

Emissions Abatement with Permits - Exercise 13.9

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This document performs Exercise 13.9 from the Integrated Assessment Model chapter of Climate Economics. It runs the underlying climate and economic modeling tasks from sections 13.1 and 13.2. It also adds the new emissions reduction rates, $R_{i,t}$ to the model, calculates the relative and absolute cost of the emissions reductions, and explores the impact on carbon dioxide concentrations and warming.

Climate Module (Lab 1)

Emissions to CO2

Five Box model of carbon dioxide concentrations. Each box follows equation 13.1:

$$CO2_{i,t} = (1 - CO2decay) * CO2_{i,t-1} + CO2convert * CO2share_i * CO2emissions_{t-1}$$

Make this into a function for regular and repeated use.

```
CO2difference <- function(CO2previous, newCO2emissions) {  
  CO2decay <- c(0, 1-exp(-1/363), 1-exp(-1/74), 1-exp(-1/17), 1-exp(-1/2))  
  CO2share <- c(0.13, 0.20, 0.32, 0.25, 0.10);  
  CO2convert <- 1/2.13/1000;  
  
  CO2concnnew = (1-CO2decay)*CO2previous + CO2convert*CO2share*newCO2emissions # Equation 13.1  
  CO2concnnew  
}
```

Now we just need some emissions data and starter values for the model.

```
# emissions data  
emissionsSince1750 <- read_sheet("https://docs.google.com/spreadsheets/d/15gnvwp5HWqPVb4_h0Dz6j1DlLiaQv/
```

Load historic emissions data

```
## v Reading from "ECON269-Emissions-data".  
## v Range '2:10000000'.  
## New names:  
## * `` -> `...1`  
names(emissionsSince1750) <- c("year", "EmissionsMMTC")  
# head(emissionsSince1750)  
  
# Graph emissions over time  
emissionsSince1750 %>%  
  ggplot(aes(year, EmissionsMMTC)) +  
  geom_line()
```

Prepare the data for the CO2 model calculations.

```
HistoricData <- emissionsSince1750

HistoricData$Box1 <- 0
HistoricData$Box2 <- 0
HistoricData$Box3 <- 0
HistoricData$Box4 <- 0
HistoricData$Box5 <- 0
HistoricData$Box1[1] <- 275

(Box1col <- which(colnames(HistoricData) == "Box1"))
```

```
## [1] 3
```

Now we implement it, year by year to use the previous year's box values and the emissions to calculate new box values.

```
for (i in 2:length(HistoricData$EmissionsMMTC)) {
  HistoricData[i, Box1col:(Box1col+4)] <- CO2difference(HistoricData[i - 1, Box1col:(Box1col+4)],
                                                         HistoricData$EmissionsMMTC[i - 1])
}

HistoricData$CO2conc <- HistoricData$Box1 + HistoricData$Box2 + HistoricData$Box3 +
  HistoricData$Box4 + HistoricData$Box5

tail(HistoricData)
```

```
## # A tibble: 6 x 8
##   year EmissionsMMTC Box1 Box2 Box3 Box4 Box5 CO2conc
##   <dbl>         <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>   <dbl>
## 1  2015         10775.  300.  34.8  41.2  15.2  1.19    392.
## 2  2016         11110.  300.  35.7  42.3  15.6  1.23    395.
## 3  2017         11257.  301.  36.6  43.4  16.0  1.27    398.
## 4  2018         11467.  302.  37.6  44.5  16.4  1.30    402.
## 5  2019         11477.  302.  38.6  45.6  16.8  1.33    405.
## 6  2020         11432.  303.  39.5  46.7  17.2  1.34    408.
```

We can plot the CO2 concentration over time.

```
HistoricData %>%
  ggplot(aes(x = year, y = CO2conc)) +
  geom_line()
```

