Paying for Drawdown: the Value of Commitment on the Cost of Ending Global Warming

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Abstract

This paper develops a mechanism to pay for drawing down excess atmospheric carbon dioxide while avoiding third party payments. Assuming this mechanism, the paper investigates the costs of reversing global warming under different levels of commitment. The costs are based on simulated auctions for emissions and carbon removal to reach a climate goal by a particular date. The paper describes a method to model and price carbon removal contracts, and estimates the value of commitment to strong versus weak contracts. The least cost trajectory requires long commitments to emissions reductions and carbon removal. The paper estimates the value of long-run versus short-run commitments and the value of the ability to manage revenue across decades. The models constrain warming robustly under different discount rates. Hotelling's rule does not apply because carbon removal makes the atmosphere a renewable resource. For reducing temperature 1.4°C by 2125, estimates range from $20.4 trillion down to $10.84 trillion (present value over 100 years at 3%) depending on commitment. These estimates for reversing global warming are far lower than other researchers' estimates simply for keeping temperature to 1.5°C. The models could be used in trading. The paper shows that drawdown costs less when emitters pay for it than when a third party pays for it.

1. Introduction: the commitments required to end global warming

1.1. The Problem

Stopping global warming requires carbon neutrality. Toward that end, the Paris Agreement[1] specifies a mechanism "to contribute to the mitigation of greenhouse gas emissions…" The voluntary mechanism aims to give guidelines for verifying carbon credits and to encourage companies to buy carbon offsets with the aspiration of global carbon neutrality. The need to raise aspirations is essential.[2] Unfortunately, natural carbon removal markets suffer moral hazards, difficulties in pricing, and large transaction costs. These problems are strong enough that the EU carbon market prohibits trade of carbon removal.[3]

The still higher aspiration of reversing global warming requires drawing down excess atmospheric carbon.[4] Drawdown requires money to remove the excess carbon in the air beyond removal for carbon neutrality. If we could solve the moral hazard of the carbon removal market, no one has proposed a payment mechanism for it.

Perhaps due to the widespread skepticism about natural carbon removal, while researchers have been studying the vast costs and alleged benefits of global warming for many years, they have paid little attention to drawdown. Almost all the research is about stabilizing to a maximum temperature, an atmospheric CO2 concentration, or a carbon "budget." Nordhaus[5,6] developed his DICE model of energy, emissions, and the main ecological components (land, layers of atmosphere, and layers of atmosphere ocean), constraining atmospheric CO2 concentration. That work did not consider the possibility of reversing global temperatures. Since then, researchers have developed many similar models, known as computable general equilibrium (CGE) models, e.g., GCAM.[7] Some researchers have merged the CGEs with agent-based simulations.[8,9] See Wei 2023 and Wang 2023 for reviews of hundreds of these models. In attempting to calculate economic benefits and costs, these macroeconomic models try to maximize "welfare" while accounting for the effects of warming on agriculture, capital, consumption, discount rates, equity, inequality[12,13], health, labor, savings, sea levels, supply chains, tax rates, by country, by city[14], by region, by sector, etc.

By 2014, the IPCC concluded "Only a limited number of studies have explored scenarios that are more likely than not to bring temperature change back to below 1.5°C by 2100 relative to pre-industrial levels…"[15] Lemoine and Rudik[16] developed an economic model with simplified climate equations and a temperature constraint. Terhaar et al[17] developed an adaptive strategy for meeting a temperature target but they ignore costs altogether. By 2023, the IPCC[18] was studying pathways with ambition only to limit warming to 1.5°C. The IPCC reports do not mention drawdown. But if the cost of drawdown were much less than people thought, perhaps the estimates would have policy implications.

Golmohammadi, Kraft and Monemina[30] studied setting of deadlines with environmental standards. Their deadline is a date by which a firm must comply, while the deadline here is a date by which the excess externality would be removed. Still, this work overlaps with literature on regulatory timing. In general, carbon pricing is effective.[31,32]

I previously[19,20] gave a model which examines the possibility of drawdown by a deadline. That model implies the need for commitments for a hundred years of future carbon removals to be paid by a third party and that model was not well calibrated to a climate model. This paper resolves the problems with that paper and goes further.

In my view, the greatest uncertainty in ending global warming is the management uncertainty, i.e., what we will do about it. Eliminating this management uncertainty means making commitments. The commitments have multiple dimensions.

- Commitment to ending global warming by a deadline.
- Commitment to an institution with the responsibility to enforce emissions rules.
- Commitment of a third party (most likely governments) to paying for drawdown or an agreement for current emitters to pay for the drawdown with a surcharge of some type.
- Commitment of buyers of carbon removal to enforce strong contracts for carbon removal.
- Commitment to long-term financial planning, enabling flexibility to transfer funds across decades.

1.2. Contributions

I will use the term “base zero” to mean a global average temperature equal to the average from 1850 to 1900, i.e., about 1.4°C lower than it is now.[21] In this paper, I examine the cost of drawing down to base zero. Rather than a carbon tax, which would not buy carbon removal,[22] or a cap-and-trade like existing ones which exclude carbon removal, I study pure cap-and-trade between emitters of greenhouse gases and carbon removers. The models impose the cap on global temperature by date rather than emissions, eliminating measure uncertainty of a surrogate metric and, more importantly, the timing uncertainty for ending global warming. In a market cleared with these models, no one would receive free allowances and no one would get paid to reduce emissions, thus reducing problems of additionality, moral hazard, and enforcement. All revenue from selling emissions permits would go toward buying carbon removal.

This work draws on economics, market design, operations research, and atmospheric science. In particular, the methods here draw on a different literature than the climate research with CGE models. The methods proposed here are types of "smart markets"[23,24] now used to clear wholesale electricity markets,[25] radio spectrum auctions,[26] industrial procurement,[27] transportation services,[28] and a wide range of other market types heavily covered by operations researchers. Combinatorial auctions fall in this literature as well.[29] The models do not maximize macroeconomic welfare as do the CGE models. Rather, a smart market model clears an auction between buyers and sellers, typically maximizing revenue or the sum of buyer and seller surplus while accounting for complex constraints that would otherwise raise transaction costs. The coefficients in the models here come directly from a climate simulator rather than the approximate modeling in the CGEs, so results are likely more certain.

The models here are ordinary linear programs, easily solvable and extendable with open source software. The models here can account explicitly for all greenhouse gases and land use change unlike the CGE models. They can be calibrated easily and accurately to any stand-alone climate simulator as I will show. DICE, by contrast, is notoriously difficult to calibrate.[33,34] The models here can account for temporary and uncertain carbon removal in contracts, which has not been done before. The models could be used in actual carbon trading.

The key metric here is the cost of ending global warming. Compared to CGEs, the models here have an important disadvantage: they do not track standard macroeconomic variables such as damage, welfare, capital, or consumption. Those dependencies can raise the uncertainty of a model's outcome.[35,36] Using trading revenue for purposes other than carbon removal raises costs and lowers certainty. These choices of model and market design address in part the widespread frustration with existing carbon pricing[37] and reduce the management uncertainty of reaching the desired ecological outcome.

Like other analogous work, I assume substantial participation of emitters. Ending global warming requires global agreement which will require new strategies for incentives.[19,38,39] Mainly, I show how to use familiar operations research methods to examine the cost of ending global warming, assuming we committed to it. From these methods flow the contributions.

