Solar Geoengineering and the Social Cost of Carbon

Abstract

We consider the socially optimal use of geoengineering as a tool to combat climate change. Geoengineering offers the possibility of reducing the damages from atmospheric greenhouse gas concentrations, potentially at a much lower cost than reducing emissions. If so, then an optimal policy path may include much less abatement than is recommended by models that do not include the possibility of geoengineering, and the price of carbon will be substantially lower. Uncertainty about both climate change and about geoengineering will affect the optimal deployment of geoengineering. Finally, solar geoengineering may reduce temperatures but will not reduce atmospheric or ocean carbon concentrations, and that carbon may cause damages apart from temperature rise. We explore these issues by modifying an integrated assessment model of optimal climate policy to include geoengineering. The optimal carbon tax is lower than the tax recommended by the model without geoengineering, substantially so depending on the parameterizations of geoengineering costs and benefits. Carbon concentrations are higher but temperature changes are lower under geoengineering. All policy paths are sensitive to calibrated parameter values, and the optimal level of geoengineering is more sensitive to climate uncertainty than is the optimal level of abatement. The point estimates should be interpreted with caution since there is a great deal of uncertainty surrounding feasibility and side effects of geoengineering.

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Geoengineering is "the poor orphan that almost nobody wants to mention." (Schelling, 2007, p. 348)
"Most economic analyses of climate change, however, have ignored geoengineering." (Barrett, 2008, p. 46)
"I suspect, however, that there is at least a small chance we would live to regret treating the whole subject [geoengineering] as taboo." (Summers, 2007, p. xxiv)

I. Introduction

Greenhouse gases (GHGs) like carbon dioxide (CO_2) contribute to climate change and thus create negative externalities. The standard Pigouvian solution to the market failure caused by negative externalities is to price the externality at marginal external damages so that producers internalize the externality and produce at the optimal quantity. The Pigouvian tax is set at marginal external damages at the optimal quantity. Geoengineering (GE, sometimes also called climate engineering) is an alternative way to reduce the damages from GHGs: instead of reducing the quantity of GHGs, GE can reduce the damages that they inflict. A Pigouvian tax on GHG emissions will do nothing to create incentives for GE. If GE is part of the optimal policy portfolio, then a Pigouvian tax alone cannot bring about the first-best. Furthermore, if the Pigouvian tax is set at the level of marginal external damages without GE, then the tax will be too high relative to the optimum level (which is equal to marginal external damages with GE) and the level of abatement and abatement expenditures will be too high, resulting in welfare loss. It has been argued that GE may be substantially cheaper than abatement, possibly creating a very large welfare loss from ignoring GE.[1]

The purpose of this paper is to investigate, theoretically and numerically, how the possibility of GE affects optimal climate policy. Does GE substantially reduce the optimal carbon tax? Does ignoring GE lead to policies that encourage too much abatement at too high a cost? How does uncertainty affect

[1] For example, McClellan et al. (2012) find that GE could be undertaken globally for as little as $1-$3 billion annually. By comparison, the EPA's cost estimate of its proposed Clean Power Plan puts the annual cost at around $4-$8 billion annually, and that policy only yields a 30% reduction in CO_2 emissions just from power plants in the United States.

optimal policy? We develop a theoretical model that captures these effects and can demonstrate the welfare losses of ignoring GE. We augment a standard integrated assessment model (IAM) of climate change by adding the possibility of a specific type of GE to the Dynamic Integrated Climate-Economy (DICE) model (Nordhaus 2008). Costs and benefits of GE are calibrated from various prior estimates, though we note that there is substantial uncertainty. Therefore, we also explore conditions under which GE will or will not represent a substantial component of optimal policy. We caution that the purpose of this paper is not to argue one way or the other about the merits of GE or to estimate the optimal level of its deployment, but rather to investigate the qualitative point that ignoring GE in models may lead to biased policy recommendations.

There is a growing literature that examines the economics of geoengineering. Barrett (2008) explores the "incredible economics of geoengineering," by which he means the fact that GE is (potentially) so much cheaper than emissions abatement that it could be undertaken by a single country.[2] This creates a unique set of administrative problems. In fact, if the key problem with administering abatement policy is the inability to achieve international consensus to act, the key problem with GE might be ensuring that there is not too *much* implemented, since any number of nations may do it independently. A series of studies examine this issue of international governance for GE. Ricke et al. (2013) look at the incentives behind the formation of coalitions to implement GE. These incentives are different than those behind coalitions to abate GHGs. With GE, there are incentives to keep coalitions small so that action can be taken. Victor (2008) argues for norms to govern the deployment of GE. Weitzman (2012) models GE as a "free-driver" problem analogous to the "free-rider" problem of abatement. He notes that GE, depending on the level at which it is undertaken and the

[2] The prospect of low-cost GE is not universally accepted. For instance, Keller et al. (2014) use an Earth system model to simulate several different types of GE in the presence of high GHG emissions (no abatement), and they find that the effects of GE on warming are limited (less than an 8% reduction) and the side effects are potentially severe.

nation in question, can be either a public good or a public bad (thus he labels it a "public gob"). Moreno-Cruz (2011) models two countries agreeing on both mitigation and geoengineering, and shows that GE can lead to inefficiently high levels of mitigation. These papers are primarily concerned with how international agreements can be crafted to implement GE (or to prevent too much implementation).[3]

By contrast, a perhaps more fundamental question (though one less-studied) is how much GE is optimal? Moreno-Cruz and Keith (2013) incorporate GE into a two-period model of climate change and solve for optimal policy. They find that the uncertainty related to GE is an important determinant of optimal policy. Including GE can reduce the overall costs of climate policy by around 2 percentage points of GDP. Abatement and GE are substitute policy levers. Other papers have added GE to the DICE model and examined the policy implications. Bickel and Lane (2009) show that GE promises potentially large net benefits, though there is substantial uncertainty. They model two types of GE: solar radiation management (SRM) and air capture (AC), and they conclude that SRM is cheaper and more cost-effective. They conduct a benefit-cost analysis of various levels of implementation of GE, and they consider how implementing GE affects carbon taxes. But, they do not solve for an optimal level of GE. Goes et al. (2011) make several modifications to the DICE model, including allowing GE and refining the climate dynamics. Their specification imposes an exogenous intermittency in GE which makes it less effective.[4] They present summaries of policies with an optimal mix of abatement and GE (subject to the intermittency), but they do not present implications for policy, i.e. carbon taxes with GE. Bickel and Agrawal (2013) extend the analysis of Goes et al. (2011) by considering alternate condition under which

[3] Barrett (2014) discusses the literature on the governance of geoengineering, what he calls "the fundamental problem posed by geoengineering." Rayner et al. (2013) present the "Oxford Principles," a set of five guidelines for international GE governance. Lloyd and Oppenheimer (2014) argue for an international agreement with a small number of nations.

[4] Jones et al. (2013) also investigate the effect of abrupt suspension of GE (a "termination effect"), using a simulation of 11 different climate models. Also see Ross and Matthews (2009).

GE would be deployed; in contrast to Goes et al. (2011), Bickel and Agrawal (2013) find that under some scenarios a substitution of GE for abatement can pass a cost-benefit test. Gramstad and Tjøtta (2010) include SRM in DICE and conduct a cost-benefit analysis of GE under various assumptions about the level undertaken and its costs. Under all specifications, GE passes a cost-benefit analysis, with net benefits ranging from $1.5 trillion to $17.8 trillion. Postponement of GE by 30-50 years reduces those net benefits by less than 10%. They do not consider carbon taxes or the optimal level of GE. [5]

The contribution of our paper relative to this other literature on the policy implications of GE is threefold. First, we use an IAM to solve for the time path of optimal policy, with a focus on how the inclusion of GE affects optimal abatement and the optimal carbon tax. Intuitively (and guided by our theoretical model), we expect that including GE will reduce the optimal carbon tax rate. Since GE appears to be so much cheaper than abatement, it is possible that including GE will drastically reduce the optimal carbon tax. It is theoretically possible that optimal policy will involve a corner solution with no abatement (and hence no carbon taxes), though we argue this is unlikely primarily because of GE's inability to deal with losses due to ocean acidification. While solving for the optimal carbon price is admittedly a straightforward extension of other papers that have used an IAM to find optimal policy, we argue that it is nonetheless an important contribution that should not be overlooked. If GE means that the optimal carbon price is much lower than current estimates of the social cost of carbon, this has very important policy implications. We calculate the welfare loss of ignoring this fact. We also explore how different assumptions about various parameter values affect the time path of optimal policy. For instance, it is well known that small changes to the discount rate used in the model can have large changes in optimal abatement paths, but little is known about how discounting affects optimal GE paths,

[5] Klepper and Rickels (2012 and 2014) provide review articles on the economics of geoengineering. Emmerling and Tavoni (2013) use a different IAM, WITCH, to model GE and abatement policy.

or how discounting affects abatement when GE is an option. Should GE be delayed, or implemented immediately? Should GE ramp up, like a carbon price does in DICE, or start high and taper? [6]

Our second contribution to the literature is our focus on uncertainty; we emphasize that there are substantial uncertainties involved in any analysis of GE given the present state of scientific understanding.[7] We also consider uncertainty in climate sensitivity by adapting DICE to model a climate sensitivity parameter as stochastic. We can explore how the use of GE might endogenously affect knowledge about its costs and benefits as well as climate sensitivity or other features of the climate. This endogenous learning effect may have implications for GE deployment. Third, ours is the first model that distinguishes between damages from carbon concentrations and damages from temperature. Unlike mitigation or abatement, solar geoengineering reduces temperatures without reducing carbon concentrations, either atmospheric or ocean. Both types of carbon stocks may lead to damages, even if temperatures are brought back to preindustrial levels. For instance, ocean acidification may deplete fisheries, and atmospheric carbon may affect precipitation patterns.

We find that GE does unambiguously lower the optimal level of abatement and the optimal price of carbon in the model. The degree to which it does so is sensitive to parameter values. In our base case specification, the optimal level of abatement is up to 25 percentage points lower than the optimal level without GE, and the elimination of all carbon emissions is delayed by five decades. Ignoring GE can increase overall costs of climate change by one-half to one percent of GDP. Optimal abatement levels are less sensitive to parameter values and to uncertainty in climate sensitivity than are optimal GE levels. The degree to which damages from climate change arise from carbon directly, rather

[6] Barrett (2014) considers four different options for the time path of GE, and Keith (2013) recommends starting at a low level of GE and gradually increasing its use.