CO2 concentrations to Temperatures

Radiative Forcing (Equation 13.3) and Temperature anomalies (Equations 13.4 and 13.5)

```
RadForc <-function(CO2) {
  5.35*log(CO2/275);
}

Temps <- function(atmtempold, oceantempold, radforc) {
  par1 <- 1.15
  par2 <- 0.0256
  par3 <- 0.00738
  par4 <- 0.00568
```

```

atmtempnew = atmtempold +
  par2*(par1*radforc-atmtempold) +
  par3*(oceantempold-atmtempold)

oceantempnew = oceantempold +
  par4*(atmtempold-oceantempold)

temps <- c(atmtempnew, oceantempnew)
names(temps) <- c("atm", "ocean")
temps
}

HistoricData$RF <- RadForc(HistoricData$CO2conc)

HistoricData$TempAtm = 0
HistoricData$TempOcean = 0

StartYear <- 1850
EndYear <- 2020

for (i in (which(HistoricData$year == StartYear)+1):which(HistoricData$year == EndYear)) {
  temp <- Temps(HistoricData$TempAtm[i-1], HistoricData$TempOcean[i-1], HistoricData$RF[i])
  HistoricData$TempAtm[i] <- temp["atm"]
  HistoricData$TempOcean[i] <- temp["ocean"]
}

```

We can now plot temp over time

```

HistoricData %>%
  ggplot(aes(year, TempAtm)) +
  geom_line()

```

Future Scenario Example: Constant Emissions

```

years <- 2020:2300

Scenario1 <- HistoricData[which(HistoricData$year == 2020), ]
Scenario1[2:length(years), ] <- 0

Scenario1$year <- years
Scenario1$EmissionsMMTC = Scenario1$EmissionsMMTC[1]

#Implement Five box model for CO2 concentrations
for (i in 2:length(Scenario1$EmissionsMMTC)) {
  Scenario1[i, Box1col:(Box1col+4)] <- CO2difference(Scenario1[i - 1, Box1col:(Box1col+4)],
                                                    Scenario1$EmissionsMMTC[i - 1])
}

# Calculate total CO2 concentration in atmosphere
Scenario1$CO2conc <- Scenario1$Box1 + Scenario1$Box2 + Scenario1$Box3 +
  Scenario1$Box4 + Scenario1$Box5

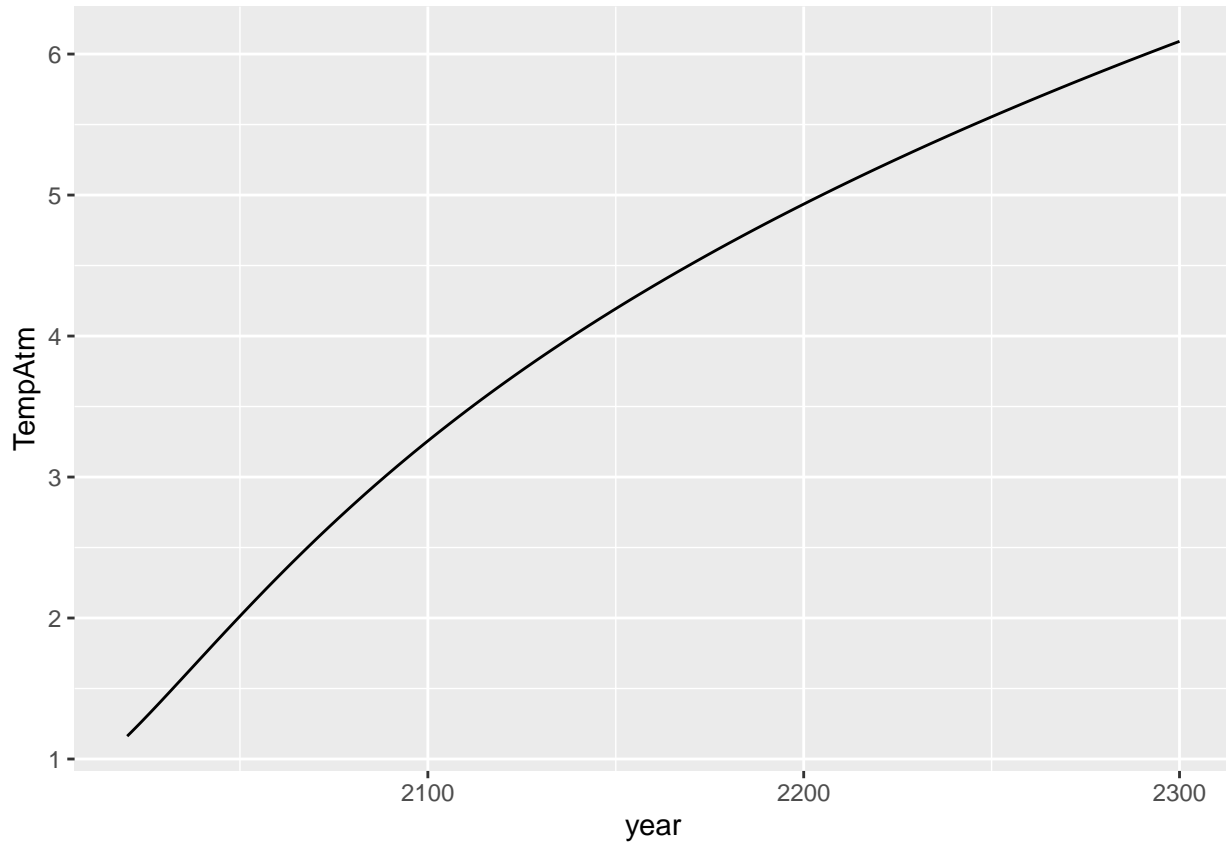
# Calculate radiative forcing
Scenario1$RF <- RadForc(Scenario1$CO2conc)

# Calculate Temperatures

