Exercise #8: Climate policy and the DICE model

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Learning Goals

After completing this exercise, you should be able to

- describe what the social cost of carbon (SCC) is
- explain in broad terms what the DICE model is and how it works
- perform simple calculations with the DICE model
- describe how uncertainties in the climate sensitivity affect the present-day social cost of carbon

Introduction

As noted in the Introduction to this e-textbook, fossil fuel use creates benefits for people, but also imposes costs in the form of climate change. Burning fossil fuels releases energy and waste products including carbon dioxide and water. The energy leads to economic productivity. However, the carbon dioxide causes long-lasting temperature increases, which lead to increased risks for people in the future. Most of the impacts associated with climate change will probably be harmful for people.

Because fossil fuel users pay less than the full cost associated with their actions, emissions of carbon dioxide are larger than the economically-optimal amount. An individual fossil fuel user pays an amount of money per unit of energy that represents the cost of extraction, processing (for example, gasoline is a highly processed derivative of oil), transportation, and profits, plus taxes and minus any subsidies. This cost does not reflect the increased risks to future people associated with climate change. Because people respond to price signals, they tend to consume more fossil fuel than they would if the price reflected the full cost to society of fossil fuel consumption (and were therefore higher).

The social cost of carbon (SCC) is the increase in climate-related damages caused by emitting an additional ton of CO_2 to the atmosphere (Nordhaus, 2013). In other words, if we were to emit one ton of CO_2 today, the SCC would be the sum of the negative impacts caused by that additional ton of CO_2, from now into the distant future. The future damages from carbon dioxide emissions are typically discounted in calculating the SCC; see Exercise 4 for a brief discussion of discounting. In 2010, the US Environmental Protection Agency estimated a value for the SCC of about \$21/t CO_2 (Interagency Working Group on Social Cost of Carbon, 2010, 2013; Johnson and Hope, 2012).

The Dynamic Integrated model of Climate and the Economy (DICE; Nordhaus, 2013; Nordhaus and Sztorc, 2013) includes the feedbacks between the climate system and the economy that are needed for estimating the SCC. As discussed previously, greenhouse gas emissions cause temperature increases, which cause climate-related damages to the economy. These damages can then motivate the development of policies and technologies that reduce emissions and possibly remove greenhouse gases from the atmosphere. A model like DICE that "closes the loop" between climate change and further emissions is necessary for accurate estimation of future damages and therefore the SCC. DICE is one of three models used by the EPA to estimate the social cost of carbon.

DICE is commonly used to identify optimal climate policies, sometimes subject to different constraints. When run in optimization mode, DICE maximizes a "utility function" that includes discounting as well as the declining marginal benefit of additional consumption. That is, rich societies benefit less from an additional dollar of income than poor ones.

However, before DICE can be optimized, some assumptions have to be made about the climate sensitivity, among other parameters. As we saw in the Introduction, the climate sensitivity represents the amount by which global mean air temperatures would increase if carbon dioxide concentrations in the atmosphere were to double. Although many studies have estimated the climate sensitivity, this parameter remains deeply uncertain.

In this exercise, we use DICE to investigate how different climate and economic variables might change in the future under an optimized climate policy, plus how different values of the climate sensitivity affect the present value of the SCC.

An important note

Carrying out this exercise will not prepare you to estimate the social cost of carbon for publication in scientific journals or for use in policy applications. The presentation of the material in this exercise has been simplified for pedagogical reasons, and this material should only be applied to "real" problems after additional training. The authors and editors of this e-textbook specifically disclaim any liability for damages associated with the use of the material presented in this exercise.

Tutorial

The version of the DICE model that we use here was translated to R by Greg Garner from an original version in the GAMS language provided by Bill Nordhaus. The `dice.R` file contains the following useful functions (among others):

- `dice.new()`: creating a new instance of the DICE model with a prechosen set of parameters
- `dice.modify()`: changing the value of model parameters in DICE
- `dice.run()`: running the DICE model into the future using a given set of parameters
- `dice.solve()`: identifying an optimal trajectory using the utility function sketched above

Open `lab8_sample.R` in RStudio and examine the code that it contains. The following lines of code explain who wrote the code, describe what the code does, `source()`s the file containing the DICE model, and loads the DICE model into memory using the `dice.new()` function.

```r
# lab8_done.R
# Patrick Applegate, patrick.applegate@psu.edu; Greg Garner, ggg121@psu.edu
#
# Optimizes the DICE model to produce a plausible climate-economic trajectory
# and performs a Monte Carlo experiment to evaluate the effects of uncertainty
# in the climate sensitivity on the present-day social cost of carbon.

# Mise en place.
rm(list = ls())
graphics.off()

# Load the DICE model.
source('dice.R')

# Create a new DICE object.
my.dice <- dice.new()
```