[7] The National Academy of Sciences is currently engaged in a project to provide a technical evaluation of GE proposals, jointly sponsored by the NOAA, the CIA, NASA, and the Energy Department: https://www8.nationalacademies.org/cp/projectview.aspx?key=49540

than from temperature, substantially affects optimal GE deployment; if a high fraction of damages are from carbon, then GE is used less intensively.

The next section of the paper introduces our theoretical model, which provides the framework for our inclusion of GE into the DICE model. Section 3 describes how we include GE in the DICE model and how it is calibrated. Section 4 presents our simulation results, and section 5 concludes.

II. Theoretical Model

Consider a representative agent who has access to an endowment of a fixed stock of capital k. That capital can be allocated one of three ways: towards production k_p, towards abatement k_a, or towards geoengineering k_g. The resource constraint is thus $k = k_p + k_a + k_g$. Allocating capital towards production yields a level of potential output $f(k_p)$, with $f' > 0$ and $f'' < 0$. This is potential output, because actual output is reduced because of damages from pollution x. Actual output (all of which is consumed) is $y = c = f(k_p)\left(1 - d(x; k_g)\right)$. The damage function d represents the fraction of potential output that is lost because of pollution x, and $d_x > 0, d_{xx} > 0$ (damages are increasing and convex in pollution). Geoengineering k_g affects damages also, with $d_k < 0$ and $d_{xk} < 0$. That is, geoengineering reduces absolute and marginal damages. Pollution x is determined by the total capital endowment and the fraction abated μ, so that $x = (1 - \mu)k$. The fraction abated is a function of abatement capital: $\mu = g(k_a)$, where $g' > 0, g'' < 0$.

The planner's problem is to allocate the capital stock so as to maximize actual output (or equivalently maximize a monotone utility function over actual output). That is,

$$\max_{k_p, k_a, k_g} f(k_p)\left(1 - d(x; k_g)\right)$$

such that

$$k = k_p + k_a + k_g$$

$$x = \big(1 - g(k_a)\big)k$$

First, consider the constrained solution to this problem that omits GE, or sets $k_g = 0$. The solution to this constrained problem is analogous to policy recommendations by IAMs that ignore GE. The first-order condition for the constrained problem, assuming interior solutions, is

$$f'\big(k_p^c\big)\big(1 - d(x^c; 0)\big) = f\big(k_p^c\big)kg'(k_a^c)d_x(x^c; 0), \qquad (1)$$

where k_p^c, k_a^c, and x^c indicate solutions to the constrained problem. The left-hand side of equation (1) is the marginal cost of an additional unit of abatement, which is the foregone marginal output that could have been produced by allocating to production k_p instead of abatement k_a. The right-hand side is the marginal benefit of an additional unit of abatement, which is the reduction in damages caused by pollution from the extra unit of abatement. In a decentralized economy, the right-hand side of this equation is the optimal pollution tax, i.e. the social cost of carbon, which GE is ignored (as it is in many IAMs).

Next, consider the unconstrained problem where GE is not fixed at zero. This solution is characterized by two first-order conditions:

$$f'\big(k_p^{opt}\big)\Big(1 - d\big(x^{opt}; k_g^{opt}\big)\Big) = f\big(k_p^{opt}\big)kg'\big(k_a^{opt}\big)d_x\big(x^{opt}; k_g^{opt}\big) \qquad (2)$$

$$d_x\big(x^{opt}; k_g^{opt}\big)g'\big(k_a^{opt}\big)k = -d_k\big(x^{opt}; k_g^{opt}\big) \qquad (3)$$

where $k_p^{opt}, k_a^{opt}, k_g^{opt}$, and x^{opt} indicate solutions to the unconstrained problem (i.e. the optimal levels). Equation (2), as in equation (1) in the constrained case, equates the marginal cost of an additional unit of abatement with its marginal benefit. In a decentralized economy, the optimal carbon tax (the social cost of carbon) is the right-hand side of equation (2). In equation (3), the left-hand side represents the marginal benefit of an additional unit of abatement (divided through by potential output f), and the right-hand side represents the marginal benefit of an additional unit of GE.

Consider the market for abatement k_a under both the constrained and unconstrained problem, as shown in the top half of Figure 1. The x-axis is the amount of abatement. The line $MC|k_g = 0$ is the marginal cost of abatement conditional on no GE ($k_g = 0$); it equals $f'(k - k_a)\left(1 - d\left(\left(1 - g(k_a)\right)k, 0\right)\right)$, which is the left-hand side of equation 1 evaluated at arbitrary k_a. The line $MB|k_g = 0$ is the marginal benefit of abatement with no GE; it equals $f(k - k_a)kg'(k_a)d_x\left(\left(1 - g(k_a)\right)k, 0\right)$. The appendix shows that MC is increasing and MB is decreasing in k_a. Where these are equal, their value is the social cost of carbon, conditional on no GE, as indicated by $SCC|k_g = 0$; this is the price determined by equation 1.

Allowing for GE affects the marginal benefit of abatement, and intuition suggests that the marginal benefit curve allowing for GE will be lower than the marginal benefit curve with no GE. GE reduces the damages from a unit of emissions, and therefore it reduces the marginal benefits of abatement. This intuition is verified in the appendix, and thus the curve $MB|k_g^{opt}$, which is the marginal benefit of abatement conditional on the optimal level of GE, is drawn in Figure 1 lower than $MB|k_g = 0$. Assuming that introducing GE does not change the marginal cost of abatement (an incorrect assumption, as it turns out, but one that we will maintain for now to clarify the point of Figure 1), then the social cost of carbon condition on optimal GE is lower than the social cost of carbon ignoring GE. Figure 1 demonstrates the deadweight loss in the abatement market (the triangle labeled DWL) from setting a carbon tax that ignores GE.

Allowing for GE also affects the marginal cost curve, though in Figure 1 we have ignored the fact that $MC\big|k_g = 0 \neq MC\big|k_g^{opt}$. The appendix shows that $MC\big|k_g = 0 < MC\big|k_g^{opt}$. This is because, for any abatement level, allowing GE makes the damages from pollution lower, and thus potential output higher, and therefore the marginal cost of abatement (foregone output) higher. But, the appendix also argues that the difference between the two marginal cost curves is likely to be small, unlike the

difference between the two marginal benefit curves, which is why we have ignored the change in MC in Figure 1. Since the marginal cost under optimal GE is (slightly) higher than under no GE, the social cost of carbon under optimal GE will be closer to the social cost of carbon ignoring GE than shown in Figure 1 ignoring the change in marginal costs. But, the deadweight loss from ignoring GE could be higher or lower than that shown in Figure 1 (although the quantity of abatement will be lower, the cost of each unit over the optimal is higher).

The bottom half of Figure 1 shows that in equilibrium, the marginal benefit of an additional unit of abatement capital will equal the marginal benefit of an additional unit of geoengineering. The left-hand side is the market for abatement, while the right-hand side presents the market for geoengineering. The curves in blue represent the marginal costs and benefits of geoengineering, at a constant level of abatement (equal to k_a^c). As k_g increases and geoengineering in implemented, the optimal level of abatement k_a decreases, so emissions increase. Thus, the marginal benefit of each unit of geoengineering increases, since more pollution is allowed and temperatures are warmer without geoengineering. This is represented by an upward shift in the marginal benefit curve to the red curve. In equilibrium, the marginal benefits of geoengineering (on the right half) will increase just enough and the marginal benefits of abatement (on the left half) will decrease just enough so that the optimal quantity of each choice variable is such that the marginal benefits are equal across the two markets. Extending the new optimal carbon price across the graphs will intersect the equilibrium in the geoengineering market.

The model in this section provides intuition but omits many important details. It is a static model, though climate change is inherently dynamic. It omits uncertainty, which is essential when considering both climate change damages and risks of GE. It has no scientifically-based specification of how emissions affect the climate over time. For these reasons and many others, in the following section we incorporate GE into an IAM that includes these features. Though the output of the IAM is difficult to

interpret intuitively (it is a "black box"), the intuition developed in this section will be carried over to the results from the IAM simulations.

III. Geoengineering and DICE

The dynamic integrated climate-economy (DICE) model by William Nordhaus is an IAM designed to be used to solve for optimal GHG abatement policy and calculate the social cost of carbon. It includes a representative-agent economic model with an endogenous capital stock and an exogenous level of technological growth in total factor productivity. Carbon emissions are a byproduct of production but can be reduced through expenditure on abatement. The climate component of the model includes several equations describing the dynamic interaction between carbon concentrations in several layers: the atmosphere and upper and lower oceans. The atmospheric carbon concentration affects the atmosphere's radiative forcing; that is, the difference between the amount of heat energy absorbed by the Earth and that radiated back into space. The human-caused change in radiative forcing is ultimately what affects atmospheric temperatures. Finally, the climate and economy sections of the model are integrated in that increases in temperature cause reductions in total economic output. A social welfare function is defined over consumption and output, and the model can be run to solve for optimal (i.e. welfare-maximizing) carbon abatement trajectories. Given marginal abatement costs, the social cost of carbon is a byproduct of the model's output. A time period in the model is one decade, and the model is typically run over several dozen periods (hundreds of years).

The DICE model and its results have been refined over the years, and summaries of the model's equations and results are available in Nordhaus (2008) as well as Nordhaus's personal webpage.[8] A key takeaway from the model runs are that the social cost of carbon in the present is positive (typically

[8] http://www.econ.yale.edu/~nordhaus/homepage/

around \$30 per ton of CO_2), and it is gradually increasing over time to reflect the increase in carbon concentrations and thus in marginal damages per ton of carbon.