```

```
for (i in 2:length(Scenario1$EmissionsMMTC)) {
  temp <- Temps(Scenario1$TempAtm[i-1], Scenario1$TempOcean[i-1], Scenario1$RF[i])
  Scenario1$TempAtm[i] <- temp["atm"]
  Scenario1$TempOcean[i] <- temp["ocean"]
}
```

```
Scenario1 %>% ggplot(aes(year, TempAtm)) +
  geom_line()
```



Economic Module (Lab 2)

Kaya Identity

$$Emissions = Pop \times \frac{GDP}{Pop} \times \frac{Energy}{GDP} \times \frac{Emissions}{Energy}$$

$$M^* = Pop \times \frac{GDP}{Pop} \times EnergyIntensity \times EmissionsIntensity$$

We will model Population, GDP, Energy Intensity, and Emissions Intensity over time and allow for variation across three economic regions of the world, the richest, middle income, and poorest regions.

Using Rich-Middle-Poor Region Data

Access the regional data from a Google Sheet

```

# regional kaya data
regional.df <- read_sheet("https://docs.google.com/spreadsheets/d/1fgR_jtz7zCLynudKfqpjCr2LbORW_tXqHrdG")

## v Reading from "Lab 02 Regional Data".

## v Range 'Sheet1'.

## New names:
## * `` -> `...3`
## * `` -> `...4`
## * `` -> `...5`
## * `` -> `...7`
## * `` -> `...8`
## * `` -> `...9`
## * `` -> `...11`
## * `` -> `...12`
## * `` -> `...13`
## * `` -> `...15`
## * `` -> `...16`

# note the regional data has some issues with the names, etc.
# because the data starts on row 4, with regional labels, etc. in earlier rows

Rich.df <- regional.df[-(1:3), c(1, 2, 6, 10, 14)]
#head(Rich.df)
Rich.df <- Rich.df %>% mutate(across(Population:Emissions, as.numeric))

Middle.df <- regional.df[-(1:3), c(1, 3, 7, 11, 15)]
names(Middle.df) <- names(Rich.df)
Middle.df <- Middle.df %>% mutate(across(Population:Emissions, as.numeric))

Poor.df <- regional.df[-(1:3), c(1, 4, 8, 12, 16)]
names(Poor.df) <- names(Rich.df)
Poor.df <- Poor.df %>% mutate(across(Population:Emissions, as.numeric))

Rich.df$Region <- "R"
Middle.df$Region <- "M"
Poor.df$Region <- "P"

```

In order to model future population, we will calculate the population growth rate from 2019 to 2020.

```

long.df <- full_join(Rich.df, Middle.df) %>% full_join(Poor.df) %>%
  group_by(Region)

## Joining with `by = join_by(Year, Population, GDP, Energy, Emissions, Region)`
## Joining with `by = join_by(Year, Population, GDP, Energy, Emissions, Region)`

PopulationGrowth2020 <- long.df %>% mutate(g.Pop = Population/lag(Population) - 1) %>%
  filter(Year == 2020) %>% select(Region, g.Pop, Year)

```

Calculate the energy intensity of GDP as the emissions intensity of energy.

```

long.df <- long.df %>%
  mutate(EnInt = Energy/GDP,
         EmInt = Emissions/Energy)

head(long.df)

