A Policy Projection Dilemma: Finding the Optimal Discount Rate for Global Carbon Emissions Scenarios

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ABSTRACT

The DICE model, constructed by William Nordhaus, is a global carbon emissions projection model that integrates economics, carbon cycle, climate science and damage in an IAM (Integrated Assessment Model). Although there is no consensus about the discount rate (pure rate of time preference) of IAM, determining the optimal discount rate would be a crucial step in feasible carbon emissions cost-benefit analyses. I adapted 2013 version of Dynamic Integrated Climate Economy Model (DICE) in order to: 1) project global carbon emissions from 2010~2100; 2) assess damage costs as the result of carbon emissions; 3) calculate the social cost of carbon from marginal damage costs; 4) optimize discount rate by superimposing with Representative Concentration Pathways (RCP) 4.5 scenario 5) find the optimized emission control rate and finally, 6) conduct cost-benefit analysis to determine if the optimal discount rate passes the test. I found that the optimal emission control rate increases as pure rate of time preference (PRTP) decreases. As a result, the global temperature increase from pre-industrial level over time is greater for higher PRTP scenario than the lower ones do. The cost- benefit analysis demonstrated that the optimal PRTP was 3%. A small change in PRTP significantly changed the global emission control rate and temperature increase. I conclude that determining the optimized PRTP is an important step in constructing an accurate and financially feasible global carbon emission projection model.

KEYWORDS

DICE model, climate change economics, global temperature, emission control rate projections, pure rate of time preference (PTRP)

INTRODUCTION

Global climate change due to anthropogenic carbon emissions has already had significant effect on the environment. The global temperature is expected to rise by 2.5 ℃ by 2100 (IPCC 2013). In response to the rapidly changing global climate, governments are setting emission reduction targets by 2050 as Intended Nationally Determined Contributions (INDC) in United Nations Framework Convention on Climate Change (UNFCCC). The major challenge in determining global level emission target is assessing the effect of carbon emissions on global temperature increase. Oftentimes, carbon emissions are greatly related to economic growth and welfare of the population. Many empirical researches found strong correlation between amount of carbon emissions and economic growth rate/GDP of a nation (Ansuategi and Escapa 2002). China for example, had the largest increase in carbon emissions in the last 20 years because the economic growth rate and population grew rapidly. Most of economic growth was the result of fossil fuel consumption. Thus, aggressively reducing the greenhouse gas emissions implies slowing of economic growth in carbon-intensive nations (Netherlands Environmental Assessment Agency 2016). Certainly, the economic component plays a large role in emissions targets. Thus, an integrated climate model that factors both climate science and economic component is necessary to determine global emissions target.

Dynamic Integrated Climate-Economy (DICE) model incorporates economics, carbon cycle, climate science and impacts in a highly aggregated model that allows a weighing of the costs and benefits of a specific emission target (Newbold 2010). The model can 1) project the effect of carbon emissions on global temperature increase 2) find optimized welfare function 3) determine optimal emission control rate and 4) conduct cost-benefit analysis of a climate policy with a specific emission target. The major components of DICE includes: 1) carbon cycle model 2) economic model 3) welfare function and 4) radiative forcing model. By integrating various quantified components of climate science with economic model, policy makers can estimate the optimal emission target scheme, which is financially feasible and environmentally friendly.

Focusing on the economic component of DICE model, welfare function is one of the most significant factors in cost-benefit analysis, which weighs the abatement cost and benefits of reducing carbon emissions in terms of dollar value. In this study, I tried optimize the discount rate in welfare function. Welfare function is a component of DICE model that determines happiness of population. From purely economists' perspective, I assumed more consumption (more money) leads to more happiness. Thus, the ranks of social states directly correlate with more consumption (Amartya 1970). The main objective of my study is finding the optimal welfare function and determining emission control rate.

Emissions control rate is the fraction of emissions that are reduced or controlled by a climate change policy. For example, if a climate change policy limits emissions to 80% of business as usual cases, the control rate is 20% (University of Chicago). Business as usual scenario is where there are no controls on emissions of CO2, or the emissions control rate is zero. When a carbon emissions climate policy mandates a certain emissions reduction, The DICE or (Integrated Assessment Model) IAM interprets emission control rate and converts to economic costs/benefits.

In addition to emissions control rate, discount rate is an important component in welfare function. To determine how much we should spend to mitigate climate change, economists need to consider the upfront costs and future costs. The discount rate is used to determine the present value of future cash flows (Rehmeyer 2010). Because the future cost is valued differently than present upfront costs, discount rates factor in the opportunity cost of saving money in the future and total value of all future cash flows (both inflowing and outflowing) (Wall Street Oasis 2017). There are two different types of discount rates, constant and pure rate of time preference (ptrp). Constant discounting rate depreciates future value of the money at a constant rate. Pure rate of time preference incorporates Ramsey discounting, which factors in welfare function (Anthoff 2016).

METHODS

Part 1: Modeling a climate dynamics model

The input (or *forcing*) to the climate dynamics model was yearly atmospheric CO_2 concentrations, measured in ppm. The output of the climate dynamics model was the yearly average temperature increase over pre-industrial temperatures in °C. The forcing to the climate dynamics model was provided in the pre existing Excel file from Dr. Anthoff. The model ran in yearly time steps, and will start in the year 2010 and run to the year 2100 (Anthoff 2016).

