j	Continuous variable that replaces the nonlinear product of the binary Y_j by the emissions level EM_j.

4.1.5 Binary variables

Y_j	Binary variable denoting whether state *j* belongs to a partnership (i.e. value equal to 1) or not (i.e. value equal to 0).

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