- General micro-economic models to estimate the costs of carbon removal to reach a climate goal, e.g., net zero or base zero, by a particular date. These models could be used for clearing emissions trading markets.
- A method to model and price different types of carbon removal contracts. A critical reason for lack of progress in global warming is the messy carbon removal market, partly due to the lack of a single purchasing institution, but also due to the difficulty of pricing carbon removal. The pricing method here is general and enables researchers to apply a raft of classical models to pricing carbon removal. I estimate the value of commitment to strong versus weak carbon removal contracts.
- A method to find emissions trajectories that are robust to discount rates. Hotelling's rule is appropriate for non-renewable resources, which makes sense only without carbon removal.
- A mechanism to pay for drawdown. To my knowledge, no one has proposed a mechanism for this and it could be viewed as the main contribution. The method may apply to some other types of smart markets. I show that the cost of drawdown is less when emitters pay for it than when a third party pays for it. This important conclusion should help settle the arguments about how to pay for drawdown.
- Recommendations for managing the costs of drawdown over time. The least cost trajectory requires long commitments to emissions reductions and carbon removal. I estimate the value of long-run versus short-run commitments and the value of the ability to manage revenue across decades.
- A method to calibrate the models to a climate simulator while accounting for all greenhouse gasses. This method of modeling avoids some of the modeling uncertainty in the CGE models.

- Optimism for ending global warming. I estimate costs for reversing and ending global warming by 2125 under different levels of commitment. The costs are much lower than other researchers' estimates simply for avoiding a temperature rise over 1.5°C.

The methods are designed for high certainty. The key state variable is temperature by date rather than surrogate measures such as emissions, global warming potential, or CO2 concentration. The models can account for every greenhouse gas, though I have omitted smaller ones here.

I will assume that supply and demand curves capture relevant direct costs to the global economy. Each greenhouse gas has its own curve of demand for emission (also known as marginal abatement cost curves). Each carbon removal option (agriculture, forestry, seaweed, etc.) has its own supply curve. Forestry contracts account for tree growth over contract terms of fixed lengths.

2. Development of the models

The modeling requires considerable data and a climate simulator, all of which are available for download with model software. This section presents simplified models for clarity.

The models here rely on a matrix W with elements $w_{p,t}$ as the marginal warming from a pulse emission of a greenhouse gas. This precision approach substitutes for the crude global warming potential metric (Terhaar et al. 2022; Jenkins 2018; Allen et al. 2018) used in existing emissions trading systems and the approximations of atmospheric physics used in the CGE models. One unit emission of pollutant p has warming of $w_{p,t}$ degrees Celsius at t periods after emission. For simplicity, assume matrix $-W$ is the marginal cooling effect of carbon removal. We can then write a linear optimization that tracks temperature consistently with a full climate simulator for the same schedule of emissions.

Let the parameter $b \geq 0$ represent the willingness to pay of emitters and let $-b$ represent the willingness to sell of carbon removers. With marginal cost pricing, the objective maximizes the sum of buyer and seller surplus.

The parameter $f < 0$ represents a required fall in temperature by a deadline, say −1.4°C by 2125.

2.1. Revenue negative formulation

Variable $0 \le q_{\mathrm{LT}} \le 1$ represents the polluting activity. The subscript on the variables indicates the long-term model *SMDAMAGE_LT*. Variable $0 \le r_{\mathrm{LT}} \le 1$ represents carbon removal activity. An upper bound of 1 on each variable indicates the maximum quantity that the bidder is willing to trade at the bid amount. An asterisk on the variable indicates an optimal value.

The simplified model of long-term commitment is as follows.

Long-term commitment *SMDAMAGE_LT*:

(1) $\max b(q_{\mathrm{LT}} - r_{\mathrm{LT}}),$

(2) $Wq_{\mathrm{LT}} - Wr_{\mathrm{LT}} \le f,$

(3) $0 \le q_{\mathrm{LT}} \le 1,\ \ 0 \le r_{\mathrm{LT}} \le 1.$

I will use dual variables π_{LT} for the constraints associated with matrix W. At the optimum, $\pi_{\mathrm{LT}}{}^{*}Wq_{\mathrm{LT}}{}^{*} - \pi_{\mathrm{LT}}{}^{*}Wr_{\mathrm{LT}}{}^{*} = \pi_{\mathrm{LT}}{}^{*}f$. Under marginal cost pricing, buyers and sellers face prices $\pi_{\mathrm{LT}}{}^{*}W$. Assume buyers and sellers have no initial rights. Assume the auction manager prohibits permit banking.[42] The auction manager receives revenue $\pi_{\mathrm{LT}}{}^{*}Wq_{\mathrm{LT}}{}^{*}$ from emitters. Emitters pay the auction manager to offset only the effects of their emissions, so they are net zero.

The auction manager pays $\pi_{\mathrm{LT}}{}^{*}Wr_{\mathrm{LT}}{}^{*}$ to carbon removers. Part of this payment to carbon removers, $\pi_{\mathrm{LT}}{}^{*}Wr_{\mathrm{LT}}{}^{*} - \pi_{\mathrm{LT}}{}^{*}f$, pays for emitters to be net zero. To draw down the excess carbon required to reach the target temperature, the auction manager must produce funds $\pi_{\mathrm{LT}}{}^{*}f$ above the revenue $\pi_{\mathrm{LT}}{}^{*}Wq_{\mathrm{LT}}{}^{*}$ collected from buyers. The value of $\pi_{\mathrm{LT}}{}^{*}f$ would be trillions of dollars over the next 100 years. The auction manager could take on such an expensive undertaking only with strong commitments from enduring institutions such as governments.[43] Model *SMDAMAGE_LT* does not decompose by time period, so the auction requires a feasible fully-committed schedule of emissions and removal over at least the next 100 years.

2.2. Revenue neutral decomposable formulation

To enable revenue neutral carbon removal and to avoid the need for long-term commitments, I next show how the auction manager could apply an implicit surcharge within the warming constraints.

Introduce a new parameter $\tau \geq 1$. Later, this parameter will differ by time period, but for now assume that τ is a scalar.

Short-term commitment *SMDAMAGE_ST*(τ):

$$\text{(4)} \qquad \max b(q_{\mathrm{ST}} - r_{\mathrm{ST}}),$$

$$\text{(5)} \qquad \tau W q_{\mathrm{ST}} - W r_{\mathrm{ST}} \leq 0,$$

$$\text{(6)} \qquad 0 \leq q_{\mathrm{ST}} \leq 1,\ 0 \leq r_{\mathrm{ST}} \leq 1.$$

Buyers face price $\tau\pi_{\mathrm{ST}}^{*}W$ and sellers face price $\pi_{\mathrm{ST}}^{*}W$. Since $\tau\pi_{\mathrm{ST}}^{*}Wq_{\mathrm{ST}}^{*} - \pi_{\mathrm{ST}}^{*}Wr_{\mathrm{ST}}^{*} = 0$, the auction manager is revenue neutral, receiving $\tau\pi_{\mathrm{ST}}^{*}Wq_{\mathrm{ST}}^{*}$ from emitters and paying $\pi_{\mathrm{ST}}^{*}Wr_{\mathrm{ST}}^{*}$ to removers.

For carefully selected τ, buyers likely face higher prices than with model SMDAMAGE_LT, so they will likely emit less, and it is likely that $q_{LT}^{*} > q_{ST}^{*}$. Further, since $\tau\pi_{ST}^{*}Wq_{ST}^{*} = \pi_{ST}^{*}Wr_{ST}^{*}$, it is likely that $Wq_{ST}^{*} < Wr_{ST}^{*}$. That is, sellers of carbon removal will remove the taxed warming effect beyond what buyers require for net zero, so buyers are net negative. The manager should apply τ to emissions in an early year to the extent of their warming effects on a later temperature-constrained year.

This procedure would not be appropriate for an auction in which rights are well defined or where constraints reflect physical limits, such as power line capacities in an hourly electricity auction. Its application for smart markets generally is probably limited. This surcharge procedure is plausible because the model does not require constraints for technological feasibility and initial rights are assumed zero.

To choose τ to fund drawdown, the auction manager can solve *SMDAMAGE_ST*(τ, ϕ) parametrically over τ with ϕ as a free variable, increasing τ until $\phi \approx f$.

SMDAMAGE_ST(τ, ϕ):

(7) $\max b(q_3 - r_3)$,

(8) $\tau W q_3 - W r_3 \leq 0$,

(9) $W q_3 - W r_3 - \phi \leq 0$,

(10) $0 \leq q_3 \leq 1, 0 \leq r_3 \leq 1$.

