What are the implications of Earth system tipping points on the optimal abatement path?

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Introduction

Climate scientists are increasingly concerned about tipping points in the Earth system, which are rapid, nonlinear, and self-amplifying changes in ecosystem states that occur when a temperature threshold is crossed (Marsden et al. 2024). This paper updates the Faulwasser et al. (2018) open-source implementation of the Nordhaus (2017) DICE2016R IAM to include three major tipping points and discusses their implications on the optimal abatement path. Unsurprisingly, tipping points imply a higher social cost of carbon (SCC) that increases more rapidly, and near-complete emissions abatement by 2040 (as $\mu \to 1$). Interestingly, the lowest optimal temperature (2.47°C) and (by far) the highest SCC (34608.6141) occur when the tipping threshold is set higher. This is counterintuitive, as normally higher tipping thresholds imply lower SCCs and higher optimal temperatures since there is less need for immediate abatement. I explain this effect through how the SCC attempts to account for tipping damages.

Motivating Tipping Points

Perhaps one of the most well-known Earth systems nearing its tipping threshold is the Greenland Ice Sheet (GIS). As the surface temperature warms, the ice melts, decreasing the albedo of the surrounding land (since white snow/ice reflects more of the sun's rays than the darker ocean surface). This decrease in albedo leads to the ocean absorbing more heat, which then melts more ice and lowers albedo even further (Box et al. 2012). The temperature at which the self-perpetuating cycle begins is called a "tipping point" (Lenton et al. 2023). Triggering these points could be catastrophic – the collapse of the GIS could cause global sea levels to rise by 7 meters, putting cities such as Boston and Copenhagen underwater (ibid.).

Despite these impacts, tipping points are not modelled into any major climate IAM, even though many economists acknowledge this deficit as a major weakness of IAMs (Nordhaus 1993). While some attempts have been made, they either (a) focus on the effect of triggering an individual tipping point like the GIS (e.g., Nordhaus 2019, Kessler 2017) or (b) assume a highly stylized global model with only one tipping point (e.g., Cai et al 2015). I attempt to model three imminent tipping points: the melting of the GIS, the melting of the West Antarctic Ice Sheet (WAIS), and the Amazon Rainforest dieback (Marsden et al 2024). While Dietz et al. (2021) have integrated these three tipping points (and more) into an IAM, this paper will be the first to do so in MPC-DICE.

The Basic Model

To integrate tipping points, I needed to answer two questions. First, when are the thresholds triggered? Second, what happens when the threshold is triggered?

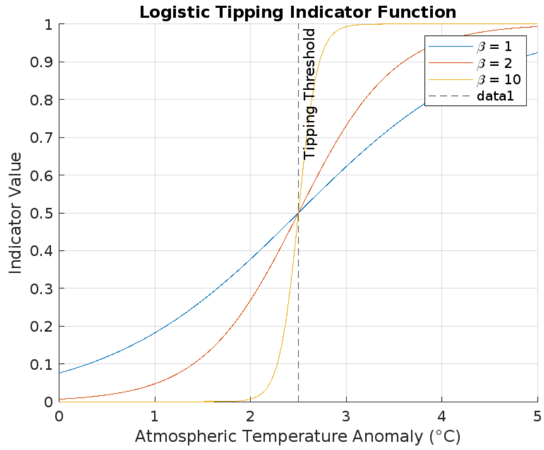
When is the threshold triggered?

Table 1: Tipping Temperature Thresholds, °C

	Low-Bound	Best-Guess	High-Bound
GIS	0.8	1.5	3
WAIS	1	2	3
Amazon Dieback	3	3.5	6

For the first question, I used the 2023 Global Tipping Points Report's temperature thresholds (Lenton et al. 2023). For each tipping point, I included a "high-bound", "best-guess", and "low-bound" tipping threshold, reflecting a wide range of scientific evidence, summarized in Table 1. Using these values, I constructed a logistic sigmoid indicator function that signals when the temperature has passed the threshold:

$$\text{indicator} = \frac{1}{1+e^{-\beta(T_{AT}-T_{\text{threshold}})}}$$



This function smoothed the transition from a pre-tipping to a post-tipping state. A smooth transition was preferable to a "hard switch" as tipping point feedback cycles are not instantaneous. Scientists predict that it may be decades before we can detect whether a tipping point has been triggered (Lenton et al. 2023). Furthermore, some scientists also argue that tipping points may be reversible if caught early enough (Marsden et al. 2024). The value of β determines how steep the transition is, with higher β values causing a sharper transition. Given the uncertainties around how sensitive earth systems are to threshold crossings, I include three values of β , $\beta \in \{1, 2, 10\}$, with the "smoothness" of the transition shown in the left figure.

Effects of Triggering the Threshold

There are two ways tipping points have typically been modelled in the literature. Some studies model it as a permanent welfare loss calculated independently from the geophysical model (Cai et al. 2015; Gjerde et al. 1999). Others model the tipping point as a shift in the dynamics of the model itself (Dietz et al. 2021; Lemoine and Traeger 2011). I follow the latter as it allows for the possibility of "cascades", where triggering one tipping point triggers another and so forth (Lenton et al. 2023). How each tipping point affects the model is summarized in Table 2.