```

```
## # A tibble: 6 x 8
## # Groups:   Region [1]
##   Year Population    GDP Energy Emissions Region EnInt EmInt
##   <dbl>      <dbl> <dbl> <dbl>      <dbl> <chr>  <dbl> <dbl>
## 1  1960         755. 7556.  1823.      1635  R      0.241 0.897
## 2  1961         765. 7939.  1870.      1684. R      0.236 0.901
## 3  1962         774. 8405.  1971.      1776. R      0.235 0.901
## 4  1963         783. 8839.  2097.      1875. R      0.237 0.894
## 5  1964         792. 9403.  2194.      1976. R      0.233 0.900
## 6  1965         801. 9928.  2372.      2044. R      0.239 0.862
```

And calculate the average growth rate of the intensities to use in modeling the future.

```
KayaIntensities <- long.df %>%
  mutate(EnInt.lag = lag(EnInt),
         EmInt.lag = lag(EmInt),
         g.EnInt = EnInt/EnInt.lag -1,
         g.EmInt = EmInt/EmInt.lag -1) %>%
  summarise(Ave.g.EnInt = mean(g.EnInt, na.rm = TRUE),
            Ave.g.EmInt = mean(g.EmInt, na.rm = TRUE)) %>%
  mutate(Year = 2020)
```

Before we model the future values of population, energy intensity and emissions intensity, we need to create the modeled GDP (Y^*) as well as capital values that we'll need for the future.

GDP

For GDP we will use the Cobb-Douglass Production function and the Solow Growth model.

$$GDP = A \times K^\alpha \times L^{(1-\alpha)}$$

where K is capital, L is labor, and A is the Total Factor Productivity.

```
CobbDouglassalpha <- .2
CobbDouglassGDP <- function(A, K, L, alpha = CobbDouglassalpha) {
  A*K^alpha*L^(1-alpha)
}
```

We are also told that capital also follows a difference equation, changing over time depending on depreciation, investment and savings.

$$K_t = K_{t-1} - \delta K_{t-1} + Investment_t$$

and because Investment = Savings, and we assume Savings is a constant share of output, $Savings = s * GDP$, then

$$K_t = K_{t-1} - \delta K_{t-1} + s * GDP_{t-1}$$

```
depreciation <- .1
savingsrate <- .2
Kapital <- function(Kold, GDPold, d = depreciation, s = savingsrate) {
  (1-d)*Kold + s*GDPold
}
```

Text says assume a starting value of capital with

$$K_{1960} = \left(\frac{s * A}{\delta} \right)^{\frac{1}{1-\alpha}} * Population$$

We've already done the calibration of the GDP model and so we know some parameters.

```
GDPparameters<- data.frame(Region = c("R", "M", "P"),
                             A = c(5.5, 0.65, 0.283), # starter values
                             g.A = c(0.0183, 0.0282, 0.0205), # growth rates
                             Year = 1960) %>%
  left_join(long.df %>% select(Year, Population, GDP))

## Adding missing grouping variables: `Region`
## Joining with `by = join_by(Region, Year)`
# These values taken from previous calibration exercises

GDPparameters <- GDPparameters %>%
  mutate(K = (savingsrate*A/depreciation)^(1/(1-CobbDouglassalpha))*Population,
         Ystar = CobbDouglassGDP(A, K, Population))

long.df <- long.df %>% left_join(GDPparameters) %>% group_by(Region)

## Joining with `by = join_by(Year, Population, GDP, Region)`
for (year in 1961:2020) {
  long.df$K[which(long.df$Year == year)] <- Kapital(
    long.df$K[which(long.df$Year == year-1)],
    long.df$Ystar[which(long.df$Year == year-1)])

  long.df$g.A[which(long.df$Year == year)] <-
    long.df$g.A[which(long.df$Year == year-1)]

  long.df$A[which(long.df$Year == year)] <-
    long.df$A[which(long.df$Year == year-1)] *
    (1 + long.df$g.A[which(long.df$Year == year)])

  long.df$Ystar[which(long.df$Year == year)] = CobbDouglassGDP(
    long.df$A[which(long.df$Year == year)],
    long.df$K[which(long.df$Year == year)],
    long.df$Population[which(long.df$Year == year)])
}
```

Now let's grab the values for year 2020, and add the future values of years 2021-2300 to model future values.

```
future.df <- long.df %>% filter(Year == 2020) %>%
  left_join(PopulationGrowth2020) %>%
  left_join(KayaIntensities) %>%
  full_join(expand.grid(Year = 2020:2300, Region = c("R", "M", "P"))) %>%
  mutate(Mstar = NA)

## Joining with `by = join_by(Year, Region)`
## Joining with `by = join_by(Year, Region)`
## Joining with `by = join_by(Year, Region)`
```