Climate Dynamics Model

The climate dynamics model I built has two parts: the first part computed how much extra energy is warming the atmosphere due to climate change and what the long term temperature effect of that extra energy would be. The second part computed the predicted yearly global average temperature increase over time. ${rf_t}^{Co2}$ is the amount of extra energy caused by rising CO2 concentrations (W/m^2). The equation to compute ${rf_t}^{Co2}$ is:

$$ {rf_t}^{Co2} = 5.35 ln \frac{C_t}{C_{pre}} $$

C_t is the atmospheric CO2 concentrations at point t in ppm. C_{pre} is the pre-industrial level of atmospheric CO2 concentrations. Other greenhouse gases also causes global warming by increasing radiative forcing. I integrated the forcing caused by other greenhouse gases as a forcing that was supplied to me as part of this baseline data sheet (Anthoff 2016). I referred the radiative forcing of other greenhouse gases as rf^{other}. The total effect of global warming with all radiative forcing was computed as:

$$ rf_t = {rf_t}^{CO2} + {rf_t}^{other} $$

The next step in the model was to compute the warming that would occur if a given level of radiative forcing lasted for a long period of time. The equation is:

$$ {T_t}^e = \lambda \times rf_t $$

${T_t}^e$ is the increase in global average surface temperature over pre-industrial levels if the radiative forcing of rf_t were to be held constant for a very long time. λ is the climate sensitivity, which was set to 0.8 (Rahmstorf 2008).

The final step was to compute the actual temperature for each time step. I used a very simple delay formulation. I assumed that the actual temperature would warm by a very small fraction of this computed difference. The equation for this process is:

$$ T_t = T_{t-1} + \mu({T_t}^e - T_{t-1}) $$

T_t is the global average temperature increase above pre- industrial times in °C at time t. μ is the parameter that controls the delay of the warming, which is 1/60 (Rahmstorf 2008).

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Part 2: Carbon cycle model

I built a carbon cycle model and coupled it with the previously built climate dynamics model. The inputs to the carbon cycle model were yearly emissions of CO2, measured in Mt C. The output of the carbon cycle model was atmospheric concentrations of CO2, measured in ppm. The two components are coupled via the atmospheric concentration of CO2, i.e. the output of the carbon cycle model is an input to the climate dynamics model. I found the excel data file for the forcing to the carbon cycle model (IPCC 2009).

The carbon cycle model consisted of a simple five-box model. Over time, each individual box reduces CO2 at different rates. On the other hand, the boxes account for new anthropogenic CO2 emissions for each year into the atmosphere. In the five-box model, the fixed shares of the five boxes were: 13% percent went into the first box, 20% into the second, 32% into the third, 25% into the fourth and the remaining 10% into the fifth box (Anthoff 2016).

The five variables represented the five boxes and each of these variables took on a different value in each year. The equation that was used to compute the amount of CO2 in box i (which took values from 1 to 5) at time t (which takes on value from 2010 to 2100) was:

$$Box_{i,t} = a_i \times box_{i,t-1} + \gamma_i \beta E_t$$

$Box_{i,t}$ was the amount of CO2 in box i at time t, measured in ppm. α_i was the share of CO2 in box i that stayed in the atmosphere until the next time period (so $1 - \alpha_i$ is the share of CO2 that disappears each year from box i). γ_i was the share of emissions that went into box i. β was a unit conversion factor: CO2 emissions in our model were measured in Mt C, but atmospheric CO2 concentrations were measured in ppm; β converted from the unit Mt C to CO2 ppm. E_t were world total emissions of CO2 in year t, measured in Mt C. I used initial values for each of the five boxes that are provided below as $Box_{i,2010}$ (Tol 2014). The final step in the carbon cycle model was to compute atmospheric CO2 concentrations at each point in time:

$$C_t = \sum_{i=1}^{5} Box_{i,t} = Box_{1,t} + Box_{2,t} + Box_{3,t} + Box_{4,t} + Box_{5,t}$$

C_t is the atmospheric concentration of CO2 at time t, was simply the sum of the five boxes at that time.

Part 2-1: Coupling

To couple the climate dynamics model with the carbon cycle model, I replaced the values in the row that had the CO2 concentration forcing in the climate dynamics model with a formula that references the output from the carbon cycle model.

Part 3: Emissions model

I added a component that computes anthropogenic CO2 emissions over time to the previously built model. I coupled the carbon cycle component to the emissions component. The new component will rely on the emissions component, which had Kaya identity:

$$E_{t,kaya} = P_t(\frac{Y_t}{P_t})(\frac{Energy,t}{Y_t})(\frac{E_{t,kaya}}{Energy,t})$$

E_t^{KAYA} was industrial CO2 emissions in Mt C at time t, P_t was population at time t, Y_t was output (or GDP or income) at time t and $Energy_t$ was energy use in EJ (exajoule) at time t (IPCC 2013). The forcing for population was provided as the initial level for 2010, and then yearly growth rates of population for all future years. The initial population level for 2010 was 6900 million people. Growth rate was given as well (IPCC 2013). The initial level of per capita income in 2010 was 8.5 thousand dollars per capita. For later years I needed to compute the levels from the yearly growth rate of per capita income that was provided as a forcing (IPCC 2013). The initial level of energy intensity for the year 2010 is 5.98 EJ per trillion $ of output. For years later than 2010, the yearly growth rates of energy intensity were given (IPCC 2013). The initial level of carbon intensity was 18.62 Mt C per EJ of energy for the year 2010 (IPCC 2013). I needed to use the growth rate of emission intensity provided as a forcing to compute the carbon intensity for future years.