IAMs like DICE have been criticized. Pindyck (2013) argues that they tell us "very little" and are "close to useless" because so many of the calibrated parameter values are ad hoc with little empirical foundation. This is demonstrated by the fact that the policy recommendations can be so sensitive to arbitrarily chosen parameter values, for instance the discount rate. Because our numerical analysis relies on DICE, it is subject to these criticisms. However, even if one accepts these critiques and is skeptical of IAMs, we argue that our analysis has merit. Though the point estimates of optimal policy paths should be interpreted with caution, how they vary with parameter values (i.e. the sensitivity analysis) still provides insight. Further, thought the point estimates may be problematic, the simulations demonstrate that it is potentially important to consider GE in optimal policy design, with or without IAMs. In these respects, the use of DICE can be seen as another argument in favor of PIndyck's (2013) and others' critiques of IAMs.

Here, we do not present all of the equations in the DICE model. Instead, we present the equations that we have modified to account for the possibility of geoengineering. We have modified DICE in the following four ways. First, while the only choice or action variable in the original DICE model is carbon abatement, we add a second choice variable to reflect the choice of the intensity of geoengineering. Second, there is a cost to implementing geoengineering, analogous to the cost of abatement. Third, we add potential damages from geoengineering, analogous to the original model's specification of damages from climate change. Fourth, the benefits of geoengineering are modeled as directly modifying the radiative forcing equation. Fifth, we decompose the damages from climate change so that they depend directly not just on temperature, but also on atmospheric and on ocean carbon concentrations. In the following five paragraphs we describe in detail each of these modifications.

The original DICE model's sole choice variable is abatement intensity a, which can take values between zero and one. When $a = 0$, there is no abatement, and $a = 1$ implies that all carbon emissions are abated (no emissions). Net carbon emissions are $E_{net} = (1 - a)E_{gross}$. We add a second choice variable for the intensity of geoengineering, g (and we maintain the choice of abatement). When this variable g equals zero, this represents no geoengineering. When $g = 1$, this represents "full" geoengineering, i.e. fully offsetting the warming effects from increased carbon concentrations (described in more detail below). However, unlike abatement intensity a, geoengineering intensity g could take a value larger than 1, representing more than fully offsetting temperature increases from climate change.

In the original DICE model, the cost of abatement is modeled as a power function of a: $AbatementCost = \theta_1(t)a^{\theta_2}$. The exponent θ_2 is 2.8 in the base case, indicating convex costs. The coefficient $\theta_1(t)$ decreases with time, halving after about 100 years (10 periods) to reflect technological advancement in abatement. The outcome variable $AbatementCost$ is the fraction of gross output that is sacrificed for abatement. For instance, in period 1 where $\theta_1(1) = 0.0561$, the cost of abating 10 percent of gross emissions would be 0.009% of gross output ($0.00009 = 0.0561 \times 0.10^{2.8}$). We define geoengineering costs analogously as a fraction of gross output: $GeoengCost = G_{coef}\theta_{GE}(t)g^{\theta_3}$. To calibrate this cost function of climate engineering, we use two sources. First, doing well-informed back-of-the-envelope calculations, Crutzen (2006) estimates the amount of sulfur needed to reduce the radiative forcing equivalent to doubling CO_2 to be equal to 5.3 Mt of sulfur. That is, we can reduce a radiative forcing equivalent to 4W/m^2 by deploying 5.3 Mt S. The second piece of information is related to the costs of delivering sulfur at the distance required to have a global impact. Crutzen (2006) has estimated something in the order of $25 Billion for 1 Mt S. Recent estimates, using new aircraft designs, estimated the costs at $3 Billion for 1 Mt S or $8 Billion to deliver 5Mt S (McClellan et al. 2012). These two pieces of data imply that reducing the radiative forcing equivalent to a doubling of CO_2 costs

between \$8 Billion and \$125 Billion. Furthermore, we assume that particles are required at an increasing rate (Rasch et al. 2008), and for simplicity the costs are quadratic (less convex than mitigation, but linear costs are unrealistic due to coagulation of particles and other such processes). GDP in 2005 was \$46 Trillion, so the lowest estimate of \$8 Billion is only 0.02% of global GDP and the highest estimate is 0.27% of global GDP. (Compare this with the 3% in terms of mitigation costs associated with the optimal policy in DICE.) Because geoengineering is a fraction in our model, then reducing a doubling of CO_2 to nothing is equivalent to setting $g = 1$. Thus our geoengineering cost estimate is $\theta_{GE}(t) = 0.0027$ and $\theta_3 = 2$. We set $\theta_{GE}(t)$ constant over time, so that unlike with abatement technology there is no learning or improvement in geoengineering technology. We also include the coefficient G_{coef} to represent a scaling of geoengineering costs. In the base case we set $G_{coef} = 1$, and we will vary this in sensitivity analysis. By using the high cost estimate and not allowing technological growth in GE technology, this base case value for GE costs is very conservative, that is, biased against deployment of geoengineering. Keith et al. (2010) argues that "long-established estimates" show that solar radiation management GE can offset climate change at least 100 times more cheaply than the cost of abatement.

In addition to these implementation costs of geoengineering, there may also be damages from geoengineering. For instance, sulfates are expected to exacerbate ozone depletion (Heckendorn et al. 2009). Precipitation could be drastically reduced (Ferraro et al. 2014, Robock et al. 2008). The sulfates injected into the stratosphere may condense and fall back to the atmosphere, contributing to acid rain (though Kravitz et al. (2009) find that this effect will be insubstantial). We model these damages in the same way that the original DICE model models damages from climate change – as a factor of total potential output that is unrealized due to these damages (and of course we keep damages from climate change as well). In the original DICE, the damage function is $\Omega(t)$, where output $Q_{net} = \frac{1}{1+\Omega(t)} Q_{gross}$ and $\Omega(t) = \psi_1 T_{AT}(t) + \psi_2 [T_{AT}(t)]^2$. The damage function is a function of atmospheric temperature at

time t, $T_{AT}(t)$, and the ψs are calibrated coefficients. We amend this by also allowing for geoengineering g to directly reduce total output. In addition to the $\Omega(t)$ term representing damages from climate change, we also include damages from geoengineering: $Q_{net} = \frac{1}{1+\Omega(t)} \times \frac{1}{1+\nu_G g^2} \times Q_{gross}$. The coefficient ν_g represents how damages from geoengineering scale net output. In our base case, we set $\nu_g = 0.03$, which implies that geoengineering at full intensity ($g = 1$) leads to damages that amount to 3% of gross output. This is similar in scale to the damages from climate change damages in DICE associated with about 6 degrees Celsius of warming, thus this damage estimate (like the cost estimate also) is very conservative (i.e. biased *against* geoengineering).

The purpose of engaging in solar geoengineering is to alter the radiative forcing of the Earth's atmosphere. Radiative forcing is the difference in net heat loss due to anthropogenic GHG emissions relative to preindustrial levels. In the DICE model, the radiative forcing equation is

$$F(t) = \eta\{\log_2\left[\frac{M_{AT}(t)}{M_{AT}(1750)}\right]\} + F_{EX}(t)$$

It is a function of the ratio of the current atmospheric carbon stock ($M_{AT}(t)$) to the pre-industrial atmospheric carbon stock ($M_{AT}(1750)$ = 596.4 Gt C, equivalent to about 280 ppm CO_2), exogenous forcing $F_{EX}(t)$ due to anthropogenic emissions of GHGs other than CO_2 (assumed exogenous in DICE), and a calibrated radiative forcing parameter η. Then, atmospheric temperature $T_{AT}(t)$ is affected by radiative forcing through the following equation:

$$T_{AT}(t) = T_{AT}(t-1) + \xi_1\{F(t) - \xi_2 T_{AT}(t-1) - \xi_3[T_{AT}(t-1) - T_{LO}(t-1)]\}.$$

This function also depends on the lower ocean temperature in the previous period $T_{LO}(t-1)$. A higher value of radiative forcing $F(t)$ (which is caused by higher atmospheric carbon $M_{AT}(t)$) leads to higher atmospheric temperatures $T_{AT}(t)$ all else equal. Our modification is to the radiative forcing equation:

$$F(t) = \left(\eta\{\log_2\left[\frac{M_{AT}(t)}{M_{AT}(1750)}\right]\} + F_{EX}(t)\right)\left(1 - \phi g(t)\right)$$

The variable $g(t)$ is the extent of geoengineering in period t, and ϕ is a positive parameter that captures the leverage of geoengineering. Higher ϕ means less geoengineering needs to be implemented to achieve a given level of radiative forcing reduction. At a value of 1, radiative forcing F is reduced to zero (regardless of the carbon stock), completely eliminating anthropogenic climate change effects on temperature.

Our final change to the DICE model is a modification of the damage function from climate change (not from geoengineering). In DICE, climate change damages are a function of temperature only: $\Omega(t)$. However, climate change damages are expected to come from more than just temperature changes. precipitation is predicted to change, independent of the temperature change due to global warming. Bony et al. (2013) find that atmospheric carbon increases account for about half of predicted tropical circulation change and a large fraction of precipitation changes from climate change. The acidification of oceans cause damages too. There is also the possibility that increased atmospheric carbon concentrations may have benefits to agricultural productivity, holding temperature and precipitation constant (Pongratz et al. 2012). Because geoengineering decreases temperatures but does not change the carbon stock in either the atmosphere or the oceans, it is crucial to decompose the damages from climate change into damages directly from temperature and damages from carbon stocks. Thus, we modify DICE's damage function $\Omega(t)$ to be a function of temperature $T_{AT}(t)$ as well as atmospheric carbon $M_{AT}(t)$ and upper ocean carbon $M_{UP}(t)$:

$$\Omega(t) = \psi_T[T_{AT}(t)]^2 + \psi_O[M_{UP}(t) - M_{UP}(1750)]^2 + \psi_{AT}[M_{AT}(t) - M_{AT}(1750)]^2$$

The temperature T_{AT} is already defined as degrees Celsius relative to preindustrial (1750) average temperature, but the other two components of damages are not, so we calculate damages by subtracting the preindustrial levels, and we allow damages to be a quadratic function of the deviation from preindustrial levels. We calibrate the new damage coefficients ψ in the following way. We impose that the original DICE model's total climate change damages in the initial period is correct, but we

allocate some of those damages to be directly from temperature, some from ocean carbon concentrations, and some from atmospheric carbon concentrations. Brander et al. (2012) suggest that find that damages from ocean acidification alone can account for 0.14% to 0.18% of gross GDP. Direct damages from atmospheric carbon concentrations are difficult to calibrate. Absent its effect on temperature, atmospheric carbon is expected to affect precipitation, which may cause damages. Furthermore, atmospheric carbon may provide a benefit to agriculture by promoting more robust crop growth. Therefore, we begin by assuming that, of the total damages from climate change in the initial period calibrated in DICE, 80% is directly a function of atmospheric temperature, 10% is a function of atmospheric carbon, and 10% is a function of upper ocean carbon. By imposing that the total damages from climate in the initial period are identical to those in DICE, this allows us to calibrate ψ_T, ψ_O, and ψ_{AT}. Specifically, in the initial period in DICE, climate change damages amount to 0.15157% of gross output ($\Omega(t) = \psi T^2 = 2.8388 \times 10^{-3} \times 0.7307^2$). We set 80% of this total a function of temperature, yielding $\psi_T = 0.00227$ ($\psi_T \times 0.7307^2 = 0.80 \times 0.0015157$). And similarly we can calibrate the other damage parameters.