Now we can model our future values

```
future.df$Mstar = future.df$Emissions
```

```

for (year in 2021:2300) {

  # Population growth rate and Population
  future.df$g.Pop[which(future.df$Year == year)] <-
    .95*future.df$g.Pop[which(future.df$Year == year-1)]

  future.df$Population[which(future.df$Year == year)] <-
    future.df$Population[which(future.df$Year == year-1)] *
    (1 + future.df$g.Pop[which(future.df$Year == year)])

  # Energy Intensity growth rate and Energy Intensity
  future.df$Ave.g.EnInt[which(future.df$Year == year)] <-
    future.df$Ave.g.EnInt[which(future.df$Year == year-1)]

  future.df$EnInt[which(future.df$Year == year)] <-
    future.df$EnInt[which(future.df$Year == year-1)] *
    (1 + future.df$Ave.g.EnInt[which(future.df$Year == year)])

  # Emissions Intensity growth rate and Emissions Intensity
  future.df$Ave.g.EmInt[which(future.df$Year == year)] <-
    future.df$Ave.g.EmInt[which(future.df$Year == year-1)]

  future.df$EmInt[which(future.df$Year == year)] <-
    future.df$EmInt[which(future.df$Year == year-1)] *
    (1 + future.df$Ave.g.EmInt[which(future.df$Year == year)])

  # Economic variables
  future.df$K[which(future.df$Year == year)] <- Kapital(
    future.df$K[which(future.df$Year == year-1)],
    future.df$Ystar[which(future.df$Year == year-1)])

  future.df$g.A[which(future.df$Year == year)] <-
    .99*future.df$g.A[which(future.df$Year == year-1)]

  future.df$A[which(future.df$Year == year)] <-
    future.df$A[which(future.df$Year == year-1)] *
    (1 + future.df$g.A[which(future.df$Year == year)])

  future.df$Ystar[which(future.df$Year == year)] = CobbDouglassGDP(
    future.df$A[which(future.df$Year == year)],
    future.df$K[which(future.df$Year == year)],
    future.df$Population[which(future.df$Year == year)])

  # Emissions (using adjusted Kaya Identity: GDP * Energy Intensity * Emissions Intensity)
  future.df$Mstar[which(future.df$Year == year)] =
    future.df$Ystar[which(future.df$Year == year)] *
    future.df$EnInt[which(future.df$Year == year)] *
    future.df$EmInt[which(future.df$Year == year)]
}

```


Bringing Together the Emissions Data across Regions

We have worked to create emissions predictions for three different regions. But we care about the global emissions.

```
future.df %>% group_by(Year) %>% summarise(Emissions = sum(Mstar))
```

```
## # A tibble: 281 x 2
##   Year Emissions
##   <dbl>   <dbl>
## 1  2020    11432.
## 2  2021    11775.
## 3  2022    12109.
## 4  2023    12445.
## 5  2024    12784.
## 6  2025    13125.
## 7  2026    13468.
## 8  2027    13812.
## 9  2028    14157.
## 10 2029    14504.
## # i 271 more rows
```

Calculate CO2 concentrations and temperature for these emissions.

```
Kaya.global <- left_join(future.df %>%
  group_by(Year) %>%
  summarise(Emissions = sum(Mstar)),
  HistoricData, by = c("Year" = "year") )

Box1col <- which(colnames(Kaya.global) == "Box1")

#Implement Five box model for CO2 concentrations
for (i in 2:length(Kaya.global$Year)) {
  Kaya.global[i, Box1col:(Box1col+4)] <- CO2difference(Kaya.global[i - 1, Box1col:(Box1col+4)],
    Kaya.global$Emissions[i - 1])
}

# Calculate total CO2 concentration in atmosphere
Kaya.global$CO2conc <- Kaya.global$Box1 + Kaya.global$Box2 + Kaya.global$Box3 +
  Kaya.global$Box4 + Kaya.global$Box5

# Calculate radiative forcing
Kaya.global$RF <- RadForc(Kaya.global$CO2conc)

# Calculate Temperatures
for (i in 2:length(Kaya.global$Year)) {
  temp <- Temps(Kaya.global$TempAtm[i-1], Kaya.global$TempOcean[i-1], Kaya.global$RF[i])
  Kaya.global$TempAtm[i] <- temp["atm"]
  Kaya.global$TempOcean[i] <- temp["ocean"]
}

Future.BAU <- Kaya.global
```

Abatement with Permits

Now we add a choice variable for each Region, G which is the amount of emissions reduced by the region in the next time period according to the allocation of emissions permits. We will also create variables for the equilibrium permit price, and now calculate the number of permits bought/sold, as well as the rate of

emissions reductions for each region as a function of the permit price.