At this point I computed emissions from industrial activities in business as usual scenarios. Another source of anthropogenic CO2 emissions that I included as an extra forcing

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was land use emissionsE^L. This category mostly covered extra emissions caused by deforestation (IPCC 2013). Total business as usual (BAU) emissions were therefore given as:

$$E_t{}^{BAU} = E_t{}^{kaya} + E_t{}^{L}$$

Part 3-1: Coupling

Finally, I coupled the carbon cycle component with the emissions component. Instead of using a forcing for the carbon cycle, I coupled with the emissions computed in the emissions component.

Part 4: Emission Reduction Option

To model 'Emission Reduction Option', I added a choice variable: the emission control rate. The emission control rate computed the amount of CO2 emissions per year we need to reduce. For business as usual scenario, I initially set the control rate to 0% (i.e. no climate policy). Later in **part 8**, I returned and adjusted emission control rate using excel optimization software. Meanwhile, I designated the emission control rate, μ_t. The new final equation for emissions therefore was:

$$E_t = (1 - \mu_t) E_t{}^{BAU}$$

Now I coupled the carbon cycle model to this new variable E_t. To calculate the size of this burden, also called abatement cost, I used a simple cost function:

$$\Lambda_t = \beta_{1,t} \mu_t{}^{\beta 2}$$

Λ_t was the cost of climate policy at time t as a share of GDP at the time t, $\beta_{1,t}$ was a parameter that changes over time and β_2 is another parameter that was set to 2.8. I added another row for the variable Λ_t to your model. Finally, in addition to Λ_t, I added one more variable to the Excel sheet that computed the cost of climate policy in trillion dollars for each year (Nordhaus 2013).

Part 5: Growth Model

I added a component that computes economic growth to the previous model. The new growth component computed output, or GDP, which was an input into the emissions component. The new growth component required an exogenous forcing (Anthoff 2016).

I built a Solow-growth model that computes GDP. Output in a specific year was computed by a production function in the Solow model that depended on three things: the amount of capital (in dollars), the amount of labor (population size) and a technology index or total factor productivity, which measured how efficient we use capital and labor to produce GDP. I used a Cobb-Douglas production function and had the following form:

$$Y_t{}^G = A_t K_t{}^\alpha P_t{}^{1-\alpha}$$

Y_t^G was gross output in trillion dollars. A_t was the total factor productivity. K_t was the amount of capital at time t available for production, measured in trillion dollars. P_t was population in million at time t, and α was called the capital share, set to 0.3 (Nordhaus 2013). Gross output did not account for the cost of climate policy. The equation for net output included abatement costs and was given as:

$$Y_t = (1 - \Lambda_t) Y_t{}^G$$

So the equation picked up the effect of the control variable from the emission abatement component I added in the previous section.

When modeling the capital stock I assumed that there was an inflow of new capital (i.e. new industrial complex and machines) and that some capital breaks over time, so there was an outflow of capital, which was sunk cost. The equation of motion for the capital stock was given as:

$$K_t = (1 - \delta) K_{t-1} + I_{t-1}$$

δ was called the depreciation rate of capital and was set to 10% per year (so the value would be 0.1). I_t was the investment rate. The initial value was 139.65 trillion dollars (Nordhaus 2013).

The amount of new investment into capital for year t was modeled as:

$$I_t = s Y_t$$

s was called the savings rate, and was fixed to 22% (Anthoff 2016).

Part 5-1: Coupling

I coupled the emissions component with the growth component. First, I modified the equation for the Kaya identity. GDP entered the Kaya identity via output per capita, the second factor in the Kaya identity. The Kaya identity in our model told us how much emission there would be if no climate policy were in place. Therefore, I linked the Kaya identity to gross output from the growth model. I made sure to convert gross output into gross output per capita in order to be consistent with units. Finally, since variables in abatement cost model depends on GDP, and coupled this with gross output from the growth model.

Part 6: Impact Model

I added a component for the impacts of climate change to the model. I modified the growth model to account for the estimate of climate impacts. We assumed that the damage done from rising temperatures in a given year as a share of gross output was:

$$D_t = \psi {T_t}^2$$

So D_t is damage as a share of gross output in GDP at year t, ψ is a parameter set to 0.003 and T_t was global average temperature in °C above pre-industrial levels at time t (Nordhaus 2013). I coupled with the temperature from the climate dynamics component.

Part 6-1: Growth Model

To close the loop, I linked the equation for net output in the growth model to account for the costs of abatement from gross output and the damages from climate change. Then I added two new variables: consumption (in trillion dollar) and per capita consumption (in dollar per person). The equation for consumption was gross output minus the costs of abatement, the damages from climate change and investment in the capital stock. To compute per capita consumption I divided consumption by population (Nordhaus 2013).

Part 7: Social Cost of Carbon

Social cost of carbon (SCC) was the net present value of the impact caused by an extra emission of 1 ton of carbon today (IPCC 2013). To compute the SCC, first, I set up a base run at year t, which was identical to the previous model setup. In the second there was an additional emission of 1 ton of carbon into the atmosphere in the year t+1. As a result of extra ton carbon, the marginal run would have slightly more warming, and that would cause slightly larger damages from climate change.

Then I computed the difference in damages between the base and marginal run for each year in dollars. This was marginal damages-a time series of additional damages caused by one additional ton of carbon emitted today (Anthoff 2016).

The next step was to compute the net present value of marginal damages. I multiplied the marginal damages in each year with the discount factor for that year. This gave me a new time series of the net present value of marginal damages (Goulder and Williams 2012). The final step was to add up the net present value estimates of marginal damages over time. This gave me the Social Cost of Carbon (SCC).