These are the five areas in which we modify DICE to include geoengineering and its costs, benefits, and damages. We have described the base case parameterizations that we use in our model, but we will also conduct a very broad range of sensitivity analyses, since many of the parameters are difficult to quantify.

Other studies have also modified DICE to include geoengineering, and here we compare our modifications to these other papers'. Table 1 summarizes. All of the papers allow solar GE to directly modify the radiative forcing equation; our paper is the only one to allow GE to enter as a multiplicative factor rather than a linear additive term. This is not a major difference, since in either case the substantive effect is to reduce the value of $F(t)$. We choose a multiplicative factor for ease of interpretation: the policy variable will be between zero and one, representing the fraction of total

anthropogenic forcing that is eliminated via solar GE. The next column notes that all of the previous studies save one allow for damages from solar GE (apart from their implementation costs). We, like Gramstad and Tjotta (2010), allow for these damages to be a quadratic function of GE intensity and to be a multiplier on gross output; in this way they are modeled analogously to damages from climate change. Next, only this paper and Goes et al. (2011) and Bickel and Agrawal (2013) modify DICE's damages from climate change function. The other two papers allow for damages to be a function both of temperature and of the rate of temperature change, based on the fact that solar GE can lead to rapid temperature changes (Matthews and Caldeira 2007). Their damage function is taken from Lempert et al. (2000). We are more direct in that we allow for damages to be a function of more than just temperature; this innovation is unique to this paper.

There are other modifications as well. Bickel and Lane (2009) is the only paper that also considers carbon capture GE, and Goes et al. (2011) and Bickel and Agrawal (2013) make several other modifications, including using a different climate model altogether.

A unique contribution of this paper is to model stochastic parameter values, rather than just sensitivity analyses. The other GE DICE papers consider sensitivity analyses, but they do not model stochastic parameters. Other papers including Baker and Solak (2011) and Kolstad (1996) modify DICE to include stochastic parameters, but without GE. Another contribution is that we allow for endogenous learning about climate parameter values, which could be a function of the extent of geoengineering.

The model is solved for optimal policy using the two-step-ahead approximation method described in Shayegh and Thomas (forthcoming). This algorithm was originally developed to find the optimal solution for the stochastic case of uncertainty in the climate sensitivity parameter in DICE. The approximation technique was tested and tuned in the deterministic case and then applied to the stochastic model. The algorithm works as follows: at each time step t, the decision maker is projecting the future values of uncertain variables for the next two steps. At any specific state the value function is

approximated by projecting the values of states in the next two time periods. The values of the two projected states are calculated under a deterministic forecast and brought back to the present time using an artificial and tunable discount rate. These values reflect the social utility under the deterministic assumption and are used to construct the value function of the current state. The optimal action (abatement, geoengineering, etc.) is found by maximizing this value function. The algorithm starts at time $t = 1$ and progress until the last time step. After calculating all value functions, these values are used to update the coefficients of approximate value function in previous states. The algorithm iterates until the error (difference between old and new coefficients) converges to zero.

Although it is designed for dealing with uncertainty in stochastic problems, the algorithm can be used in a deterministic model to approximate the optimal solution. We adopt this algorithm and modify it for the case of two actions: abatement and geoengineering. The algorithm is developed in Matlab and is available upon request.

IV. Simulation Results

IV.A Deterministic Simulations

In order to understand the way geoengineering affects optimal climate policy, we start by analyzing the deterministic case. We compare the outcomes of the base case scenario to the case of no geoengineering; that is, the current state of affairs. The results are presented in Figure 2. The first panel shows how abatement is affected when geoengineering is introduced as a viable policy instrument. The introduction of geoengineering lowers the level of abatement and delays the time when we transition to a clean economy. Once abatement reaches it maximum level, geoengineering begins to decline. However, it stays positive for some time because of the lag in the effect of emissions on temperature.

The introduction of geoengineering, therefore, has important implications for climate outcomes. In the next two panels we look at carbon dioxide concentration and temperature changes. Because of

the lower level of abatement, carbon dioxide concentration peak at a higher level and later in the presence of geoengineering. Concentrations peak at the 800ppm mark, before they come down. This is high relative to the case of no geoengineering where concentrations peak at 660ppm. But with geoengineering, temperature peaks much earlier and it is kept at check below the 2 degrees mark. This is the buying-time effect, often cited in the literature, where geoengineering keeps the system below deleterious levels of climate change while the abatement technology improves enough to eliminate emissions. This is done at the costs of allowing for higher levels of concentrations. Thus, there is a tradeoff between carbon damages and temperature damages, as well as geoengineering costs and abatement costs.

Finally, we see the effects of geoengineering on the price of carbon. The last panel in Figure 2 shows that the carbon price is lower when geoengineering is introduced; it peaks at a lower level before it starts to decline at the rate of learning by which the costs of the backstop technology decline.

What is remarkable about all these results is that they do not arise because geoengineering is very cheap, since we are very conservative about the costs and damages of GE. These results are due to the use of geoengineering directly on the radiative forcing. This reduces the inertia of the climate system, allowing to reduce the amount of abatement that is needed today to reduce concentrations in the future. Thus, by postponing costly abatement to future periods, geoengineering helps to reduce the aggregate costs of climate change.

IV.A.1 Sensitivity analysis.

Now we allow certain parameters to change and recalculate the optimal policy. First, if we increase the costs of geoengineering (increase G_{coef}), the damages associated to its implementation (increase ν_g) or make it less effective at counterbalancing radiative forcing (decrease ϕ), the amount of geoengineering is reduced, the amount of abatement is increased, and the carbon price is also increased. But even if we make geoengineering 10 times more costly than abatement, there is a

substantial amount of warming that is still compensated by geoengineering. This again reflects the fact that by eliminating the inertia of the carbon cycle and therefore allowing for postponing abatement, geoengineering decreases the total costs of climate change and increases welfare. Increasing the damages associated directly to carbon concentrations (i.e. ocean acidification) we find that the amount of geoengineering is reduced as more abatement is used to compensate for direct carbon emissions. This in turn suggests that carbon concentrations are kept at lower levels and peak earlier. It is also the case that temperatures will be lower and peak earlier and at a lower level the more acidification

Finally, increasing the discount rate decreases the amounts of both abatement and geoengineering, as well as the carbon price.

In all of these sensitivity analyses, the level of abatement varies but eventually reaches 100%. Can we find reasonable parameter values where abatement is never used in the long run? That is, geoengineering in theory could be so cheap that the optimal solution ends up at a corner solution with no use of abatement at all. However, even when we reduce the geoengineering costs to 1% of its base case value and geoengineering damages to 10% of its base case value, and we reduce the fraction of climate change damages attributable to atmospheric and ocean carbon to just 1% each, we are still left with a case where abatement eventually reaches 100% intensity. It is much delayed, not occurring until period 35 (relative to period 200 in the no-GE case). Geoengineering intensity reaches 100% after the first period since it is so cheap. But because abatement becomes cheaper and cheaper over time, and there still are damages from carbon not managed by GE, abatement is still a part of the optimal policy toolbox.

IV.B Stochastic Simulations

We now allow DICE to be solved assuming a stochastic distribution of certain parameters. We allow the model to converge, and then solve the model 1000 times for different draws of the stochastic parameter based on a specified distribution. We then evaluate the mean of the policy outcome

variables as well as their distribution. We can examine how, for instance, the uncertainty in parameter values affects both the mean of policy variables and the distribution of values. This method differs from simply solving the deterministic model a number of times under different parameter values because…

Initially we allow the climate sensitivity parameter to be stochastic. This parameter describes the equilibrium temperature change that results from a doubling of atmospheric carbon. In our deterministic case this is set to 3. We now allow it to take on a truncated log-normal distribution, calibrated based on the IPCC report (IPCC 2013). The lower and upper bounds are 0.1 and 20, respectively; the mean and standard deviation are 1.1 and 0.55, respectively. This parameterization is used in Shayegh and Thomas (forthcoming).

Figure 3 presents the policy simulation results for abatement, geoengineering, and the price of carbon. We present the mean value, calculated across 1000 simulations drawn from the specified distribution of climate sensitivity, as well as the 5^{th} and 95^{th} percentiles. As in the deterministic simulations, the plots of the mean value demonstrate that all three policy variables gradually ramp up over the first 20 or so decades of the simulation. At about period 25, abatement reaches 100% and stays there, which results in the carbon price gradually falling as technological innovation makes 100% abatement cheaper. Geoengineering levels off at around 90% starting around period 20.

The dashed lines showing the 5^{th} and 95^{th} percentile values demonstrate that uncertainty over climate sensitivity affects optimal geoengineering policy much more so than it affects optimal abatement policy. This is notable, since the only stochastic variable in this simulation is the climate sensitivity variable, which is not directly related to geoengineering. The 5^{th} to 95^{th} percentile bands for abatement and carbon price are very narrow.

We can also repeat these stochastic simulations under different distributions of the climate sensitivity parameter. In particular, we consider alternate values for the standard deviation of the parameter, both higher (1.0) and lower (0.20) than the base case (0.55). We find that the level of

uncertainty of climate sensitivity does not substantially affect the mean values for abatement action or the carbon price, although it does (unsurprisingly) affect the percentile bands. A smaller standard deviation of beliefs about climate sensitivity leads to a narrower confidence interval. However, the standard deviation of climate sensitivity does affect both the mean and the percentile bands for optimal GE action. A larger standard deviation in climate sensitivity leads to a lower mean level of geoengineering action. While in the base case in the graph, GE action flattens out at about 93%, in the case when the standard deviation of climate sensitivity is just 0.20, it plateaus at about 99%. With a higher standard deviation of climate sensitivity (1.0), GE plateaus at just around 82%.