Note that in the last lab $R_{r,t}$ was a choice variable, but now it gets calculated as a function of the permit price.

Set our overall reduction Rate,

```
GlobalR = 0.1
```

```
future.df <- long.df %>% filter(Year == 2020) %>%
  left_join(PopulationGrowth2020) %>%
  left_join(KayaIntensities) %>%
  full_join(expand.grid(Year = 2020:2300, Region = c("R", "M", "P"))) %>%
  mutate(Mstar = Emissions,
         Madjusted = Mstar,
         Yadjusted = Ystar,
         G = GlobalR*Mstar,
         Pi = 0,
         R = GlobalR,
         P = 0,
         PermitCosts = 0,
         TACosts = 0,
         NetCosts = 0,
         MACosts = 0)
```

```
## Joining with `by = join_by(Year, Region)`
## Joining with `by = join_by(Year, Region)`
## Joining with `by = join_by(Year, Region)`
```

Now we can model our future values, but note that after estimating several of the economic variables, Y^* , M^* , etc., now we estimate the permit price first, then estimate the various other policy variables like R , etc.

$$\pi_t = \frac{\sum_r G_{r,t}}{\sum_r \frac{(M_{r,t}^*)^2}{2\beta Y_{r,t}^*}}$$

```
GSUM <- future.df %>% filter(Year == 2020) %>% ungroup() %>% summarise(sum(G))

Denom <- future.df %>% filter(Year == 2020) %>% mutate(DenomReg = Mstar^2/2/.1/Ystar) %>%
  ungroup() %>% summarise(sum(DenomReg))

GSUM/Denom
```

```
##      sum(G)
## 1 0.0598808
```

```
for (year in 2021:2300) {
  # Population growth rate and Population
  future.df$g.Pop[which(future.df$Year == year)] <-
    .95*future.df$g.Pop[which(future.df$Year == year-1)]

  future.df$Population[which(future.df$Year == year)] <-
    future.df$Population[which(future.df$Year == year-1)] *
    (1 + future.df$g.Pop[which(future.df$Year == year)])

  # Energy Intensity growth rate and Energy Intensity
  future.df$Ave.g.EnInt[which(future.df$Year == year)] <-
    future.df$Ave.g.EnInt[which(future.df$Year == year-1)]
```

```

future.df$EnInt[which(future.df$Year == year)] <-
  future.df$EnInt[which(future.df$Year == year-1)] *
  (1 + future.df$Ave.g.EnInt[which(future.df$Year == year)])

# Emissions Intensity growth rate and Emissions Intensity
future.df$Ave.g.EnInt[which(future.df$Year == year)] <-
  future.df$Ave.g.EnInt[which(future.df$Year == year-1)]

future.df$EmInt[which(future.df$Year == year)] <-
  future.df$EmInt[which(future.df$Year == year-1)] *
  (1 + future.df$Ave.g.EnInt[which(future.df$Year == year)])

# Economic variables
future.df$K[which(future.df$Year == year)] <- Kapital(
  future.df$K[which(future.df$Year == year-1)],
  future.df$Yadjusted[which(future.df$Year == year-1)])

future.df$g.A[which(future.df$Year == year)] <-
  .99*future.df$g.A[which(future.df$Year == year-1)]

future.df$A[which(future.df$Year == year)] <-
  future.df$A[which(future.df$Year == year-1)] *
  (1 + future.df$g.A[which(future.df$Year == year)])

future.df$Ystar[which(future.df$Year == year)] <- CobbDouglassGDP(
  future.df$A[which(future.df$Year == year)],
  future.df$K[which(future.df$Year == year)],
  future.df$Population[which(future.df$Year == year)])

future.df$Yadjusted[which(future.df$Year == year)] <-
  future.df$Ystar[which(future.df$Year == year)] *
  (1 - .1*future.df$R[which(future.df$Year == year-1)]^2)

# Emissions (using adjusted Kaya Identity: GDP * Energy Intensity * Emissions Intensity)
future.df$Mstar[which(future.df$Year == year)] =
  future.df$Yadjusted[which(future.df$Year == year)] *
  future.df$EnInt[which(future.df$Year == year)] *
  future.df$EmInt[which(future.df$Year == year)]

# Set G at 10% of Mstar
future.df$G[which(future.df$Year == year)] =
future.df$Mstar[which(future.df$Year == year)]*GlobalR

# Calculate Pi, Permit Price which depends on G and YStar and Mstar from all regions
GSUM <- future.df %>% filter(Year == year) %>% ungroup() %>% summarise(sum(G))
Denom <- future.df %>% filter(Year == year) %>%
  mutate(DenomReg = Mstar^2/2/.1/Ystar) %>% ungroup() %>% summarise(sum(DenomReg))

future.df$Pi[which(future.df$Year == year)] = as.numeric(GSUM/Denom)

# Now we can calculate R
future.df$R[which(future.df$Year == year)] =
  future.df$Pi[which(future.df$Year == year)] *