Part 7-1: Discount Factor

I used discount factors that are parameterized on a constant discount rate. The equation for these discount factors is:

$$DF_t = \frac{1}{(1+r)^t}$$

Here DF_t was the discount factor for time step t. t = 0 corresponded to the year 2010, t = 1 to 2011 and so on. r was the discount rate and you should initially set it to 3% and was adjusted in the latter cost-benefit analysis (Goulder and Williams 2012).

Part 8: Welfare function

I computed the optimal climate policy trajectory over time. First, I added a welfare function to the model. Second, I installed a numerical optimization package from Excel and 3) I ran this numerical optimization package to find the optimal policies for a variety of different ptrp discount rate cases.

To calculate the overall social welfare for a given policy, I used the welfare function:

$$SWF = \sum_{t=0}^{T} P_t lnC_t(\frac{1}{1+\rho})^t$$

P_t was the population size at time t (in million people) and c_t was per capita consumption at time t (in $/capita). I coupled these two variables from the previous economics model. ρ was the pure rate of time preference, and T was the time horizon of my model.

Part 8-1: Preparing the model

Previously constructed model could set a different mitigation level (emission control rate) for each year of our analysis. This amounted to 291 decision variables for each corresponding year time span of the model. In order to find the best value for each of these decision variables, I used the numerical optimization package. Because of the limited computing power, I divided 291 variables into 10 decision variables with each variable's life span of a decade.

The first 9 of these stood for the emission control rates for each of the first 9 decades of our model (a decade increments like 2010~2019 up to 2100). The tenth decision variable was the emission control rate for the years 2100-2300.

I first created a new row in your Excel sheet that holds these 10 new decision variables. I left these variables blank so the solver can find values that maximize the welfare function. The existing row for the emission control rate needed to reference the correct cells in this new row. For example, the ten cells for the emission control rate in the years 2010-2019 should all reference the same one cell in the new row that stands for the decision in the year 2010-2019 (Anthoff 2016).

Next, I enabled the numerical optimization package in excel. I followed the general instructions from Wabash College's Introductory Econometrics lecture.

Here was how to enable it in Excel 2010 for Windows:

Click on File->Options->Add-Ins

Make sure “Excel Add-ins” is selected in the “Manage” field

Click “Go…”

Select “Solver Add-in”

Click “Ok.”

Here is how you can enable it in Excel 2011 for Mac:

Click on Tools -> Add-Ins...

Make sure the box is checked for “Solver.Xlam” in the “Add-Ins available” field

Click “Ok”

This adds an item “Solver” under Data->Analysis in the main Excel window, and you can start Solver clicking on that new item (Wabash College 2010).

Next, I told Solver what cell it should try to maximize, and which cells it can modify in order to find the best combination of values for the decision variables. I started Solver, and then selected the cell with the value for your social welfare function for the “Set Objective” field. Next, I selected the range of your ten new decision variables for the field “By changing variable cells”. At this point Solver tried to find the combination of values that gives the highest value for the cell that I selected as the objective (in this case gives the highest social welfare) (Tol 2014).

Before I ran Solver, I had to make sure if the range of values that makes sense for the decision variables. In our case the decision variables were emission control rates that can take values from 0 to 1 (i.e. 0% to 100%). Since I didn’t want emission control rate to be out of these range, configured that by setting up constraints in Solver. I added two separate constraints, one that said the decision variable always had to be greater or equal to 0, and one that says it always had to be smaller or equal to 1. I added two constraints by clicking the “Add” button. In cell reference, I selected the same cells as the decision variables, then I selected the correct condition (i.e. >= for the first and <= for the second constraint) and finally in the field constraint I added either 0 for the first and 1 for the second constraint. The both constraints were listed in the main window of Solver in the field “Subject to the Constraints”. Finally, I set the solve method to “Evolutionary” and then closed Solver’s windows (Tol 2014).

Part 8-2: Run the optimization package

I found the optimal emission control rate for each policy with three different specifications of the pure rate of time preference. I created three copies of the base model sheet so that each copy could hold the optimal policy for one of the pure rate of time preferences. The three rates were ptrp 0.1%, 1% and 3%.

For each sheet, I ran Solver. The solver generated the 10 decision variable cells to the values that maximize the welfare function.

The final step was to create two graphs that compared the optimal policies for the three pure rates of time preferences. The first graph compared the emission control rate over time for the three discount rates. The second graph compared the temperature trajectories for the three discount rates over.

Results: I found that emission control rate over time for ptrp .1% scenario was larger than ptrp 1% or 3% scenario. The optimal emission control rate increases as ptrp percentage decreases (Figure 2.1).