Next, we combine the model with a stochastic distribution of the climate sensitivity parameter with sensitivity analysis over other parameters of the model, in particular the parameters describing the costs and benefits of geoengineering. These results are present in Figure 4, which presents the optimal abatement rate and optimal geoengineering rate under a stochastic specification of climate sensitivity and for three different values of two parameters. First, we allow ν_G, the parameter on geoengineering damages, to vary from its base case of 0.001 to two orders of magnitude larger. Second, we allow G_{coeff}, the coefficient on geoengineering costs, to vary from its base case of 1 (indicating roughly identical costs of abatement and geoengineering) to an order of magnitude lower and an order of magnitude higher.

Under these large variations in geoengineering cost parameters, there is moderate variation in optimal abatement but large variation in optimal geoengineering. Across the range of parameters, the optimal abatement rate reaches 100% between 20 to 25 periods from the present. At period 15, the optimal abatement rate varies from 45% under the parameters most favorable to geoengineering to 65% under the parameters least favorable to geoengineering. The range of optimal geoengineering paths is much broader, and full geoengineering at 100% intensity is reached only under the most favorable parameters of geoengineering. The range of optimal geoengineering at period 15 ranges from

5% to 100%. When geoengineering is costlier or has higher damages, there is less geoengineering and more abatement employed. Lastly, Figure 4 also presents the percentage difference in GDP between each of the cases considered and the no-GE case. The cost-savings of allowing geoengineering ranges from about one-tenth of one percent of GDP to more than 1 percent of GDP, and larger cost savings are associated with cheaper geoengineering.

IV.C Endogenous Learning

We can also use this model to investigate how GE can be used to learn about the climate system and what effect this has on the optimal timing of GE. Keith (2013) argues for an initially low level of GE deployment that gradually increases over time, in part to allow for time for learning about the effects and possible problems with GE. Conceivably, deployment of GE could actually be used to reduce some of the uncertainties surrounding the climate. MacMynowski et al. (2011) argue that GE can be tested and that its use can also give us information on the climate system.

If so, then an optimal policy path ought to respond to the potential learning that comes about from use of geoengineering. We can use DICE to examine this learning effect. We can specify an initial distribution of beliefs about climate sensitivity, for instance the base case distribution calibrated earlier from the IPCC. Then, we can make assumptions about how implementation of geoengineering affects beliefs about this parameter. Implementation can both narrow the confidence bands of the parameter value, or it could shift the mean value (for instance, the use of geoengineering may alert scientists to the fact that the climate is much more sensitive to carbon concentrations than previously thought). The ability to use GE to learn about the climate will presumably be a further incentive to undertake geoengineering, which can be explored through our model. Alternatively, a slow deployment of geoengineering can help us learn about the impacts of geoengineering on the climate and the economy. Starting from a prior distribution about possible geoengineering impacts, we can learn from observing the results and this way narrow the distribution. Results are forthcoming.

V. Conclusion

Solar geoengineering has the potential to lower the costs of dealing with climate change and reducing the need for high levels of abatement and a high carbon price. Models that ignore geoengineering may prescribe policies that abate too much, cost too much, and have a carbon price that is too high. We explore this issue through both a simple static theoretical model and an integrated assessment model of climate change. Our modification of the DICE model provides some quantitative insights as to how geoengineering can affect optimal abatement policy. The level of abatement can be about 25% lower when allowing for geoengineering, and the optimal atmospheric carbon concentrations can be more than 25% higher. Despite that, temperature changes can nearly revert back to preindustrial levels because of the use of geoengineering, and total GDP losses can be lower by one-half to one percentage point of GDP. However, these results under base case parameterizations are of course sensitive to the parameter values, and those parameter values are very uncertain. Still, under a wide (two orders of magnitude) range in parameters describing the costs of geoengineering, the optimal carbon price and level of abatement do not vary substantially, although the optimal level of geoengineering does vary substantially (ranging from nearly no geoengineering to 100% geoengineering). As with all climate models, more precise parameter values are essential for pinning down specific policy recommendations.

We caution that these results should not be interpreted as a policy prescription for immediate deployment of geoengineering. The uncertainties surrounding the calibration of the model, in particular the damages associated with geoengineering, are too great to be able to do so. Instead, the main contribution of this paper is in its qualitative and quantitative exploration of how including GE in climate models affects the optimal deployment of abatement and the social cost of carbon. This paper provides

one reason why previously estimated carbon prices may be too high; there are also other reasons why they may be too low.

Still, the fundamental contribution made by this study has important policy implications. It is not efficient to merely estimate the marginal external damages of a ton of carbon and institute that carbon tax, if the external damages are estimated in a model without the possibility of geoengineering. Our results suggest that this may in fact be the case, and that for this reason the social cost of carbon currently being used by policymakers may be too high.[9] Of course, there are many other potential reasons why the social cost of carbon currently used may be too low – estimates may omit many benefits from carbon reductions.[10]

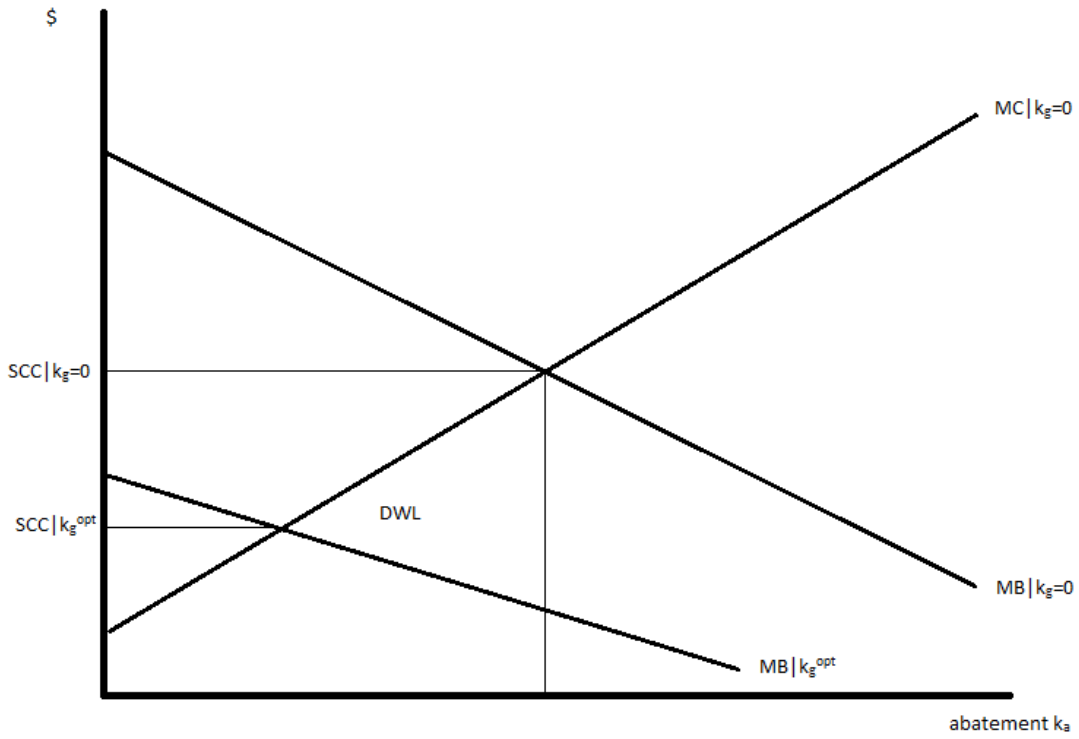
Our research emphasizes the need for more information on costs and benefits of geoengineering. Furthermore, refinements to the model may yield valuable policy lessons – for instance expanding the set of parameters modeled as stochastic variables, or adding refinements to either the climate model in DICE or its treatment of economics costs or growth. The damages from GE represent probably the most "unknown" of all of the features of this model. Finally, there are many issues related to GE that we do not and cannot address using an IAM – including a fat-tailed distribution of risks, discontinues in costs of damages, and ethical issues related to the question of abatement versus GE.

[9] The EPA and other federal agencies use an SCC of $37 per ton of CO_2: http://www.epa.gov/climatechange/EPAactivities/economics/scc.html.
[10] See for instance Howard (2014).

Table 1 – Summary of modifications to DICE

	Radiative Forcing	Damages from Solar GE	Climate Change Damages	Other modifications	Outcomes
Bickel and Lane (2009)	Linear term in forcing equation	None	No Modifications	Also model carbon capture geoengineering	Cost-benefit analysis for fixed levels of GE; carbon price
Gramstad and Tjotta (2010)	Linear term in forcing equation	Quadratic multiplier on gross output	No Modifications	None	Cost-benefit analysis for fixed levels of GE
Goes et al. (2011) and Bickel and Agrawal (2013)	Linear term in forcing equation	Linear function of aerosols deployed	Damages a function of temperature and rate of temperature change	Alter discounting formula; change climate model to DOECLIM; intermittency in GE	Cost-benefit analysis for fixed levels of GE and for optimal GE/abatement mix; Bickel and Agrawal (2013) considers sensitivity analysis of Goes et al. (2011)
This paper	Multiplicative factor in forcing equation	Quadratic multiplier on gross output	Damages a function of temperature, atmospheric carbon, and ocean carbon	Stochastic analysis of climate sensitivity; endogenous learning	Optimal levels of GE and abatement; carbon price; sensitivity analyses