```

```

future.df$Mstar[which(future.df$Year == year)] /2/.1/
future.df$Ystar[which(future.df$Year == year)]

# Now P, permit purchases
future.df$P[which(future.df$Year == year)] = future.df$G[which(future.df$Year == year)] -
  future.df$Pi[which(future.df$Year == year)] *
  future.df$Mstar[which(future.df$Year == year)]^2/2/.1/
future.df$Ystar[which(future.df$Year == year)]

future.df$PermitCosts[which(future.df$Year == year)] =
  future.df$P[which(future.df$Year == year)] *
  future.df$Pi[which(future.df$Year == year)]

future.df$TACosts[which(future.df$Year == year)] =
  .1*future.df$R[which(future.df$Year == year)]^2*
  future.df$Ystar[which(future.df$Year == year)]

future.df$NetCosts[which(future.df$Year == year)] =
  future.df$TACosts[which(future.df$Year == year)] +
  future.df$PermitCosts[which(future.df$Year == year)]

future.df$MACosts[which(future.df$Year == year)] =
  2*.1*future.df$R[which(future.df$Year == year)] *
  future.df$Ystar[which(future.df$Year == year)] /
  future.df$Mstar[which(future.df$Year == year)]

future.df$Madjusted[which(future.df$Year == year)] =
  future.df$Mstar[which(future.df$Year == year)] *
  (1 - future.df$R[which(future.df$Year == year-1)])
}

```

Example values for year 2021.

```

future.df %>% filter(Year==2021) %>%
  select(Region, Ystar, Mstar, G, Pi, R, P, TACosts, NetCosts, MACosts) %>%
  head()

```

```

## # A tibble: 3 x 10
## # Groups:   Region [3]
##   Region Ystar Mstar      G      Pi      R      P TACosts NetCosts MACosts
##   <chr>   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>   <dbl> <dbl>
## 1 R      43368. 3505.  351. 0.0604 0.0244 265.    2.58    18.6  0.0604
## 2 M      15201. 7088.  709. 0.0604 0.141  -289.    30.1    12.7  0.0604
## 3 P       4459. 1170.  117. 0.0604 0.0792  24.3    2.80     4.27  0.0604

```

In order to see the impacts on CO2 concentrations and warming, we need to add up the adjusted emissions across the three regions for each year and feed these into our Climate Model.

Calculate CO2 concentrations and temperature for these emissions.

```

Kaya.global <- left_join(future.df %>%
  group_by(Year) %>%
  summarise(Emissions = sum(Madjusted)),
  HistoricData, by = c("Year" = "year") )