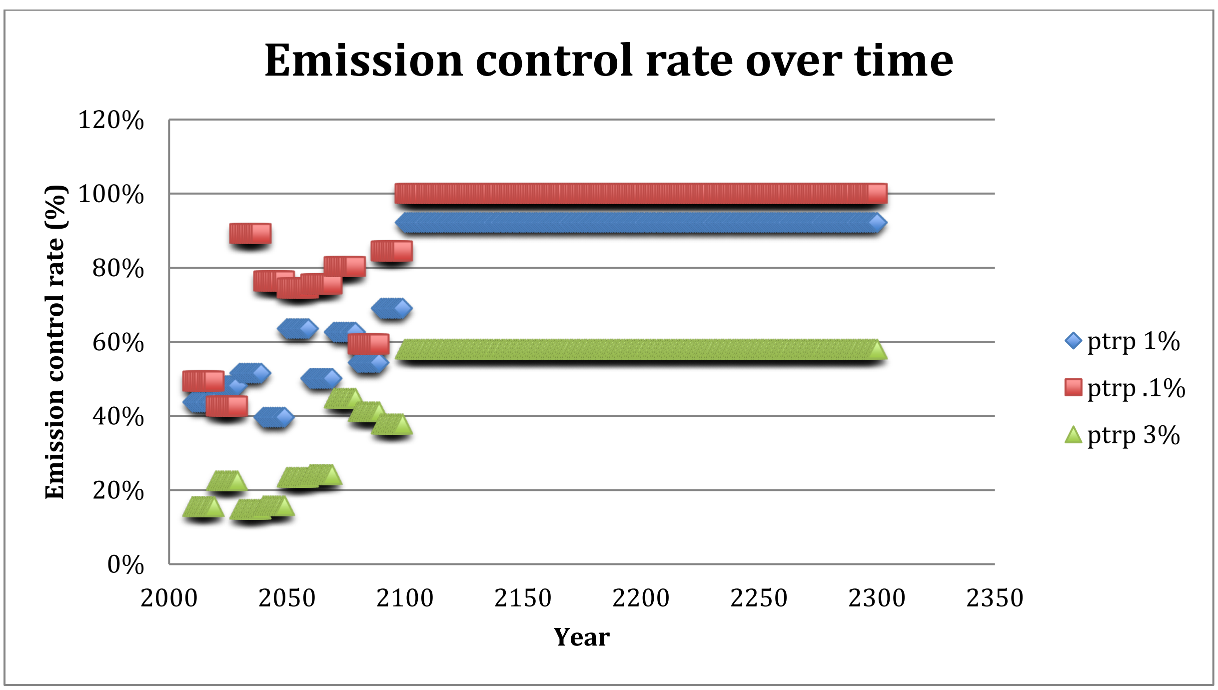

Figure 2.1. The comparison of the effect of optimized ptrp scenarios on emission control rate over time.

Results: I found that temperature increase from pre-industrial level over time is greater for higher ptrp scenario than the lower ones do (Figure 2.2)

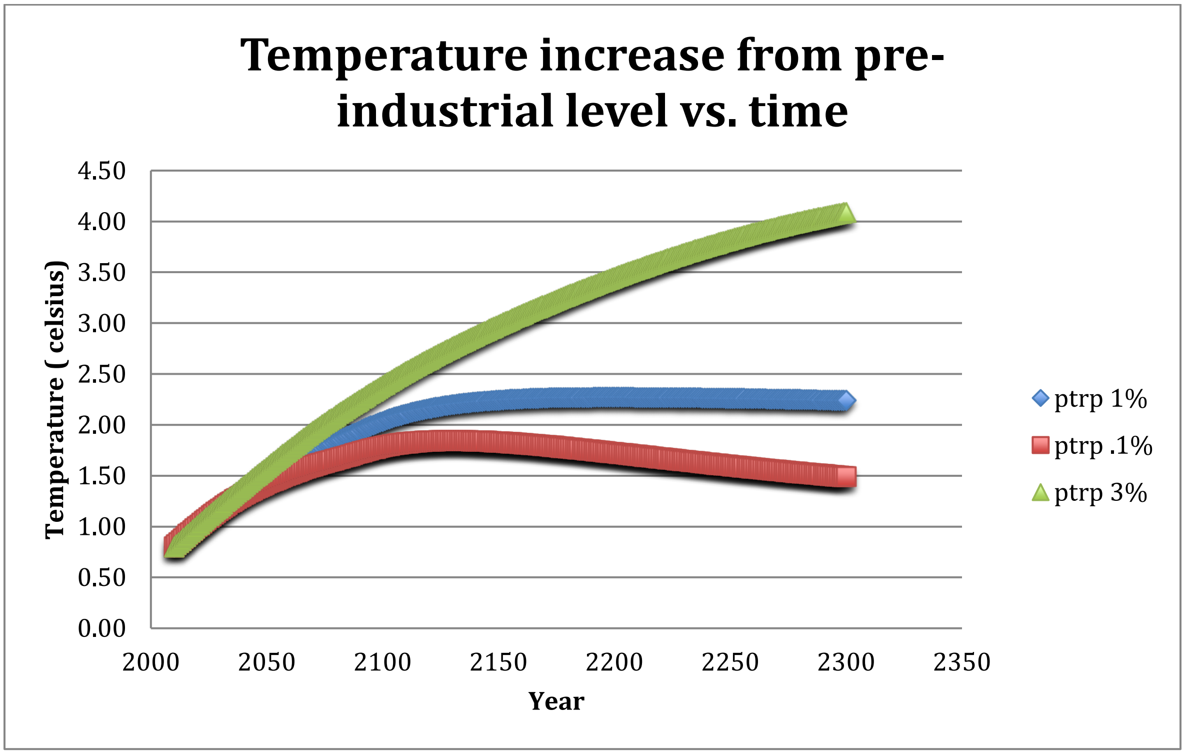

Figure 2.2. The effect of ptrp percentage on temperature increase from pre-industrial level over time.

Part 8-3: Further Analysis: Superimposing derived projections with other studies.

I compared figure 2.2 with SRES Scenarios and RCPs (Rogelj et al. 2012) and check if three optimal prtp scenarios we generated were similar to the pre-existing scenarios.