Figure 1 – Static Model



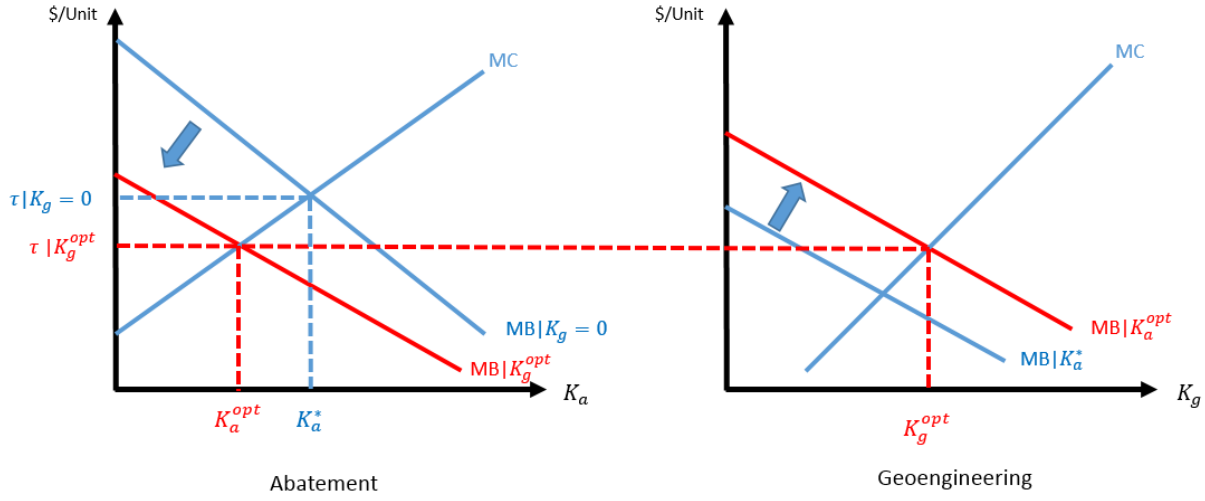
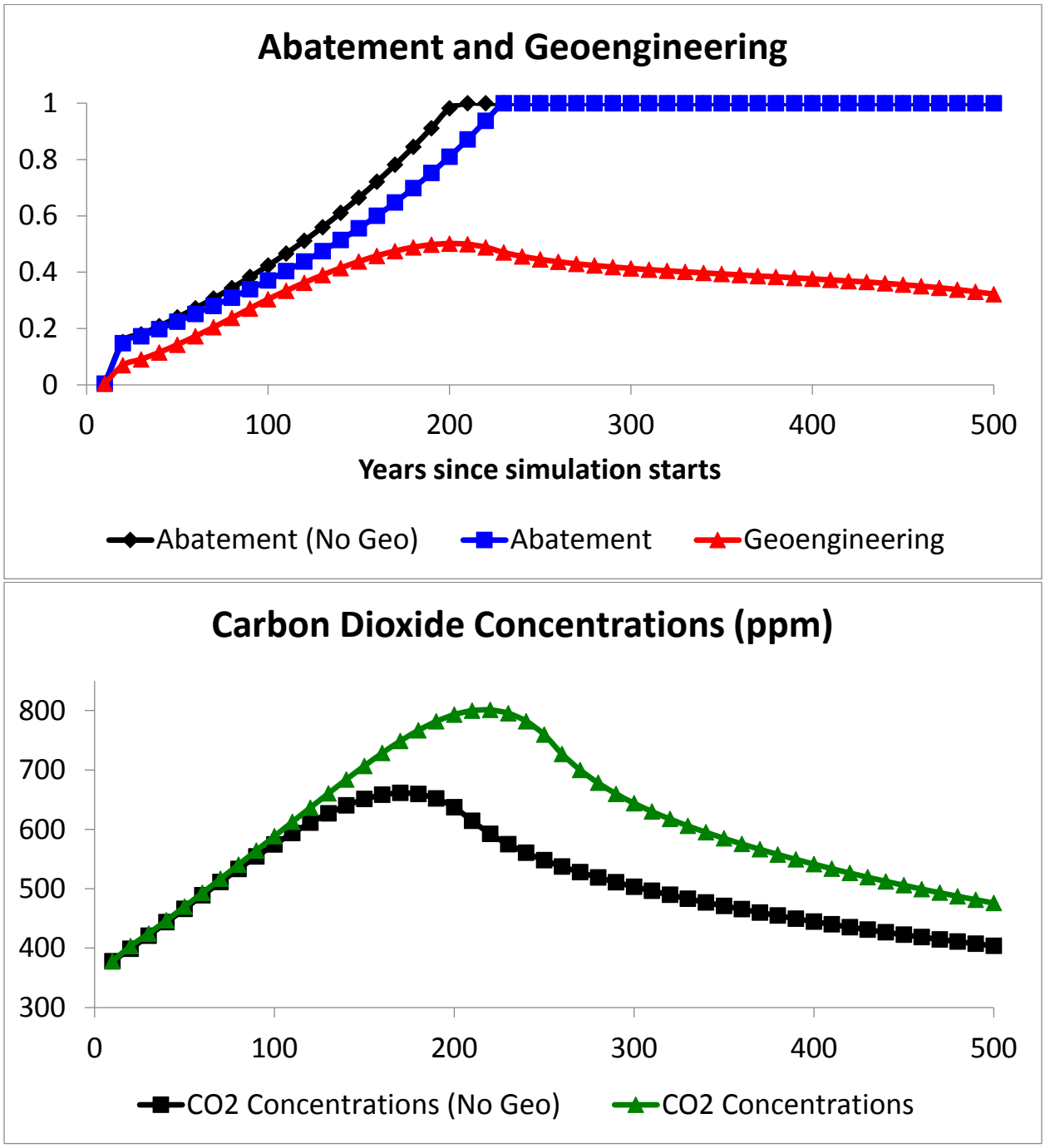
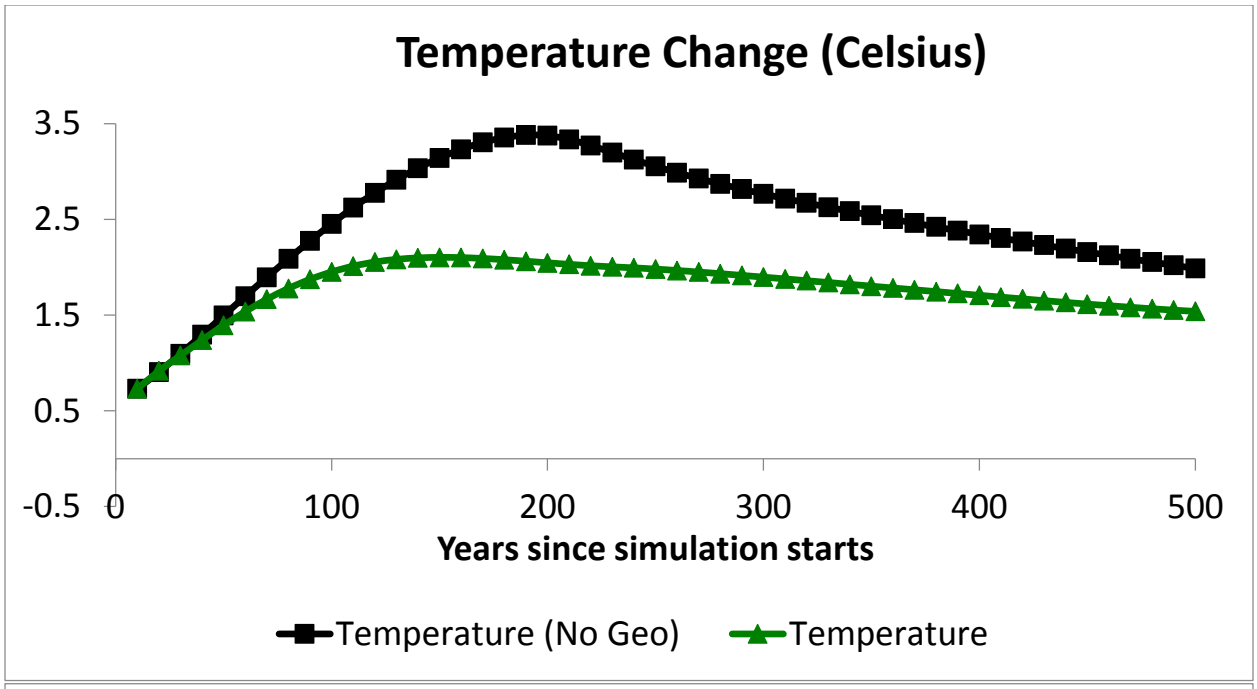


Figure 2 – Base Case Simulation Results




Temperature Change (Celsius)
3.5
2.5
1.5
0.5
-0.5
0
100
200
300
400
500
Years since simulation starts
Temperature (No Geo)
Temperature