```

```

Box1col <- which(colnames(Kaya.global) == "Box1")

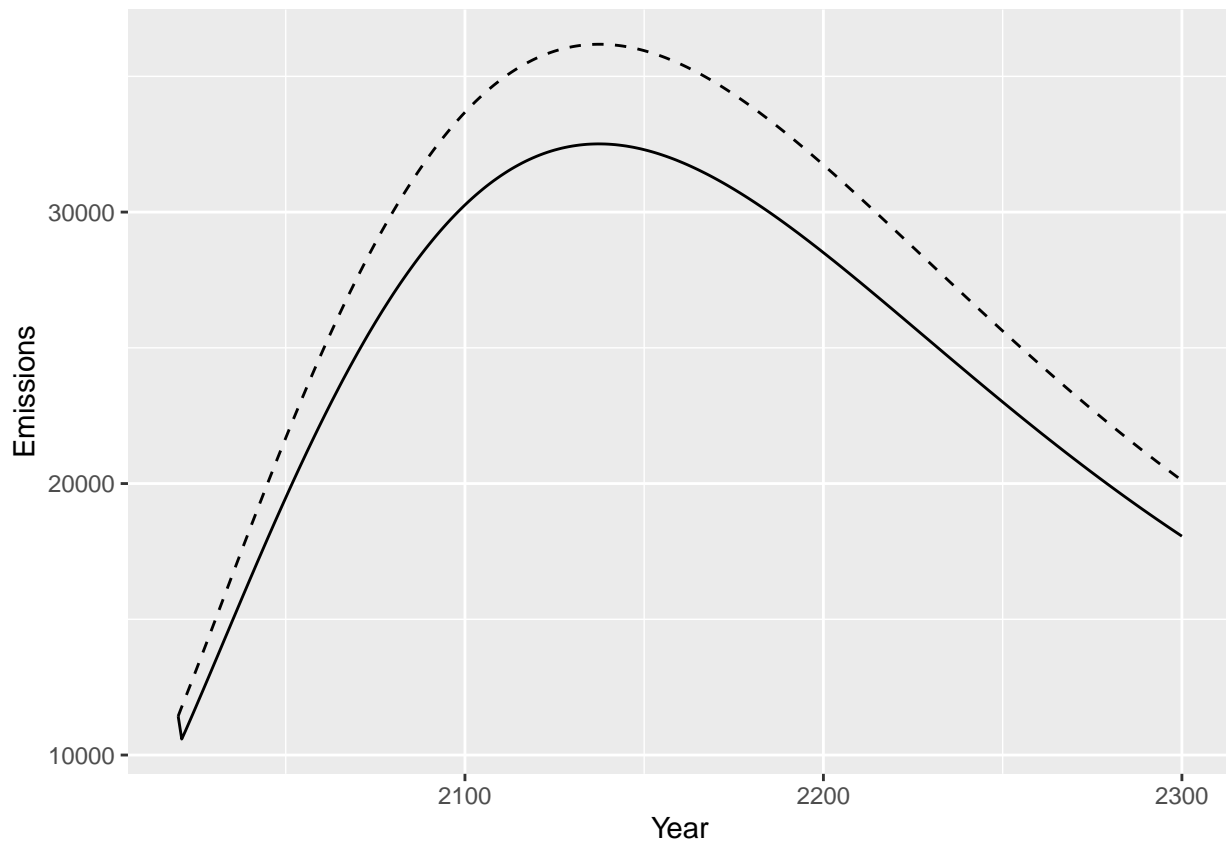
#Implement Five box model for CO2 concentrations
for (i in 2:length(Kaya.global$Year)) {
  Kaya.global[i, Box1col:(Box1col+4)] <- CO2difference(Kaya.global[i - 1, Box1col:(Box1col+4)],
    Kaya.global$Emissions[i - 1])
}

# Calculate total CO2 concentration in atmosphere
Kaya.global$CO2conc <- Kaya.global$Box1 + Kaya.global$Box2 + Kaya.global$Box3 +
  Kaya.global$Box4 + Kaya.global$Box5
# Calculate radiative forcing
Kaya.global$RF <- RadForc(Kaya.global$CO2conc)
# Calculate Temperatures
for (i in 2:length(Kaya.global$Year)) {
  temp <- Temps(Kaya.global$TempAtm[i-1], Kaya.global$TempOcean[i-1], Kaya.global$RF[i])
  Kaya.global$TempAtm[i] <- temp["atm"]
  Kaya.global$TempOcean[i] <- temp["ocean"]
}

Future.R0.1 <- Kaya.global

ggplot(data = Future.R0.1, aes(x = Year)) +
  geom_line(aes(y = Emissions)) +
  geom_line(data = Future.BAU, aes(x = Year, y = Emissions), linetype = "dashed")

```



```

ggplot(data = Future.R0.1, aes(x = Year)) +
  geom_line(aes(y = TempAtm)) +

```

```
geom_line(data = Future.BAU, aes(x = Year, y = TempAtm), linetype = "dashed")
```