Next, we optimize the DICE model using the utility function described in the Introduction and pull some time-dependent output out of the object that results.

```r
# Solve the DICE object for the optimal control policy.
# NOTE: THIS STEP MAY TAKE A COUPLE OF MINUTES!
dice.solve(my.dice)

# Set sensible names for the time-dependent variables to extract from DICE.
names <- c('Time (yr)',
           'Emissions (Gt CO_2/yr)',
           'Atmospheric [CO_2] (ppm)',
           'Global mean T anomaly (C)',
           'Climate damages (10^12 $)',
           'Social cost of carbon ($/t CO_2)')

# Make a place to store time-dependent output from optimized DICE.
opt.output <- matrix(data = NA, nrow = length(my.dice$year), ncol = 6)
colnames(opt.output) <- names

# Put the time.dependent output from optimized DICE into opt.output.
opt.output[, 1] <- my.dice$year
opt.output[, 2] <- my.dice$e
opt.output[, 3] <- my.dice$mat
opt.output[, 4] <- my.dice$tatm
opt.output[, 5] <- my.dice$damages
opt.output[, 6] <- my.dice$scc
```

The script also makes a plot of the time-dependent output.

```r
# Plot the time-dependent output from the optimized DICE object.
pdf('lab8_plot1.pdf', width = 5, height = 8.5)
par(mfrow = c(5, 1))
plot(opt.output[, 1], opt.output[, 2], type = 'l', bty = 'n', xlab = names[1],
     ylab = names[2])
plot(opt.output[, 1], opt.output[, 3], type = 'l', bty = 'n', xlab = names[1],
     ylab = names[3])
plot(opt.output[, 1], opt.output[, 4], type = 'l', bty = 'n', xlab = names[1],
     ylab = names[4])
plot(opt.output[, 1], opt.output[, 5], type = 'l', bty = 'n', xlab = names[1],
     ylab = names[5])
plot(opt.output[, 1], opt.output[, 6], type = 'l', bty = 'n', xlab = names[1],
     ylab = names[6])
dev.off()
```

Running DICE in optimization mode and examining its time-varying output

If you haven't already done so, download the .zip file containing the scripts associated with this book from www.scrimhub.org/raes. Put the file `lab8_sample.R` in an empty directory. Execute `lab8_sample.R` using the `source()` command or button (remember to set your working directory first), and look at the `.pdf` file that results. It should look like Figure 1.

The script also prints out the assumed climate sensitivity value and the present-day social cost of carbon (`opt.scc <- opt.output[1, 6]`) obtained using the optimization.