Model *SMDAMAGE_ST*(τ, ϕ) decomposes by time period. A global mechanism, such as the one contemplated by the United Nations,[1] could use *SMDAMAGE_ST* for annual auctions without the need for third-party funds nor long-term commitments of removals.

Current emitters will argue this surcharge is unfair for many reasons. A counterargument is that the surcharge omits the costs of damage and mitigation. This paper will argue further that the surcharge results in a cheaper solution. Other costs such as for environmental justice must still be negotiated as side payments. Because the market prices emissions and carbon removal over time, it can price temporary carbon storage.[44] In a regional mechanism such as the European Union, participants could be net negative, but asking one region's participants to pay for the full global drawdown would be unreasonable.

Besides potential use in an emissions trading system, we can use models *SMDAMAGE_LT*, *SMDAMAGE_ST*(τ), and *SMDAMAGE_ST*(τ, ϕ) to estimate the direct costs of ending global warming by the date of our choosing.

2.3. Modeling of carbon removal contracts

Carbon removal projects have proven notoriously weak.[45] Figure 1 is an influence diagram of the problems in carbon removal. As a result this weakness, policymakers have excluded removal from emissions trading systems. Indeed, some people think that cheap removal credits could undermine reductions and they may view offsets as legalizing pollution.[46] Many of these problems could be solved with the smart market approach. Centralizing contract writing would lower the cost of contracting, lower the cost of removal measurement, improve contractor truthfulness, and reduce incentives to cheat.

Figure 1. Influence diagram for weak carbon removal

We can bring classical operations research tools to bear on the contracting process by pricing contracts on their warming. This paper uses warming factors $w_{p,t}$ for emission of each greenhouse gas p. Here is how I extend these factors to contracts for carbon removal with forestry.

The associated variable $q_{p,t}$ has units of hectares of a given tree type planted under contract p in year t. Thus, the warming factors $w_{p,t}$ must have units in degrees Celsius per hectare. Define Y_p to be the contract length in years (e.g., 10, 50, 100) and define $C_{p,y}$ as the tons carbon removed per hectare[47] in tree growth year $y = 0, 1, 2, \ldots, Y_p$. To get the associated factors $w_{p,u}$ for warming u periods after planting a hectare of contract p, we convolve the warming of a ton of carbon $w_{\text{carbon},\, u}$ with carbon removed $C_{p,y}$ in each year y of tree growth:

(11) $w_{p,u} = -\sum_{y=0}^{\min(u,Y_p)} C_{p,y} w_{\text{carbon},\, u-y}$ for $u = 0, \ldots, 295$ years, i.e., the length of the model horizon.

In this paper, the factors $C_{p,y}$ are deterministic. A contracting manager could account for environmental conditions, fire, the fate of the carbon at the end of the contract, etc., based on the type of tree and location, likely with a Markov model.[48,49] The manager could choose confidence levels for $C_{p,y}$, recognizing carbon removal only if sufficiently confident of it. The manager can then maintain a library of relevant simulations for contract types, applying the relevant one for each new contract. This ability to model carbon removal in detail shows the value of a centralized removal market.

2.4. Calibration and validation

We want the optimization to find an emissions and removal schedule (q^*, r^*) starting in 2025 at 1.4°C above base zero and ending at the deadline (e.g., 2125) at base zero. To validate this schedule (q^*, r^*)

from *SMDAMAGE_LT* or *SMDAMAGE_ST*, we put (q^*, r^*) into a climate simulator. The optimization is calibrated if the climate simulator with the same emissions and removal schedule reaches base zero at the 2125 deadline. With a calibrated optimization, the schedule is more likely to satisfy the temperature target without the environmental mistake of ending too warm or the economic mistake of ending too cold.

This calibration requires consistency between the warming factors W in the optimization and the climate simulation. To develop and calibrate W, I used the climate simulator Hector,[50] but any climate simulator would do. The Hector package includes historical emissions and standard scenarios, such as the IPCC representative concentration pathway (RCP) 2.6.[51] As far as I know, this calibration method is new.

Omitted gasses. The standard Hector implementation includes many factors omitted in the optimization model: black carbon, C6F14, CCl4, CFC11, CFC113, CFC114, CFC115, CFC12, CH3Br, CH3CCl3, CH3Cl, CO, HALON1202, halon1211, halon1301, halon2402, HCF141b, HCF142b, HCF22, HFC227ea, HFC23, HFC245fa, HFC32, HFC4310,N2O, NH3, NMVOC, NOX, OC, SO2, and SOx. These activities were omitted because emissions demand data were hard to find. These factors together have less than 0.1°C effect on the deadline of 2125. The omission affects only the cost totals, not the temperature target. When Hector simulates the temperature trajectory of the optimization output, Hector uses all these factors, so the calibrated temperature should be correct. The simulations assume those gases follow the RCP 2.6 pathway, implicitly getting these pathways at zero cost. As explained a bit later, land use change bears a special role in this paper; the optimization treats land use change differently depending on the desired analysis.

Timelines. The optimization has various endpoints: the temperature deadline (e.g., 2125), the last period of bidding (e.g., 2274), the last period of constrained temperature (e.g., 2274). Hector runs to 2300, so the input repeats the 2274 optimization values to 2300. I developed the initial uncalibrated marginal warming parameters by modeling a pulse for each gas in 2005, resulting in $w_{p,t}$ running from $t = 0, \ldots, 295$ years (steps 1 – 3 below).

Omitted history. In place of historical emissions, the uncalibrated optimization substitutes an initial temperature burden of 1.4°C. The calibration may prescribe a different initial temperature burden. The uncalibrated optimization produced schedules more aggressive than needed, so the calibrated initial temperature was typically less than 1.4°C. When put into the climate simulator, the calibrated schedules meet the temperature target (Figure 2).

Warming factors W. Hector can supply an initial matrix of marginal warming factors W. To obtain and improve W, we can follow these steps.

1. Run Hector with RCP2.6. Obtain temperatures $temp_t$(RCP2.6) for years $t = 1765$ through 2300.

2. Run Hector with a modified RCP2.6(p) for each gas p. For the year 2005, for one gas p at a time, we change $q_{p,2005}$ to $q'_{p,2005} = 0$. Obtain $temp_t$(RCP2.6(p)) by year for years $t = 1765$ through 2300.

3. Models RCP2.6 and RCP2.6(p) differ only in the emission reduction for gas p in year 2005, so temperatures differ only for years 2005,…, 2300. For each gas p and year $t = 2005$ to 2300, build matrix W as $w_{p,t} = (temp_t(\text{RCP2.6}) - temp_t(\text{RCP2.6}(p)))/q_{p,t}$. Contracts for forestry require a convolution of carbon removed by tree growth over the contract.

4. Solve model *SMDAMAGE_LT* or *SMDAMAGE_ST* as desired based on W and the initial temperature. Obtain emissions and removal schedule (q^*, r^*) and a temperature trajectory $Temp(W, q^*, r^*)$.

5. Run Hector with emissions and removal schedule (q^*, r^*). Obtain temperature trajectory $HTemp(q^*, r^*)$.

6. If $Temp(W, q^*, r^*) \approx HTemp\ (q^*, r^*)$, especially for the deadline year, consider (q^*, r^*) adequate.

7. Else, to improve the optimization, we want to fit a new W', especially elements $w_{\text{carbon},t}$, so $Temp(W', q^*, r^*) \approx HTemp(q^*, r^*)$. To find the improved W', model *SMDAMAGE_ST* is easily modified to model *Fit_W* as described in the Appendix. *Fit_W* produces a calibrated matrix W' and a calibrated initial temperature. Go back to step 4.