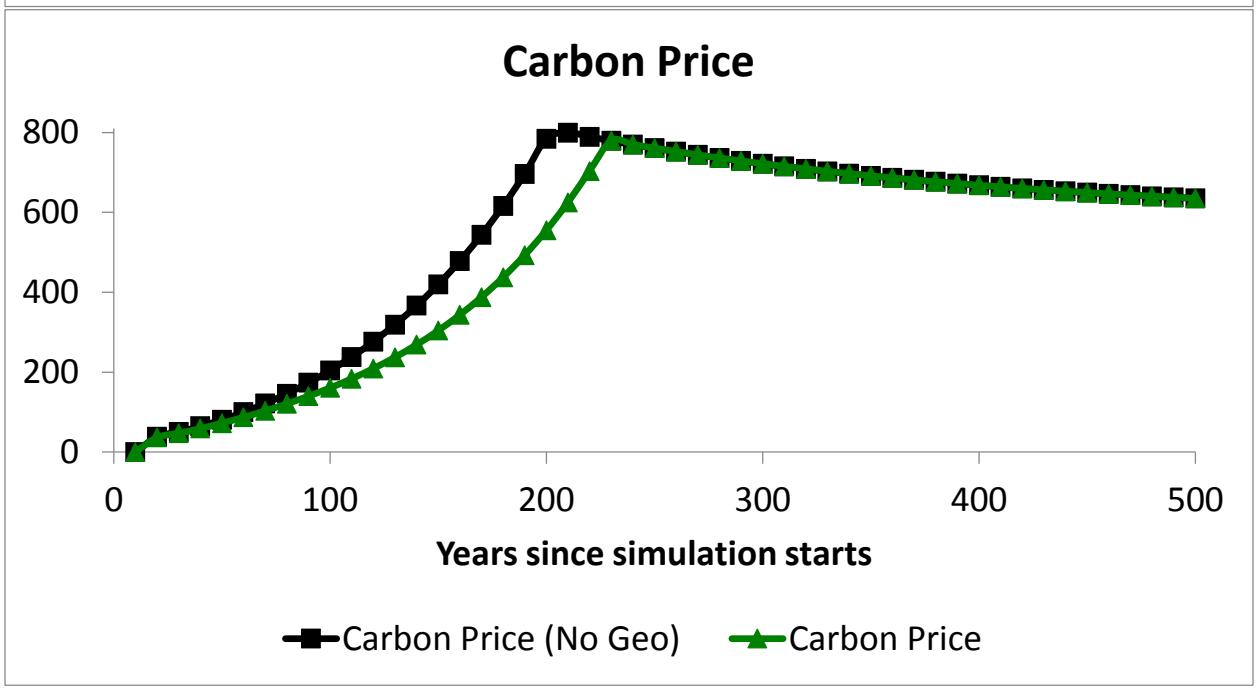
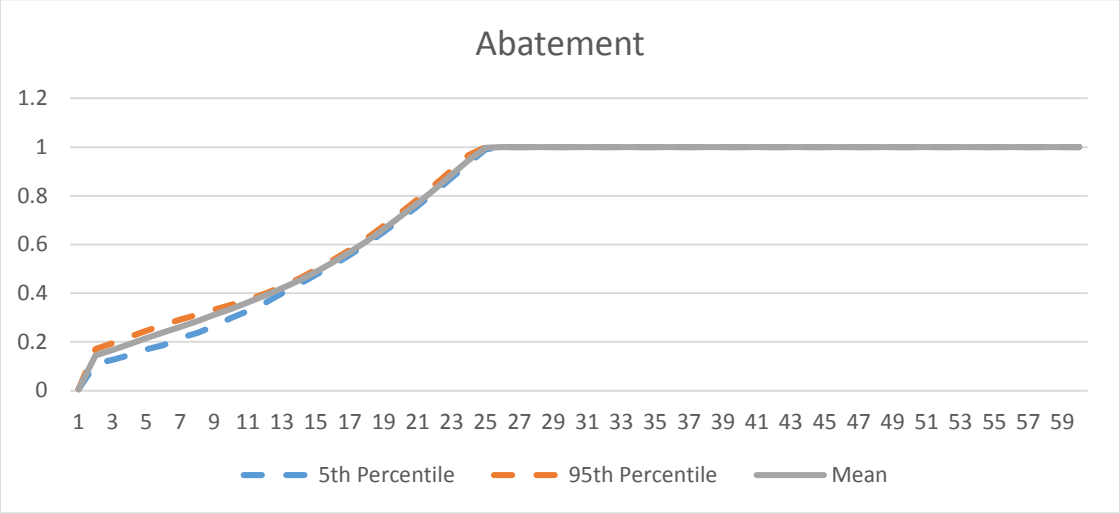
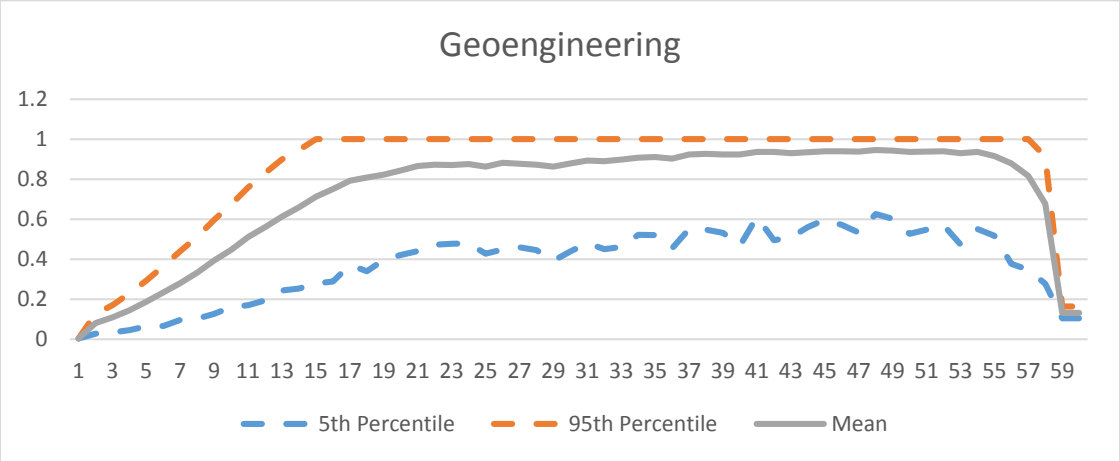

Carbon Price
800
600
400
200
0
0
100
200
300
400
500
Years since simulation starts
Carbon Price (No Geo)
Carbon Price

Figure 3 – Stochastic Simulation Results





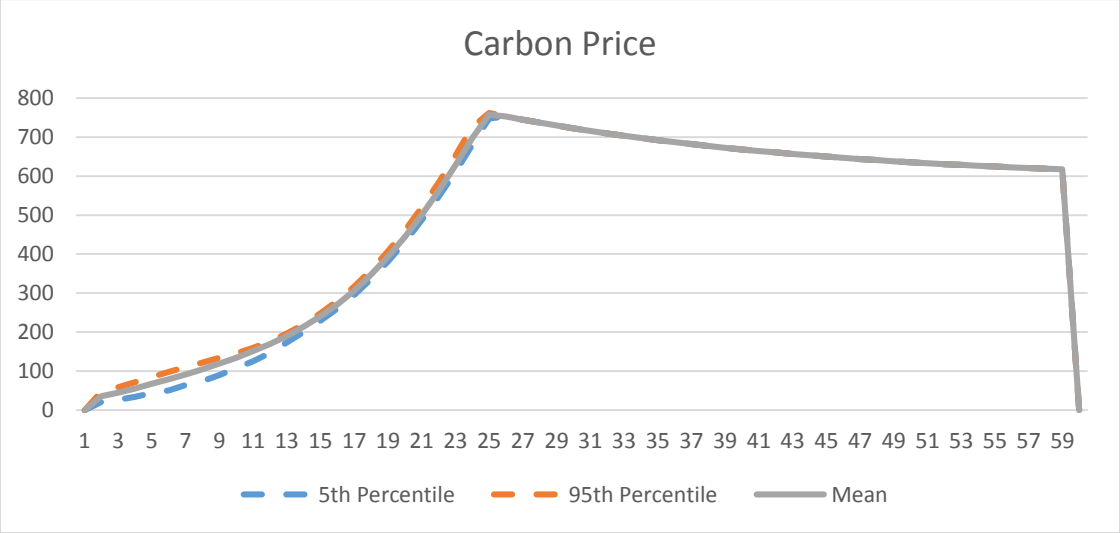
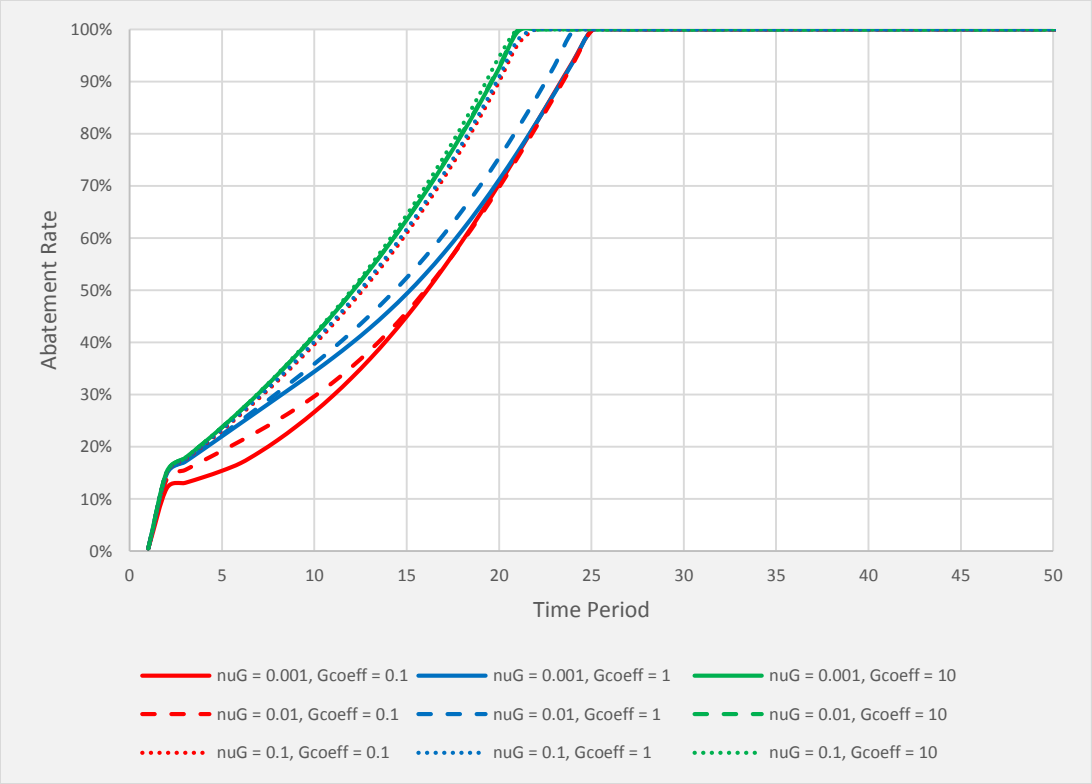
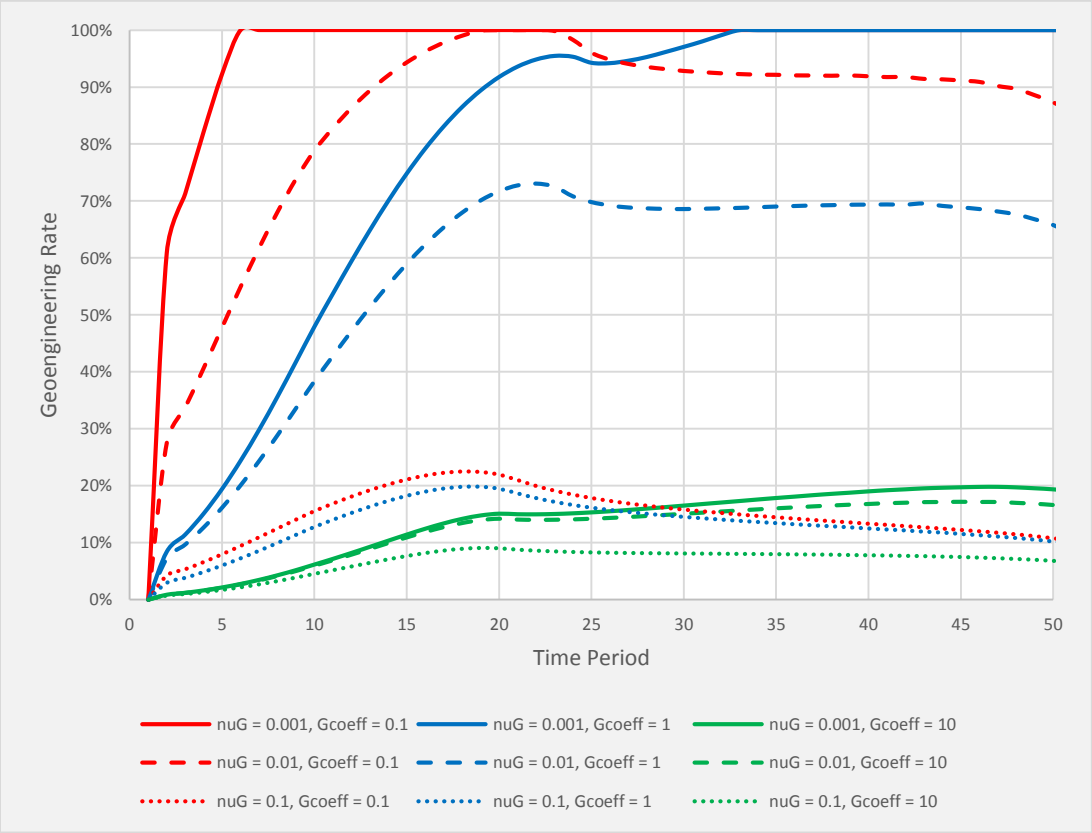
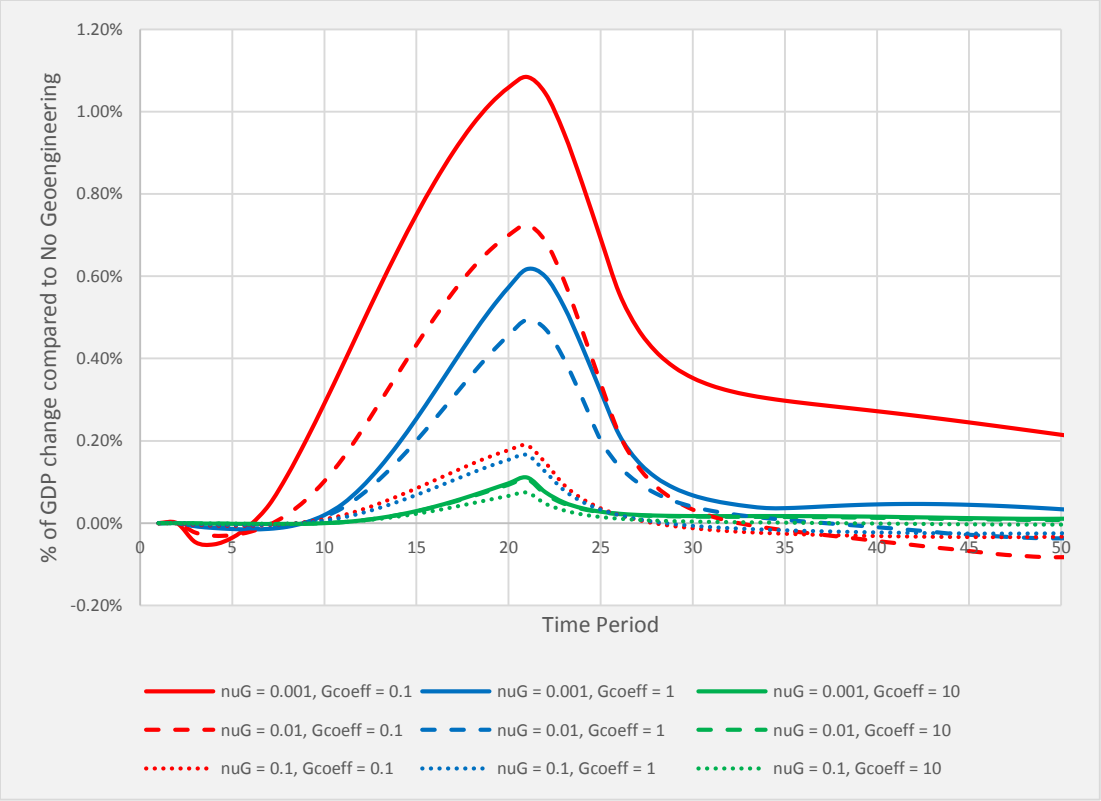