Results: SRES B1 and RCP4.5 scenarios, which were most likely projections, superimposed (with 66% range of probability) with optimal policy with ptrp 3% (Figure 2.3 and 2.4). SRES B1 scenario also superimposed with both optimal policies with ptrp of 1% and .1% (Figure 2.3). Other published scenarios: SRES A1T, B2, A1B, A2, A1F1, RCP 6, RCP 8.5 did not superimposed with any of three ptrp % scenarios. They required greater than 3% ptrp (Figure 2.3 and 2.4).

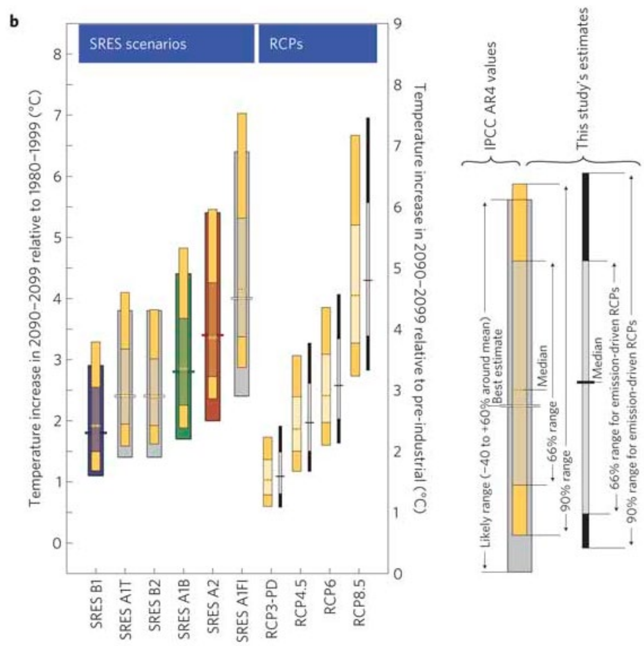

Figure 2.3. Ranges of estimated average temperature increase between 2090 and 2099 for SRES scenarios and RCPs respectively. Note that results are given both relative to 1980–1999 (left scale) and relative to pre-industrial (right scale). Yellow and thin black ranges indicate results of this study; other ranges show the AR4 estimates (see legend at right-hand side). Color-coding of AR4 ranges is chosen to be consistent with the AR4 (see Figure SPM.5 in ref. 1). For RCPs, yellow ranges show concentration-driven results, whereas black ranges show emission-driven results (Rogeli et al. 2012).

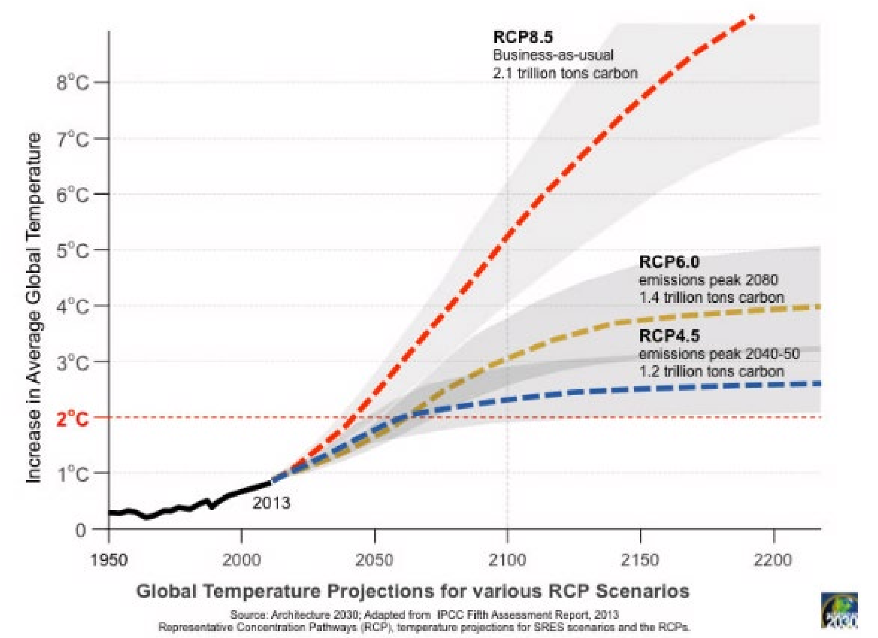

Figure 2.4. RCP 4.5 Global Temperature Projections (IPCC 2013).

Part 9: Cost Benefit Analysis

I computed the net present value of costs and benefits of the optimized policies in part 8-2. The costs in this case were the abatement costs of the policy; the benefits were the avoided damages. I compared six different discount schemes: a constant discount rate of 2.5%, 3% and 5% per year, and a ramsey discount rate with a pure rate of time preference of 0.1%, 1% and 3%. Then I computed the net present value of abatement costs for a given policy (Figure 2.4), and separately computed the net present value of the damages prevented by the policy (Figure 2.5).

I listed the net present value of costs and benefits of each of the three optimized policies for the six discounting schemes. Finally, I could determine if each policy and discounting combination of policies would pass cost-benefit analysis.

Results: The Optimal prtp .1% CBA passed except in constant discount rate of 3%, 5% and ptrp 3%. The optimal prtp 1% CBA passed except in constant discount rate of 5% and ptrp 3%. The optimal prtp 3% CBA passed (Figure 2.6).