In practice, model *Fit_W* works very well. Figure 2 shows an example *SMDAMAGE_ST* solution with a deadline of 2125. Model *SMDAMAGE_ST* found a solution (q^*, r^*) drawing down the excess 1.4°C by 2125. Hector with (q^*, r^*) found more cooling, so the optimization underestimated the cooling effect, and the true solution is cheaper than found by the initial *SMDAMAGE_ST*. Recalibrating *W* with model *Fit_W* results in (q^*, r^*) closely matching Hector's temperatures, only 0.008 degrees apart at the deadline of 2125. The parameter $\tau = 2.5$ is larger than necessary to reach base zero, but the figure shows the technique's ability to calibrate the optimization and its economic effectiveness.

Figure 2. Temperature trajectories for an example uncalibrated and calibrated trajectory.

3. Numerical results

3.1. Long term commitment: a third party commits to paying for drawdown, robustness to discount rate

Using model *SMDAMAGE_LT* implies that emitters are net zero and a third party is willing to pay for drawdown with a stream of payments over the next 100 years.

Estimate 1. For the case with a 3% discount rate, emitters pay about $8.39 trillion over the 100 years to carbon removers. Emitters are carbon neutral. The auction manager must find a third party to pay an additional $4.75 trillion for drawdown. Total drawdown therefore costs about $13.06 trillion. Emitters and removers face an average price of about $10.94/tC ($40.13/tCO2). From 2025 to 2125, total carbon emissions are 761 GtC.

Selection of discount rate is a long-standing controversy with global warming analysis[52–55]. DICE is highly sensitive to discount rate. Nordhaus,[56] for example, shows large variations in CO2 emissions with discount rates varying 1% to 5%. We can sidestep the question of discount rate by committing to a temperature constraint, which may not maximize welfare nor utility. Rather, the objective minimizes the cost of ending global warming by a deadline, which is a different question than maximization of welfare or utility.

Figure 3 shows temperature trajectories for a calibrated model *SMDAMAGE_LT* with discount rates ranging from 0% to 6%. The figure shows higher temperature peaks with higher discount rates as the schedule postpones carbon removal, but all trajectories reach base zero by the deadline. In an auction, a policy maker's socioeconomic discount rates would not apply. Rather, market participants would use their own financial costs of capital, likely higher than a risk-free rate.

Figure 3. Temperature trajectories with full commitment, a 2125 deadline, and four different discount rates

3.2. Long term commitment: emitters pay for drawdown

Using model *SMDAMAGE_ST*, the auction manager can apply a surcharge on emitters, avoiding the need for third party payments.

Figure 4 shows annual carbon emissions (omitting other greenhouse gasses and removals) for τ ranging from 1.0 to 2.5. Rather than declining all at once, emissions fall slowly up to the deadline. The reason is due to the shape of the warming factors W (Figure 8) and the commitment to the deadline. Assume warming factors for carbon emissions and removals are the same but of different sign. Emissions today increase warming most over the soonest 20 years with less warming in the far future, so emissions should be lowest just before the deadline to reduce their impact. Carbon removal today cools the most over the soonest 20 years with less cooling in the far future, so removals should be greatest just before the deadline to increase their impact. When drawdown is complete, the auction can redeploy carbon removal capacity from drawdown to carbon neutrality, allowing an increase in emissions and a lower price of emissions.

Figure 4. Carbon emissions with full commitment, a 2125 deadline, 3% discount rate, and four surcharge rates τ

As a result of these timing effects, the commitment requires managing the flow of funds over time. Figure 5 shows net revenue each year for τ ranging from 1.0 to 2.5. From 2025 to about 2060, net revenue is positive as emissions decline while carbon removal ramps up. The auction institution must commit to saving this positive revenue to spend from about 2062 to 2125 while net revenue is negative. Even with a net zero scenario (τ = 1.0) with no drawdown, the least cost trajectory specifies saving the positive revenue in the early years to spend in later years. Net cash flows are never more than $200 billion per year.

Figure 5. Discounted net revenue with full commitment, a 2125 deadline, 3% discount rate, and 4 surcharge rates τ

Figure 6 shows the temperature trajectory for different values of τ. When τ = 1.0, emitters are net zero and no drawdown occurs. For larger values of τ, emitters are net negative. When τ = 1.5, the temperature almost reaches base zero in 2128. With τ = 2.5, the global temperature falls more than necessary. Higher τ reach base zero sooner.

Figure 6. Temperature trajectories with full commitment, a 2125 deadline, 3% discount rate, and 4 surcharge rates τ

Estimate 2. Solving *SMDAMAGE_ST*(τ, ϕ) iteratively resulted in τ = 1.6 with a temperature of 0.009°C above base zero in 2125. In this case, emitters pay about $10.9 trillion (3% discount rate) over the 100 years to carbon removers with no third party payments. The auction is not perfectly net zero from 2025-2125 because the auction continues through 2275; removers get about $11.2 trillion over the 100 years. Because emitters pay the surcharge τ = 1.6 for drawdown, emitters face an average price of about $16.09/tC ($59.98/tCO2). Removers receive $10.06/tC ($36.87/tCO2). From 2025 to 2125, total carbon emissions are 681 GtC. When emitters pay for drawdown, they emit less than they do when a third party pays for drawdown, thereby lowering the load on carbon removers.

The price trajectory shown in Figure 7 appears to differ in magnitude and shape from almost all in the literature. Prices do not increase with the discount rate; if they did, the price would be $264/ton C ($968/ton CO2) in 2125.

Figure 7. Price trajectory with full commitment, a 2125 deadline, 3% discount rate, and $\tau = 1.6$

3.3. The effect of weak carbon removal contracts

This paper thus far has assumed that the effective cooling of natural carbon removal is the negative of the warming from fossil fuel emissions. Using an analogy to the approximate metric of global warming potential, a ton of carbon emitted has global warming potential of 1, so the assumption here is like assuming that a ton of natural carbon removal has a global warming potential of −1. A skeptic may argue that this assumption results in underestimating the cost of reaching base zero, because a contracted ton of natural carbon removal has a much weaker cooling effect than an emission of a ton of carbon. That argument assumes that removal contracts must be weak. I think the notorious weakness of carbon removal contracts is due to institutional weakness in the ability to set and enforce strong contracts, not the inability of people to develop projects with natural carbon removal.

We can model contracts of different strengths by using different warming factors W from Hector. I believe this is a new approach to modeling and pricing carbon removal contracts. Hector's RCP2.6 scenario data has separate emissions inputs for fossil fuels and land use change. These activities have different warming factors, as Figure 8 shows. Warming from land use change is less than warming from fossil fuel emissions because land use change is heterogeneous, because carbon removal can be temporary, and because emissions include greenhouse gases other than CO2 [48]. Using the W sampled from Hector, land use change has a global warming potential of about $\sum^{100}_{t=1} (w_{\text{land use change},t})/(\sum^{100}_{t=1} \sum w_{\text{fossil fuel emissions},t}) \approx 0.43$. So a ton of carbon removed with the weaker contracts would have global warming potential of −0.43.

Figure 8. Illustrative warming factors $w_{\text{fossil fuel emissions},t}$ and $w_{\text{land use change},t}$

Estimate 3. After calibrating model *SMDAMAGE_ST* for $w_{\text{land use change},t}$ and $w_{\text{fossil fuel emissions},t}$, setting $\tau = 2.1$ resulted in a schedule with a temperature of 0.008°C below base zero for 2125. In this case, emitters pay about \$20.4 trillion (3% discount rate) over the 100 years to carbon removers with no third party payments. Emitters face an average price of about \$44.58/tC (\$163.46)/tCO2). Removers receive only \$7.33/tC (\$26.86/tCO2) because of the reduced cooling per ton of removed carbon. From 2025 to 2125, total carbon emissions are about 420.9 GtC. Weak contracts result in a more costly drawdown.

I use the phrase "weak contract" here to mean a weak cooling effect of the contract. In an actual market, the auction manager would be responsible for writing strong contracts for carbon removal,[57] assuming a legal implementation pathway could be found.[3] As mentioned above, the manager could use biological simulation to estimate warming factors for a given carbon removal contract, considering local factors such as weather and fire risk. The optimization can then price the contract.