Figure 4 – Stochastic Sensitivity Analysis


100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Abatement Rate
0
5
10
15
20
25
30
35
40
45
50
Time Period
nuG = 0.001, Gcoeff = 0.1
nuG = 0.001, Gcoeff = 1
nuG = 0.001, Gcoeff = 10
nuG = 0.01, Gcoeff = 0.1
nuG = 0.01, Gcoeff = 1
nuG = 0.01, Gcoeff = 10
nuG = 0.1, Gcoeff = 0.1
nuG = 0.1, Gcoeff = 1
nuG = 0.1, Gcoeff = 10


100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Geoengineering Rate
0
5
10
15
20
25
30
35
40
45
50
Time Period
nuG = 0.001, Gcoeff = 0.1
nuG = 0.001, Gcoeff = 1
nuG = 0.001, Gcoeff = 10
nuG = 0.01, Gcoeff = 0.1
nuG = 0.01, Gcoeff = 1
nuG = 0.01, Gcoeff = 10
nuG = 0.1, Gcoeff = 0.1
nuG = 0.1, Gcoeff = 1
nuG = 0.1, Gcoeff = 10



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Appendix: Details of Static Model

In the appendix we verify that 1) the marginal cost of abatement is increasing in k_a, 2) the marginal benefit of abatement is decreasing in k_a, 3) the marginal cost of abatement is higher for a positive value of GE k_g than it is for $k_g = 0$, and 4) the marginal benefit of abatement is lower for a positive value of GE k_g than it is for $k_g = 0$. We also argue that the difference in marginal costs (3) is likely to be smaller in magnitude than the difference in marginal benefits (4).

The marginal cost of abatement as a function of abatement k_a is $f'\big(k - k_a - k_g\big)\Big(1 - d\Big(\big(1 - g(k_a)\big)k, k_g\Big)\Big)$, for some fixed k_g. The first half is increasing in k_a since f is concave. The second half is increasing in k_a since g is increasing and d is decreasing in x. Thus, marginal cost is monotone increasing.

The marginal benefit of abatement is $f\big(k - k_a - k_g\big)kg'(k_a)d_x\Big(\big(1 - g(k_a)\big)k, k_g\Big)$. Because f is increasing the first part is decreasing in k_a. Assuming that g is concave, the middle part is decreasing in k_a. Lastly, because the cross-partial derivative $d_{xk} < 0$, the third part of this expression is decreasing in k_a, and so the entire expression for marginal benefit is monotone decreasing.

The marginal cost of abatement at zero GE is $f'(k - k_a)\Big(1 - d\Big(\big(1 - g(k_a)\big)k, 0\Big)\Big)$, and for an arbitrary level of GE (for instance, k_g^{opt}) it is $f'\big(k - k_a - k_g\big)\Big(1 - d\Big(\big(1 - g(k_a)\big)k, k_g\Big)\Big)$. Because f is concave, the first part of the expression is higher for $k_g > 0$. Because $d_k < 0$, the second part of the expression is higher for $k_g > 0$. Thus, the marginal cost of abatement is higher for a positive value of GE k_g than it is for $k_g = 0$.

The marginal benefit of abatement at zero GE is $f(k - k_a)kg'(k_a)d_x\Big(\big(1 - g(k_a)\big)k, 0\Big)$, and for an arbitrary level of GE it is $f\big(k - k_a - k_g\big)kg'(k_a)d_x\Big(\big(1 - g(k_a)\big)k, k_g\Big)$. Because f is increasing,

the first part of this expression is lower for $k_g > 0$. Because $d_{xk} < 0$, the second part of the expression is lower for $k_g > 0$. Thus, the marginal benefit of abatement is lower for a positive value of GE k_g than it is for $k_g = 0$.

Lastly, we argue that the magnitude of the difference in the two marginal benefit curves is likely to be large, while the magnitude of the difference in the two marginal cost curves is likely to be small. This cannot be mathematically demonstrated like the rest of the claims in the appendix. Rather, it follows from our intuition of the application of the model. Consider first the difference in marginal costs. The first half of the expression is the difference between $f'(k - k_a)$ and $f'\big(k - k_a - k_g\big)$. This is likely to be small, because k_g is likely to be very small relative to k (i.e. only a small fraction of total capital will be spent on GE). The second difference between the two expressions is $1 - d\left(\big(1 - g(k_a)\big)k, 0\right)$ versus $1 - d\left(\big(1 - g(k_a)\big)k, k_g\right)$. This is also likely to be small because the damages from climate change as a proportion of total potential output (d) is likely to be only a few percentage points. Thus, even if the optimal level of k_g completely eliminated climate change damages ($d = 0$), the value of $1 - d$ would change only from, say, 98% to 100%.

Consider instead the differences in marginal damages. The first difference is the difference between $f(k - k_a)$ and $f\big(k - k_a - k_g\big)$, which from the argument in the previous paragraph is likely to be small since k_g is small relative to k. The other difference is the difference between $d_x\left(\big(1 - g(k_a)\big)k, 0\right)$ and $d_x\left(\big(1 - g(k_a)\big)k, k_g\right)$. This difference is likely to be large (first-order). Even though damages d may be small (a few percentage points), the difference in the marginal damages d_x may be large depending on the presence of GE. At the extreme, if k_g is sufficiently high to eliminate any damages from climate change, then $d_x\big(x, k_g\big)$ will be zero though $d_x\big(x, k_g\big)$ is positive.