	NPV Cost (trill$)					
	Discounting schemes					
Policy name	*Constant 2.5%*	*Constant 3%*	*Constant 5%*	*ptrp .1%*	*ptrp 1%*	*ptrp 3%*
optimal prtp .1%	86.79668172	63.10349137	25.8203045	244.630562	108.041807	35.2069292
optimal prtp 1%	38.06356967	25.1785979	7.72804566	138.226397	50.3979297	11.4714766
optimal prtp 3%	5.301375739	3.413564432	0.92449964	20.4039501	7.13777256	1.4352566

Figure 2.4. Cost analysis of optimal prtp policies in six discounts rates.

	NPV Benefit (trill$)					
	Discounting schemes					
Policy name	*Constant 2.5%*	*Constant 3%*	*Constant 5%*	*ptrp .1%*	*ptrp 1%*	*ptrp 3%*
optimal prtp .1%	102.815031	49.6007584	5.62509984	1053.69521	189.268057	11.9672917
optimal prtp 1%	79.69328626	37.2701362	3.78021094	894.853267	153.664013	8.473803
optimal prtp 3%	39.14252969	18.1698283	1.77442907	460.825658	77.8964063	4.07498709

Figure 2.5. Benefit analysis of optimal prtp policies in six discounts rates.

	CBA (trill$)					
	Discounting schemes					
Policy name	Constant 2.5%	Constant 3%	Constant 5%	ptrp .1%	ptrp 1%	ptrp 3%
optimal prtp .1%	16.01834928	-13.50273299	-20.195205	809.064651	81.2262497	-23.239637
optimal prtp 1%	41.62971659	12.09153835	-3.9478347	756.62687	103.266084	-2.9976736
optimal prtp 3%	33.84115395	14.7562639	0.84992943	440.421708	70.7586338	2.63973049
					Passes CBA=Green	
					Fail=Orange	

Figure 2.6. Cost-Benefit Analysis of optimal prtp policies in six discounts rates.

Analysis

The optimization of discount factors in welfare function of the IAM (integrated assessment model) is an important step in order to accurately calibrate the projected cost-benefit of a Greenhouse gas mitigation policy. If an appropriate discount factor is determined, policy makers can set specific emission targets. Using the optimization package in excel, I determined that ptrp 3% best fits with the current emissions projection model with (Representative Concentration Pathway) RCP 4.5 scenario, the most probably climate scenario (IPCC 2013 and Liu et al. 2015). My findings suggest that Ramsey discounting (pure time rate of preference) of 3% is optimal for the first 100 years of integrated assessment model. In addition, I found that optimal 3% ptrp scenario passed the cost-benefit analysis in all discount factors.

First, I analyzed the effects of various ptrp-discounting schemes on welfare function of optimization package on emission control rates and global temperature increase. Note that this discount schemes were only associated with welfare functions necessary to run optimization package in excel, not the actual discount rate to calculate net present values in cost-benefit analyses. Optimization package is an excel program that determines the optimal emission control rate based on the optimized welfare function.

I observed the effect of discount rate (pure time rate preference) on emission control rate. We found that emission control rate over time for ptrp .1% scenario was larger than ptrp 1% or 3% scenario. The optimal emission control rate increases as ptrp percentage decreases. When I ran the optimization package, the IAM (Integrated Assessment Model), interpreted values of pure time rate preference as a marginal change in carbon emissions at some future date t. In other words, the greater ptrp percentage value is, lesser the emission control rate would be because higher discount rate indicates lower preference of present investment in abatement costs and higher preference for spending damage costs due to present carbon emissions (Rahmstorf 2008). In graph 3.1, I could observe that emission control rate over time varies greatly with ptrp values. Thus, adjusting the optimal ptrp value is a crucial step in determining the optimal emission control rates.

Next, I observed the effect of discount rate (pure time rate preference) on global temperature increase. I found that temperature increase from pre-industrial level over time is greater for higher ptrp scenario than the lower ones. Previously, lower optimal ptrp value resulted in lower emission control rate. As a result of lower emission control rate, leads to global temperature increase. The emission control rate is the fraction of emissions that are reduced or controlled by a climate change policy. Higher emission control rate leads to less anthropogenic carbon emissions, which deters global temperature increase from greenhouse effect (IPCC 2013). Ptrp discount factor is inversely correlated with global temperature increase projections because emission control rate is also inversely correlated with discount factor. The ptrp value in welfare function greatly influenced emission control rates and global temperature projections.

The three leading climate policy evaluations all have greatly variable discount rates and implications for the policy. As shown in Table 3.2, the choice of income elasticity, growth factor and pure time rate of preference varies greatly in three leading climate policy projections.

	ρ	η	g	r_{SW}
Stern (2007)	0.1%	1.0	1.3%	1.40%
Cline (1992)	0.0%	1.5	1.3%	2.05%
Nordhaus (2007)	3.0%	1.0	1.3%	4.30%

Table 3.2 Disagreements in pure rate of time preference, income elasticity, growth factor and discount rate in three climate policies (Stanford University 2012).

Despite the major disagreements among published projection models, income elasticity and growth factors were somewhat in consensus. Thus, in this study, I set income elasticity to 1 and growth factor to 1.3%. Previously, I adjusted pure time rate of preference in welfare function in order to observe the effects of ptrp values on optimized emission control rate and global temperature increase. Next, I compared each ptrp .1%, 1% and 3% scenarios' projected global temperature increase by 2100 with RCP (Representative Concentration Pathways) 4.5 scenario where carbon emissions peak by 2050. Many studies revealed that carbon emissions would peak by 2050 (Liu et al. 2015).