3.4. Short-term versus long-term commitments

This paper thus far has assumed that an institution could save revenue from the early years before the deadline to pay for increasing removal in the later years before the deadline. We can simulate an institution that lacks this ability by running a series of models *SMDAMAGE_ST* with short trading periods, e.g., two years at a time. These two-year models simulate one auction for t and t+1 for each interval t = 2025, 2027, 2029, …, 2272, past the deadline of 2125. Each two-year auction is revenue neutral. Setting auctions for only two years is conservative, because traders would want to purchase emissions rights and sell removal contracts further into the future.

Despite the short auction trading, the optimization retains constraints on warming for the far future. Each removal contract can start only during the two trading years, but contracts such as for forestry must be able to continue longer. As the simulation advances in two-year intervals, the simulation treats trades from previous intervals as constant.

Estimate 4. This estimate is based on a calibrated model *SMDAMAGE_ST* and strong contracts with the reasonable assumption that auction managers would improve contract strength over time. A value of τ = 1.5 suffices to reach the 2125 deadline temperature of 0.002°C above base zero. Emitters pay about \$12.7 trillion (3% discount rate) over the 100 years to carbon removers with no third party payments. Emitters face an average price of about \$16.30/tC (\$59.78/tCO2). Removers receive \$10.87/tC (\$39.85/tCO2). From 2025 to 2125, total carbon emissions are about 688 GtC.

3.5. Time-varying τ_t

Estimate 5. The estimate 4 temperature trajectory had excess cooling of about 1.14°C around 2253 resulting in excess cost. We can address the excess cooling by adding a subscript for year to τ. Using *SMDAMAGE_ST*(τ, ϕ) as in Estimate 2, classic subgradient optimization found τ_t resulting in virtually no excess cooling. Emitters pay about \$10.84 trillion (3% discount rate) over the 100 years to carbon removers with no third party payments. Emitters face an average price of about \$16.04/tC (\$58.83/tCO2). Removers receive \$10.10/tC (\$37.04/tCO2). From 2025 to 2125, total carbon emissions are about 682 GtC. Over time t, τ_t varied from 1 to 1.42 then back to 1.

3.6. Climate "inertia" and Hotelling's Rule

One of the few papers with an explicit temperature constraint is Lemoine and Rudik [16]. They proved that an explicit temperature constraint can result in a lower cost trajectory than one constrained by CO2. In my view, their result demonstrates the benefit of using the correct metric of temperature rather than CO2 concentration or global warming potential. More controversially, they argued that "inertia" in the atmosphere allows a delay in removals while meeting the temperature deadline. Their graphs show the conventional Hotelling path (different to Figure 7) and their least cost path (similar to Figure 7).

Mattauch et al[58] disputed their result, claiming that Lemoine and Rudik misunderstood climate models. They wrote, "The least-cost policy path that limits warming to 2°C implies that the carbon price starts high and increases at the interest rate. It cannot rely on climate inertia to delay reducing and allow greater cumulative emissions." Lemoine and Rudik[59] replied defending the correctness of their first paper.

I would not use the word "inertia," but atmospheric physics do allow a delay in removals assuming immediate commitment. Figure 4 shows high initial emissions declining and later increasing. I explained this above, but here is a trivial example for intuition: an emitter and a remover bid over two periods with a requirement to reduce temperature by 0.5°C at the end of period 2. Period 1 emissions increase period 2 temperature by 0.4°C. Period 2 emissions increase period 2 temperature by 1°C. Removals have the same effect but negative. A corresponding linear program could look like this:

(12) Maximize $\text{emit}(1) + \text{emit}(2) - \text{remove}(1) - \text{remove}(2)$,

(13) subject to $0.4\ \text{emit}(1) + \text{emit}(2) - 0.4\ \text{remove}(1) - \text{remove}(2) \leq -0.5$

(14) $\text{emit}(1) \leq 1$, $\text{emit}(2) \leq 1$, $\text{remove}(1) \leq 1$, $\text{remove}(2) \leq 1$.

The solution is emit(1) = 1 and remove(2) = 0.9. Temperature increases least for emissions in period 1. Temperature decreases most for removal in period 2. Forestry growth complicates these calculations, but the effect remains.

Something else is also happening here. Researchers widely believe that Hotelling's rule for non-renewable resources provides the optimal emissions trajectory; the main disagreement is which interest rate one should use. See Gollier,[60] for example, on Hotelling's rule in CGE models. Hotelling's rule does not apply in this two-sided emissions market, because removal turns the atmosphere into a renewable resource and because the deadline makes abatement today differ from abatement tomorrow. Hopefully, these results give the climate research community second thoughts about the applicability of Hotelling's rule for the optimal emissions trajectory.

4. Conclusion: commitment lowers costs

This paper examined the costs for different levels of commitment to ending global warming, supposing a commitment to a single institution running a global two-sided auction for emissions permits and carbon removal.

Table 1 summarizes the five cost estimates from highest to lowest. Commitment to strong contracts lowers costs. Commitment to emitters paying for drawdown lowers costs. Commitment to flexibility in funds management over time lowers costs. An ability to adjust the surcharge over time lowers costs.

Table 1. Summary of 100-year present value cost estimates to end global warming, 3% discount rate, 2125 deadline

	Estimate 3	Estimate 1	Estimate 4	Estimate 2	Estimate 5
Model	ST, weak contracts	LT	ST, short auctions	ST	ST, time-varying τ
Third party pays	\$0	\$4.75 trillion	\$0	\$0	\$0
Average emitter price	\$44.58/tC (\$163.46)/tCO2)	\$10.94/tC (\$40.13/tCO2)	\$16.30/tC (\$59.78/tCO2)	\$16.09/tC (\$59.98/tCO2)	\$16.04/tC (\$58.83/tCO2)
Average remover price	\$7.33/tC (\$26.86/tCO2)	\$10.94/tC (\$40.13/tCO2)	\$10.87/tC (\$39.85/tCO2)	\$10.06/tC (\$36.87/tCO2)	\$10.10/tC (\$37.04/tCO2)
Emissions 2025-2125	420.9 GtC	761 GtC	688 GtC	681 GtC	682 GtC
Removal cost 2025-2125	\$20.4 trillion	\$13.06 trillion	\$12.7 trillion	\$11.2 trillion	\$10.84 trillion

Compare these estimates with van Vuuren et al.[36] With a higher discount rate of 5%, their meta-model predicts abatement costs of \$15 to \$30 trillion (\$US 2020) for avoiding a temperature rise of 2°C and 1.5°C targets respectively above base zero. For target temperatures of 2.5 to 3°C, they say that their largest uncertainty is "our limited understanding of the climate system and carbon cycle." In my view, the greatest uncertainty in ending global warming is what we will do about it. For lower targets, they say that the largest uncertainties are the mitigation costs and, besides willingness to commit, I agree with that. They also identify uncertainty from non-CO2 greenhouse gases which my model avoids. In any case, the market mechanisms proposed here, if adopted, could lead to whichever target outcome we choose.

Numerical mistakes are easy to make in work encompassing wide data collection, optimization, climate simulation, and calibration. A different version of Hector will likely produce slightly different results. These estimates may be too low for various reasons. The models ignore institutional constraints,[61] but the point of the paper is to examine costs if we could break those constraints. The models implicitly assume that a few omitted activities follow the RCP 2.6 pathway, effectively getting them for free; those activities are small. The models assume the bid curves account for switching costs. The bid curves ignore changes in population and size of the economy. High emissions prices could result in emissions falling so far and so fast that the auction manager would have to raise the surcharge to continue paying for drawdown; this could be tested, but fast falling emissions seems like a good thing. During this writing, news reports indicate a global temperature of 1.6°C above base zero.

The estimates may be too high for various reasons. The bid curves ignore learning and technological change in both emissions and carbon removal.[62] The energy transition could be cheap.[63] Researchers can add more options to the model, e.g., carbon capture and storage;[64] the models could price geo-engineering but cannot assess the associated risks. Estimates of carbon removal by forestry can be improved.[49,65] This work has not even come close to assessing the full range of nature based solutions[66] and adding options will only lower the cost. The models ignore the non-temperature damage from fossil fuels. The models omit costs of damage from global warming, but lower temperatures sooner with more certainty would likely lower the damage cost of higher temperatures with higher uncertainty.