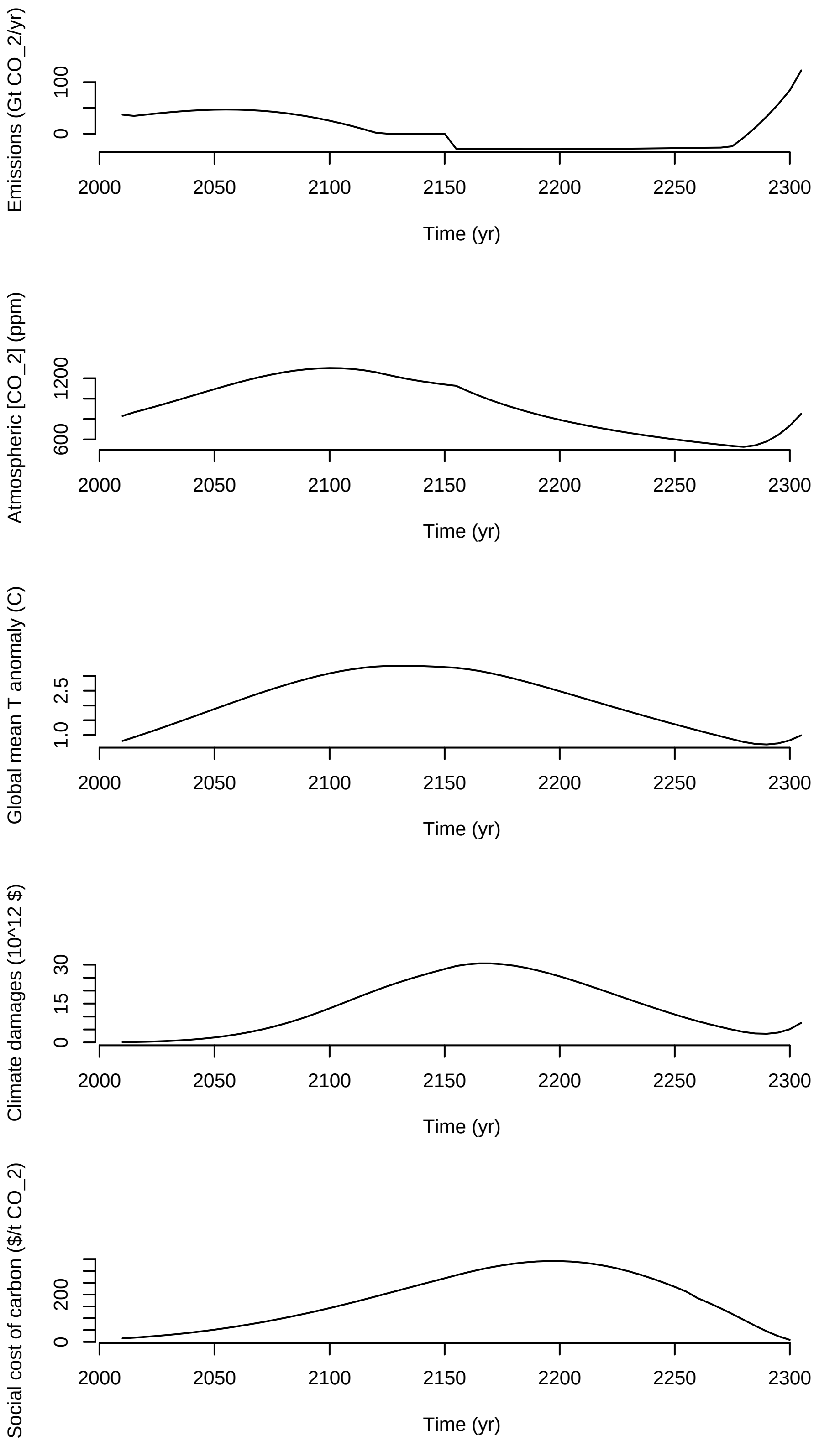

Figure 1: Time-dependent output from the optimized DICE model using the built-in parameter set. See text for discussion.

```
# Also extract the preset climate sensitivity and social cost of carbon
# from the DICE object.
opt.t2xCO$_2$ <- my.dice$t2xCO$_2$
opt.scc <- opt.output[1, 6]

# Print some key quantities.
print(sprintf('The assumed climate sensitivity for optimization is %2.2f C/doubling',
              opt.t2xCO$_2$))
print(sprintf('The optimized social cost of carbon in %d is $%4.2f/t CO_2',
              opt.output[1, 1], opt.scc))
```

Several interesting observations come out of Figure 1:

1. Each model curve bends sharply upward in the last few decades.
2. Ignoring the last few decades of model results, the peak of each curve is lagged in time relative to the peak of the preceding curve; so, peak temperatures occur after peak carbon dioxide concentrations, which occur after peak emissions.
3. The social cost of carbon is not constant; it starts out relatively small and grows over time until about 2200, when it begins to decline again.

We can ignore the last few decades of each time series shown in Figure 1. The DICE model assumes, in effect, that the world ends shortly after 2300 and that this apocalypse is known in advance, so that the people of the world start burning fossil fuels again.

The lags between the peaks in each curve happen for the following reasons.

- The atmospheric CO_2 concentration continues to increase after maximum net CO_2 emissions because the rate at which CO_2 is removed from the atmosphere is still smaller than the rate of release. Once net CO_2 emissions balance with the rate of CO_2 removal from the atmosphere, the atmospheric CO_2 peaks and subsequently declines as the net CO_2 emissions continue to drop.
- The atmospheric temperature peaks later than the atmospheric CO_2 due to the way energy (in the form of heat) is moved between the atmosphere and the ocean. Although the atmosphere responds quickly to additional forcing, the oceans are slow to remove the heat from the atmosphere. The peak in atmospheric temperature occurs when the ocean heat uptake balances the radiative forcing produced by the level of CO_2 in the atmosphere.
- The climate damages are a function of atmospheric temperature and gross world product. Once atmospheric temperatures begin to decrease, the damages as a fraction of the gross world product decreases; however, the gross world product is constantly increasing over time, and this continued increase results in the delayed peak in climate damages.
- As discussed earlier, the social cost of carbon represents the sum of future climate damages from the emission of a single ton of CO_2. Because the model assumes that the world ends shortly after 2300, the future damages due to a unit increase in CO_2 emissions decline as the model simulation approaches the end of the simulation period. As a result, the social cost of carbon first increases, then decreases.