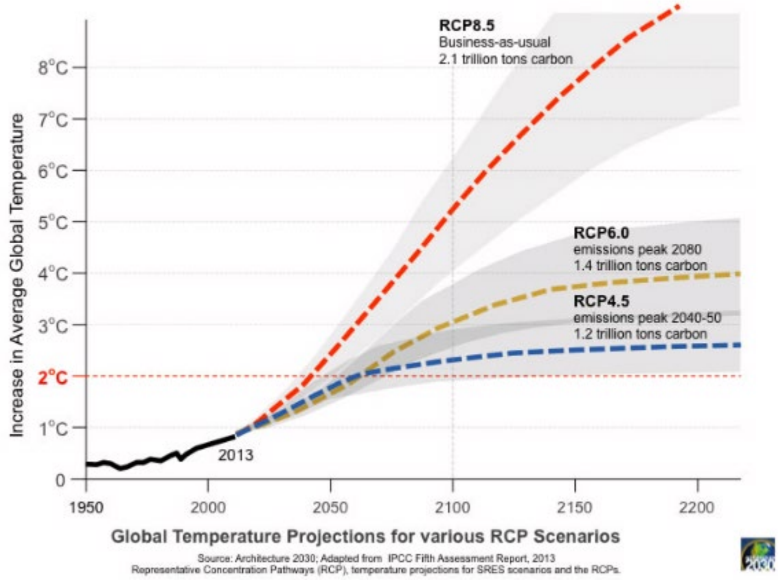

Figure 3.3 RCP 4.5 Global Temperature Projections (IPCC 2013).

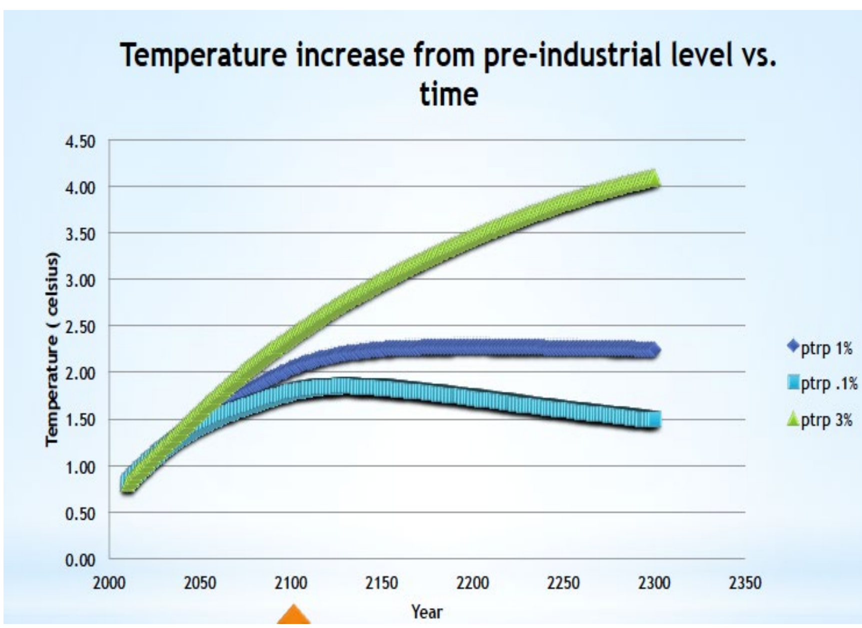

Figure 3.4 The effect of ptrp values on global temperature increase.

The comparison between my projection model and RCP 4.5 scenario revealed that ptrp 3% is the most reliable projection model because ptrp 3% scenario aligned with the projected global temperature increase of 2.5 degree Celsius, which was supported by many studies including RCP 4.5 from IPCC (IPCC 2013 and Liu et al. 2015).

The cost-benefit analyses (CBA) also indicated that the optimal discount rate is 3%. The optimization package in excel solved the optimal emission control rate in optimal prtp .1%, 1% and 3% scenarios The optimized emission control rate determined the abatements costs and social cost of carbon. In order to assess financial feasibility of these three optimal ptrp climate policy scenarios, I conducted a comprehensive cost-benefit analysis with three different constant and ptrp discounting schemes for each optimal prtp policy. I found that ptrp 3% scenario passed the CBA with every discount rate cases.

The optimal emission control rate projection model can only generate predictions until 2100. After 100-year projections, the optimal discount rate must be recalibrated in order to factor in new parameters, such as damage costs, changes in emission control rate, income elasticity and growth factor. Another caveat of the IAM is the social welfare function assumes more consumption leads to higher social utility. The measure of social welfare is debatably highly subjective and leads to disagreements as to the appropriate form and parameters of the social welfare function (Goulder and William 2012).

In order to overcome the limitations of my study, I can conduct more empirical studies to measure social preference of consumption and determine more accurate parameters for my climate projection model. Rather than relying on the previously established parameters, constructing the model from bottom-up approach would eliminate large uncertainties from aggravating several components of climate models.

The interdisciplinary climate projection model provided crucial knowledge for the future climate economists. The ptrp in welfare function played an important role in determining the optimal emission control rate and the projected global temperature increase. I concluded that optimal ptrp 3% case best fits with the most widely accepted scenario, RCP 4.5. Later, the cost-benefit analysis with three constant and Ramsey discounting scenarios verified that optimal ptrp 3% is financially feasible. I demonstrated a welfare function based methodology of determining optimal emission control rate, so the future policy makers can set specific emission targets. In addition, I conducted CBA showing ptrp 3% scenario is financially feasible. This study would be useful in constructing more empirical parameter values for integrated climate projection models.

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