Apart from the estimates, the models are a key contribution. The models enable pricing of carbon removal. Any researcher can update the models with new data on supply and demand, whether due to better science, new technology, or global events, thus finding an improved cost estimate, supposing policymakers decide to make the necessary commitments. The models are easy to solve with open source linear programming software. They can be used to calculate the costs of delaying implementation, of changing the deadline, of imperfect enforcement analogous to Sigman,[67] and of constraining the peak temperature. Analysts could add secondary metrics. The mechanism to pay for drawdown, the main contribution, makes all this possible. A straight forward extension to stochastic optimization[68] could account for a range of uncertainties.

National security researchers must study nuclear war, "unthinkable" in its pessimism. The commitments studied in this paper seem unthinkable in their optimism. The ideal cost estimate would be based on outcomes of an actual market. Unlike macroeconomic models, the models described here could be implemented by an institution. The value of setting up an institution to operate such an auction seems to be on the order of the value of the environmental and economic damage from following a longer path to ending global warming minus the value of the environmental and economic damage if we committed to a deadline and a trajectory.

Consider the implications of Figure 4 for the fossil fuel industry. The industry need not end and indeed could resume almost fully if they would concede some decades of reduction. The need for reductions gets steeper and stronger the longer they continue in intransigence. They could save their industry by fully committing to the most rigorous and economical way of reversing and ending global warming.

Appendix: detailed formulations

Formulations for *SMDAMAGE_LT* and *SMDAMAGE_ST*

Models *SMDAMAGE_LT* and *SMDAMAGE_ST* differ only in constraint set A4 below.

Indices

$a = 1,\ldots, A$, agent.

$p = 1,\ldots, P$, activity (pollutant or removal contract).

$t, u = 1,\ldots, T$, period, where $T \approx 200$ years. Generally, subscript u indicates the period of emission and t indicates the period of warming.

Parameters

Cap_t = allowed increase in degrees Celsius in period t, relative to some baseline temperature, e.g., −1.4°C.

$B_{a,p,u}$ = bid price by agent a to produce a unit of activity p in period u, e.g., a kiloton of SF_6 released or a hectare of forest to remove atmospheric carbon. For emitters, $B_{a,p,u} > 0$. For removers, $B_{a,p,u} < 0$.

$Q_{a,p,u}$ = upper bid quantity by agent a, units of activity p (e.g., kilotons CO_2 or hectares forest) in period u.

T = final year that Cap_t is constrained, e.g., the year 2301.

T_B = final year of denomination for contracts in the current year, specified by the auction manager.

τ_t = surcharge for period t.

Y = first year in which Cap_t is constrained, e.g., 2125.

$W_{p,u}$ = marginal temperature increase, u periods after one unit of activity p [5, 23]. $W_{p,u} \leq 0$ for removal activity.

Decision variables

$q_{a,p,t}$ = quantity allocated to agent a to produce activity p (e.g., pollutant or removal contract) in period t.

$v_{p,t}$ = total activity p in period t. We can interpret this variable as the total emissions or removal by sector p.

$\pi_{p,t}$ = market price, \$ per unit (e.g., kilotons or hectares) of activity p in period t. This is the dual price on constraint 3 below.

Models SMDAMAGE_LT and SMDAMAGE_ST

(A1) maximize $\sum^{A}_{\text{agent } a=1} \sum^{P}_{\text{activity } p=1} \sum^{T_B}_{\text{period } t=1} B_{a,p,t}\, q_{a,p,t}$,

(A2) $q_{a,p,t} \leq Q_{a,p,t}$, for agent a=1,…, A, activity p=1,…,P, and period t=1,…, T_B,

(A3) $\sum^{A}_{\text{agent } a=1} q_{a,p,t} = v_{p,t}$, for activity p = 1,…,P, and period t = 1,…,T_B, dual price $\pi_{p,t}$, (A4) *SMDAMAGE_LT*: $\sum^{t}_{\text{emission period } u=0} \sum^{P}_{\text{activity } p=1} W_{p,\, t-u}\, v_{p,u} \leq Cap_t$, for $t = Y, Y{+}1, Y{+}2, \ldots, T$,

(A4) *SMDAMAGE_ST*: $\sum^{t}_{\text{emission period } u=0} \tau_t \sum^{P}_{\text{activity } p=1} W_{p,\, t-u}\, v_{p,u} \leq 0$, for $t = Y, Y{+}1, Y{+}2, \ldots, T$,

(A5) $q_{a,p,t} \geq 0$ for all agents a, activities p, and periods t.

Explanation

(A1) Maximize the value of the traded contracts to market participants.

(A2) Respect agents' upper bid limits, as specified in their bids.

(A3) Calculate the total quantity of activity p each period as the sum of the agents' allocated quantities. The dual price $\pi_{p,t}$ serves as the price for activity p in period t.

(A4) Cap warming effects in period Y and thereafter. With *SMDAMAGE_ST*, the auction manager should choose τ_t so that

$$\sum^{t}_{\text{emission period } u=0} \sum^{P}_{\text{activity } p=1} W_{p,\, t-u}\, v^{*}_{p,u} \leq Cap_t, \text{ for } t = Y, Y{+}1, Y{+}2, \ldots, T.$$

(A5) Variables $q_{a,p,t}$ are nonnegative. The model does not need non-negativity constraints for $v_{p,t}$ because equations 3 and 5 together ensure the nonnegativity of $v_{p,t}$.

Model ***Fit_W***

We simply modify linear program *SMDAMAGE_ST* so the activity schedule $v_{p,t}$ is the constant and the warming factor W is the variable, changing their case here for emphasis.

Parameters:

T = last model year, e.g., 2300.

$V_{p,t}$ = amount of activity p in year t from solution of *SMDAMAGE_LT* or *SMDAMAGE_ST*.

$HectorTemp_t$ = the temperature in year t from Hector simulating solution $V_{p,t}$.

Y_p = contract length in years for a forestry contract p.

$C_{p,y}$ = the tons carbon removed per hectare in tree growth year $y = 0, 1, 2, \ldots, Y_p$.

Variables:

$w_{p,u}$ = marginal effect on warming after u periods from activity p.

$over\_error_t$ = error below $HectorTemp_t$ in year t.

$under\_error_t$ = error above $HectorTemp_t$ in year t.

$initial\_temperature$ = starting temperature.

(A6) Minimize $\sum_{t=1}^{T} (over\_error_t + under\_error_t)$ subject to

(A7) $initial\_temperature + \sum_{\text{activity } p=1}^{P} \sum_{\text{emission period } u=0}^{t} w_{p,t-u,} V_{p,u} - over\_error_t + under\_error_t =$ $HectorTemp_t$, for $t = Y, Y+1, Y+2, \ldots, T$,

(A8) $w_{p,u} \geq w_{p,u+1}$ for $u \geq 20$ for p = fossil fuel emissions and land use change. This constraint ensures a monotonic decline in the marginal warming factors with increasing u, to impose logical consistency.

(A9) $over\_error_t$, $under\_error_t$, $w_{p,u} \geq 0$ for all p and periods t.

(A10) $w_{p,u} = -\sum_{y=0}^{\min(u,Yp)} C_{p,y} w_{\text{carbon},\, u-y}$ for $u = 0, \ldots, 295$ years, i.e., the length of the model horizon, for each forestry contract p.

Model *Fit_W* is easy to expand. If we like, we can add variables to measure the difference between the old $W_{p,t}$ and the fitted $w_{p,t}$, or we can fit one $w_{p,t}$ matrix to k solutions $V^k_{p,t}$. In practice, the calibrated temperature trajectories from models *SMDAMAGE_ST* and *SMDAMAGE_LT* closely match the climate simulator's trajectory.