Accounting for uncertainty in the climate sensitivity

DICE assumes a climate sensitivity value of 2.9 C per doubling of CO_2 concentration in the atmosphere. Although this value is reasonable, it doesn't capture our uncertainty in the actual value of the climate sensitivity. If we were to change this parameter within reasonable limits, we would get different climate and economic trajectories (Fig. 1), and a different present-day value for the social cost of carbon.

We could account for the effects of uncertainty in the climate sensitivity on present-day social cost of carbon values by performing a Monte Carlo experiment; however, we would first need a well-defined distribution for the climate sensitivity. We could then run DICE repeatedly with climate sensitivity values sampled from this distribution and examine the distribution of present-day social cost of carbon values that came out.

One *approximate* method involves matching a lognormal distribution to the probabilistic statements of the Intergovernmental Panel on Climate Change on climate sensitivity. The lognormal distribution is only defined for positive values, and is therefore appropriate for variables like climate sensitivity that can't be negative. The latest IPCC report says, "Equilibrium climate sensitivity is... extremely unlikely less than 1°C... and very unlikely greater than 6°C..." (Alexander et al., 2013). Mastrandrea et al. (2010, their Table 1) suggest that "extremely unlikely" corresponds to a likelihood of 0-5%, and "very unlikely" corresponds to a likelihood of 0-10%.

The following code block accomplishes this matching, assuming the largest likelihood values for "extremely unlikely" and "very unlikely" (5% and 10%, respectively). It also generates a vector of random values from the resulting distribution.

```
# Set some values.
xs <- c(1, 6)       # climate sensitivities corresponding to the probabilities
                    # in ps
ps <- c(0.05, (1- 0.1))
                    # (approximate) probabilities of the climate sensitivity
                    # being less than xs[1] or greater than xs[2], according
                    # to IPCC AR5 WG1
n.trials <- 300     # number of Monte Carlo trials

# Define a function for matching the lognormal distribution to two (or more)
# tie points.
lnorm.rmse <- function(dist.params, xs, ps) {
  # dist.params, vector of meanlog and sdlog values;
  # see help(dlnorm)
  # xs, vector of values of the distributed variable to match
  # ps, probabilities of the values in xs
  logmu <- dist.params[1]
  logsigma <- dist.params[2]
  trial.xs <- qlnorm(ps, logmu, logsigma)
  rmse <- sqrt(mean((xs- trial.xs)^ 2))
  return(rmse)
}

# Identify the parameters of the lognormal distribution that produce the best
# match to the IPCC's statements about climate sensitivity.
lnorm.optim <- optim(log(c(2.9, 1.5)), lnorm.rmse, gr = NULL, xs = xs, ps = ps,
                     method = 'L-BFGS-B', lower = c(0, 0), upper = c(Inf, Inf))

# Generate a vector of climate sensitivity values.
set.seed(1)
tx2CO$_2$s <- rlnorm(n.trials, meanlog = lnorm.optim$par[1],
                  sdlog = lnorm.optim$par[2])
```

Exercise

Make a copy of `lab8_sample.R` by saving it under a different file name. Modify this copy so that it performs the Monte Carlo experiment described above using a `for` loop, with `n.trials <- 300` samples. For each value in `tx2CO$_2$s`, you'll need to

1. set the value of climate sensitivity in DICE using `dice.modify(my.dice, "t2xCO$_2$", tx2CO$_2$s[i])`
2. run the DICE model using `dice.run(my.dice)`
3. extract the 2010 value of the social cost of carbon from the DICE object and store it in the `i`th element of a vector `sccs`

Your modified script should make a plot with two panels. The top panel should show the distribution of climate sensitivity values based on fitting a lognormal distribution to the IPCC's probabilistic statement, with a vertical line to show DICE's default climate sensitivity value. The bottom panel should show the distribution of present-day social cost of carbon values that you obtained from your Monte Carlo experiment, with vertical lines showing the mean of these values and the social cost of carbon value from optimizing DICE with the default parameter values.

Questions

1. The mean social cost of carbon from your Monte Carlo experiment reflects an estimate of the social cost of carbon given our remaining uncertainty in climate sensitivity. Is this value higher or lower than the social cost of carbon value from optimizing DICE with the base parameters? How much higher or lower is it? Express your answer as a percentage.
2. How sensitive is your answer to question 1 to the likelihoods you assign to "extremely unlikely" and "very unlikely," given the likelihood ranges specified for these terms by Mastrandrea et al (2010, their Table 1)? Does one bound have more of an effect on the mean social cost of carbon from your Monte Carlo experiments than the other?
3. If we are uncertain about the actual value of climate sensitivity, should we spend more or less money on reducing carbon dioxide emissions now, compared to a case in which we are sure about the value of climate sensitivity? Justify your answer based on your responses to questions 1 and 2.

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