Code and data availability

The open-source Hector climate simulator is available at https://jgcri.github.io/hector/. Python code to pull the warming matrix from Hector, the SMDAMAGE family of models, the calibration model, all data, and full output is available at https://github.com/JohnFRaffensperger/SMDAMAGE. Agriculture data is from figure 11.17 of Smith et al.[69] (A more recent one is Bamière et al.[70]) Forestry data was extracted from Stavins and Richards[47] and section 4.3.7.2 of de Coninck et al.[71] Bid data for CO_2 is from Anger et al.[72] Data for remaining chemicals is from Ehhalt et al,[73] Ravishankara et al,[74] Tonkovich,[75] and Prinn.[76]

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References

1. United Nations. *Paris Agreement*. (United Nations, 2015).

2. Iyer, J., G. ;. Ou, Y. ;. Edmonds *et al.* Ratcheting of climate pledges needed to limit peak global warming. *Nat. Clim. Change* **12**, 1129–1135 (2022).

3. Rickels, M., Wilfried; Proelß, Alexander; Geden, Oliver; Burhenne, Julian; Fridahl. Integrating Carbon Dioxide Removal Into European Emissions Trading. *Front. Clim.* **3**, (2021).

4. Heal, G. Greens are Right to be Suspicious of Carbon Offsets. *NBER Work. Pap. Ser.* **Working Paper 33170**, (2024).

5. Nordhaus, W. *Strategies for the Control of Carbon Dioxide*. https://elischolar.library.yale.edu/cowles-discussion-paper-series/675 (1977).

6. Nordhaus, W. Projections and Uncertainties about Climate Change in an Era of Minimal Climate Policies. *Am. Econ. J. Econ. Policy* **10**, 333–60 (2018).

7. Pacific Northwest National Laboratory. GCAM: Global Change Analysis Model. https://gcims.pnnl.gov/modeling/gcam-global-change-analysis-model (2024).

8. Niamir, T., Leila; Ivanova, Olga; Filatova. Economy-wide impacts of behavioral climate change mitigation: Linking agent-based and computable general equilibrium models. *Environ. Model. Softw.* **134**, 104839 (2020).

9. Yu, S., Fan, Y., Zhu, L. & Eichhammer, W. Modeling the emission trading scheme from an agent-based perspective: System dynamics emerging from firms' coordination among abatement options. *Eur. J. Oper. Res.* **286**, 1113–1128 (2020).

10. Wei, A., T. ;. Aaheim. Climate change adaptation based on computable general equilibrium models - a systematic review. *Int. J. Clim. Change Strateg. Manag.* **15**, 561–576 (2023).

11. Wang, K. A. S. Z. J. Z. C. How can computable general equilibrium models serve low-carbon policy? A systematic review. *Environ. Res. Lett.* **18**, (2023).

12. Andreoni, M., P. ;. Emmerling, J. ;. Tavoni. Inequality repercussions of financing negative emissions. *Nat. Clim. Change* **14**, 48–54 (2024).

13. Gazzotti, G., P. ;. Emmerling, J. ;. Marangoni *et al.* Persistent inequality in economically optimal climate policies. *Nat. Commun.* **12**, 3421 (2021).

14. Monge, J. J. & McDonald, G. W. Assessing the economic implications of national climate change mitigation policies on cities: A CGE analysis of Auckland, New Zealand. *J. Clean. Prod.* **418**, 138150 (2023).

15. IPCC. *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report.* (2014).

16. Lemoine, I., Derek; Rudik. Steering the Climate System: Using Inertia to Lower the Cost of Policy. *Am. Econ. Rev.* **107**, 2947–2957 (2017).

17. Terhaar, J., Frölicher, T. L., Aschwanden, M. T., Friedlingstein, P. & Joos, F. Adaptive emission reduction approach to reach any global warming target. *Nat. Clim. Change* **12**, 1136–1142 (2022).

18. IPCC. *Climate Change 2023: Synthesis Report.* 1–34 (2023) doi:10.59327/IPCC/AR6-9789291691647.001.

19. Raffensperger, J. F. A price on warming with a supply chain directed auction. *Discov. Sustain.* **2**, (2021).

20. Raffensperger, J. F. Correction : A price on warming with a supply chain directed market. *Discov. Sustain.* **5**, 61 (2024).

21. NOAA. Climate at a Glance Global Time Series. *National Oceanic and Atmospheric Administration, National Centers for Environmental Information Atmospheric Administration* https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series (2024).

22. Marron, E. J. & Toder, D. B. Tax Policy Issues in Designing a Carbon Tax. *Am. Econ. Rev. Pap. Proc.* **104**, 563–568 (2014).

23. Rassenti, R. L., S. J. ;. Smith, V. L. ;. Bluffing. A Combinatorial Auction Mechanism for Airport Time Slot Allocation. *Bell J Econ.* **13**, 402–417 (1982).

24. McCabe, V., Kevin; Rassenti, Stephen; Smith. Smart computer-assisted markets. *Science* **254**, 534–538 (1991).

25. Derinkuyu, K., Tanrisever, F., Kurt, N. & Ceyhan, G. Optimizing Day-Ahead Electricity Market Prices: Increasing the Total Surplus for Energy Exchange Istanbul. *Manuf. Serv. Oper. Manag.* **22**, 700–716 (2020).

26. Günlük, O., Ladányi, L. & de Vries, S. A Branch-and-Price Algorithm and New Test Problems for Spectrum Auctions. *Manag. Sci.* **51**, 391–406 (2005).

27. Gallien, J. & Wein, L. M. A Smart Market for Industrial Procurement with Capacity Constraints. *Manag. Sci.* **51**, 76–91 (2005).

28. Lafkihi, M., Pan, S. & Ballot, E. The Freight Transportation Game: Operational Challenges for Carriers in Online Spot Market Platforms. *Inf. Trans. Educ.* (2025) doi:10.1287/ited.2024.0091.

29. Pekeč, A. & Rothkopf, M. H. Combinatorial Auction Design. *Manag. Sci.* **49**, 1485–1503 (2003).

30. Golmohammadi, A., Kraft, T. & Monemian, S. Setting the deadline and the penalty policy for a new environmental standard. *Eur. J. Oper. Res.* **315**, 88–101 (2024).

31. Ahmad, M., Li, X. F. & Wu, Q. Carbon taxes and emission trading systems: Which one is more effective in reducing carbon emissions?—A meta-analysis. *J. Clean. Prod.* **476**, 143761 (2024).

32. Yang, W. *et al.* Optimization on emission permit trading and green technology implementation under cap-and-trade scheme. *J. Clean. Prod.* **194**, 288–299 (2018).

33. Folini, D., Kübler, F., Malova, A. & Scheidegger, S. The climate in climate economics. Preprint at https://doi.org/10.48550/arXiv.2107.06162 (2022).

34. Ziesmer, J., Jin, D., Thube, S. D. & Henning, C. A Dynamic Baseline Calibration Procedure for CGE models. *Comput. Econ.* **61**, 1331–1368 (2023).

35. van der Wijst, D. P., KI. ;. Hof, A. F. ;. van Vuuren. On the optimality of 2°C targets and a decomposition of uncertainty. *Nat. Commun.* **12**, 2575 (2021).

36. van Vuuren, D. P. *et al.* The costs of achieving climate targets and the sources of uncertainty. *Nat. Clim. Change* **10**, 329–334 (2020).

37. Rosenbloom, L., Daniel; Markard, Jochen; Geels, Frank W. ;. Fuenfschilling. Why carbon pricing is not sufficient to mitigate climate change—and how 'sustainability transition policy' can help. *PNAS* **117**, (2020).

38. *Global Carbon Pricing: The Path to Climate Cooperation.* (MIT Press, 2017).

39. Bakalova, I. & Eyckmans, J. Simulating the impact of heterogeneity on stability and effectiveness of international environmental agreements. *Eur. J. Oper. Res.* **277**, 1151–1162 (2019).

40. Jenkins, M. R., S. ;. Millar, R. J. ;. Leach, N. ;. Allen. Framing Climate Goals in Terms of Cumulative CO2-Forcing-Equivalent Emissions. *Geophys. Res. Lett.* **45**, 2795–2804 (2018).

41. Allen, J. S., M. R. ;. Shine, K. P. ;. Fuglestvedt *et al.* A solution to the misrepresentations of CO2-equivalent emissions of short-lived climate pollutants under ambitious mitigation. *Npj Clim Atmos Sci* **1**, 16 (2018).

42. Jaehn, F. & Letmathe, P. The emissions trading paradox. *Eur. J. Oper. Res.* **202**, 248–254 (2010).

43. Ugurlu-Yildirim, E. & Kocaarslan, B. The role of government integrity in the impact of environmental taxes on comparative advantage in environmental goods and climate change in emerging markets. *J. Clean. Prod.* **478**, 144014 (2024).

44. Brunner, R., C. ;. Hausfather, Z. ;. Knutti. Durability of carbon dioxide removal is critical for Paris climate goals. *Commun Earth Env.* **5**, 645 (2024).

45. Trencher, G., Nick, S., Carlson, J. & Johnson, M. Demand for low-quality offsets by major companies undermines climate integrity of the voluntary carbon market. *Nat. Commun.* **15**, 6863 (2024).

46. EEB.org. *Joint Statement: Why Carbon Offsetting Undermines Climate Targets*. https://eeb.org/library/joint-statement-why-carbon-offsetting-undermines-climate-targets/ (2024).

47. Stavins, R. N. & Richards, K. R. *The Cost of US-Based Carbon Sequestration.* (2005).

48. Fearnside, P., P. M. ;. Lashof, D. A. ;. Moura-Costa. Accounting for time in Mitigating Global Warming through land-use change and forestry. *Mitig. Adapt. Strateg. Glob. Change* **5**, 239–270 (2000).

49. Dai Li, W., Immorlica, N. & Lucier, B. Contract Design for Afforestation Programs. in *Web and Internet Economics* (eds Feldman, M., Fu, H. & Talgam-Cohen, I.) 113–130 (Springer International Publishing, Cham, 2022). doi:10.1007/978-3-030-94676-0_7.

50. Hartin, B. P., C. A. ;. Patel, P. ;. Schwarber, A. ;. Link, R. P. ;. Bond-Lamberty. A simple object-oriented and open-source model for scientific and policy analyses of the global climate system - Hector v1.0. *Geosci. Model Dev.* 939–955 (2015).

51. IPCC. *Summary for Policymakers - Climate Change 2023: Synthesis Report.* 1–34 (2023) doi:10.59327/IPCC/AR6-9789291691647.001.

52. Schoenmaker, D. & Schramade, W. Which discount rate for sustainability? *J. Sustain. Finance Account.* **3**, 100010 (2024).

53. Millner, A. & Heal, G. Choosing the Future: Markets, Ethics, and Rapprochement in Social Discounting. *J. Econ. Lit.* **61**, 1037–1087 (2023).

54. Arrow, K. J. *et al.* How Should Benefits and Costs Be Discounted in an Intergenerational Context? The Views of an Expert Panel. SSRN Scholarly Paper at https://doi.org/10.2139/ssrn.2199511 (2013).

55. Weitzman, M. L. On Modeling and Interpreting the Economics of Catastrophic Climate Change. *Rev. Econ. Stat.* **91**, 1–19 (2009).

56. Nordhaus, W. *DICE 2023: Introduction and User's Manual.* https://yale.app.box.com/s/whlqcr7gtzdm4nxnrfhvap2hlzebuvvm/file/1539632845931 (2024).

57. Editorial. Cautious carbon removal. *Nat. Clim. Change* **14**, 549–549 (2024).

58. Mattauch, F., Linus; Matthews, H. Damon; Millar, Richard; Rezai, Armon; Solomon, Susan; Venmans. Steering the Climate System: Using Inertia to Lower the Cost of Policy: Comment. *Am. Econ. Rev.* **110**, 1231–1237 (2020).

59. Lemoine, I., Derek; Rudik. Steering the Climate System: Using Inertia to Lower the Cost of Policy: Reply. *Am. Econ. Rev.* **110**, 1238–1241 (2020).

60. Gollier, C. The cost-efficiency carbon pricing puzzle. *J. Environ. Econ. Manag.* **128**, 103062 (2024).

61. Bertram, L., C. ;. Brutschin, E. ;. Drouet *et al.* Feasibility of peak temperature targets in light of institutional constraints. *Nat. Clim. Change* **14**, 954–960 (2024).

62. Creutzig, W. F., F. ;. Roy, J. ;. Lamb *et al.* Towards demand-side solutions for mitigating climate change. *Nat. Clim. Change* **8**, 260–263 (2018).

63. The energy transition will be much cheaper than you think. *The Economist* (2024).

64. Kazlou, J., T. ;. Cherp, A. ;. Jewell. Feasible deployment of carbon capture and storage and the requirements of climate targets. *Nat. Clim. Change* **14**, 1047–1055 (2024).

65. Peng, J., L. ;. Searchinger, T. D. ;. Zionts *et al.* The carbon costs of global wood harvests. *Nature* **620**, 110–115 (2023).

66. Seddon, B., Nathalie; Chausson, Alexandre; Berry, Pam; Girardin, Cécile A. J. ;. Smith, Alison; Turner. Understanding the value and limits of nature-based solutions to climate change and other global challenges. *Philos. Trans. R. Soc. B* **375**, 20190120 (2019).

67. Sigman, H. F., Hilary; Chang. The Effect of Allowing Pollution Offsets with Imperfect Enforcement. *Am. Econ. Rev. Pap. Proc.* **101**, 268–272 (2011).

68. Willett, K., Caplanova, A. & Sivak, R. Emission Discharge Permits, Ambient Concentrations, and a Margin of Safety: Trading Solutions with a Computer-Assisted Smart Market for Air Quality. *Environ. Model. Assess.* **20**, 367–382 (2015).

69. Smith, H., P. ;. Bustamante, M. ;. Ahammad, H. ;. Clark, H. ;. Dong *et al.* Agriculture, Forestry and Other Land Use (AFOLU). in *Climate Change 2014: Mitigation of Climate Change* (Cambridge University Press, 2014).

70. Bamière, L. *et al.* A marginal abatement cost curve for climate change mitigation by additional carbon storage in French agricultural land. *J. Clean. Prod.* **383**, 135423 (2023).

71. de Coninck, M., H. ;. Revi, A. ;. Babiker, M. ;. Bertoldi, P. ;. Buckeridge *et al. Strengthening and Implementing the Global Response*. (2018).

72. Anger, J., Niels; Sathaye. *Reducing Deforestation and Trading Emissions: Economic Implications for the Post-Kyoto Carbon Market*. ftp://ftp.zew.de/pub/zew-docs/dp/dp08016.pdf (2008).

73. Ehhalt, E. J., D. ;. Prather, M. ;. Dentener, F. ;. Derwent, R. ;. Dlugokencky *et al.* Atmospheric Chemistry and Greenhouse Gases. in *IPCC Third Assessment Report Climate Change 2001: The Scientific Basis* (2001).

74. Ravishankara, R. W., A. R. ;. Daniel, J. S. ;. Portmann. Nitrous Oxide (N2O): The Dominant Ozone-Depleting Substance Emitted in the 21st Century. *Science* **326**, 123–5 (2009).

75. Tonkovich, G. *Air Quality, Energy, and Greenhouse Gas Emissions Impact Analysis, Talbert Extraction Well Decommissioning Project.* (2019).

76. Prinn, D. M., R. G. ;. Weiss, R. F. ;. Fraser, P. J. ;. Simmonds, P. G. ;. Cunnold *et al.* A History of Chemically and Radiatively Important Gases in Air deduced from ALE/GAGE/AGAGE. *J Geophys Res* **105**, 17,751-17,792 (2000).