Table 2: Effects of Triggering Tipping Points

Tipping Point	**Effect**
GIS	η doubles from 3 to 6
WAIS	Damages become cubic
Amazon Dieback	CO_2 decay weakens by 75%

These choices largely align with the scientific literature, although with some stylized assumptions. I model the Amazon Dieback as weakening the CO_2 decay by 75%. As the Amazon is one of the world's largest carbon sinks, its collapse would lead to a significant loss in the Earth's ability to move carbon from the atmosphere to the ocean (Friedlingstein et al. 2020). The choice of 75% is somewhat arbitrary, but is consistent with Lemoine and Traeger (2011) and reflects the Amazon's status as the largest land-based carbon sink (Philipps and Brienen 2017). I have also chosen to differentiate the effects of triggering the GIS' and WAIS' tipping points. The GIS is a land-based ice sheet, meaning that even when its tipping threshold is crossed, large-scale sea level rise is unlikely to occur within the next 100 years. Comparatively, the WAIS is a marine-based ice sheet, meaning it is much more unstable than the GIS and hence is more prone to immediate collapse (Bamber et al. 2009). Therefore, I choose to model the WAIS as an increase in damages to reflect the more immediate harm from the collapse of the WAIS, and the GIS as doubling climate sensitivity to reflect albedo feedback cycles (Dietz et al. 2021).

To integrate these effects into the model, I use the indicator variables constructed above to signal when certain effects are triggered. For example, to convert damages to cubic from quadratic when the tipping threshold is crossed, I constructed two new equations:

$$gis_t = a_3 + \Delta exp\_damage \times indicator\_dmg$$
$$\Omega_{new}(T_{AT}) = 1 - \frac{a2 \times T_{AT}^{gis_t}}{1 + a2 \times T_{AT}^{gis_t}} = \frac{1}{1 + a2 \times T_{AT}^{gis_t}}$$

gis_t is close to $a_3 = 2$ when $indicator_{dmg} = 0$, which occurs when the temperature is far from the tipping point, as shown in the figure above, and approaches 3 when the threshold is crossed. Thus, $T_{AT}^{gis_t} = T_{AT}^2$ before the tipping point and switches gradually (depending on β) to T_{AT}^3 once the threshold has been crossed. I repeated this process for the other variables, which led to:

$$effective_{t2xco2} = (1 - indicator_{t2x}) \times (3.1) + indicator_{t2x} \times t2xco2_{post}$$
$$b_{12,eff} = (1 - indicator_{decay}) \times b_{12} + indicator_{decay} \times (decay_{reduction} \times b_{12})$$

Here, $t2xco2$ represents climate sensitivity, raised to 6 after the tipping point. b_{12} equates to ζ_{12} in Faulwasser et al. (2018), representing diffusion from the atmosphere to upper ocean carbon reserves. I then used the "effective" parameters to replace wherever $t2xco2$ and b_{12} appear, including dynamically recalculating Φ_M.

Limitations

This model is *not intended* to produce empirically accurate estimates of the SCC or optimal abatement pathway. First, MPC-DICE is not calibrated to include tipping points. Second, MPC-DICE is a deterministic model that cannot account for the inherently probabilistic nature of triggering tipping points (Marsden et al. 2024). Third, I have had to model some tipping effects roughly, most notably the Amazon Dieback. The Amazon is a land-based carbon reservoir, and MPC-DICE combines upper ocean and biosphere reservoirs (Nordhaus 2017). I have used this framework to approximate the Amazon Dieback's effect on carbon decay, but it should be noted that this is unlikely to be scientifically accurate. This model **only roughly** sketches the effects of tipping points on climate policy.

Observations

Including Tipping Points

No matter the value of β I used, we see that the inclusion of tipping points leads to a much higher SCC than the base (roughly \$3550/$GtCO_2$ vs. \$300/$GtCO_2$), achieving complete emissions much sooner (2040 vs. 2110), and much lower optimal PPM levels (roughly 410 PPM vs. 637 PPM in the DICE2016R run), as shown below.

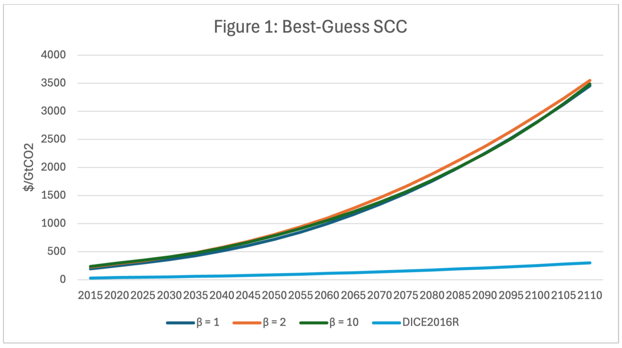


Figure 1: Best-Guess SCC

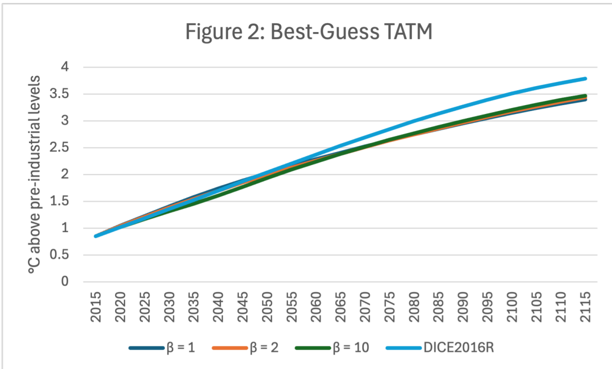


Figure 2: Best-Guess TATM

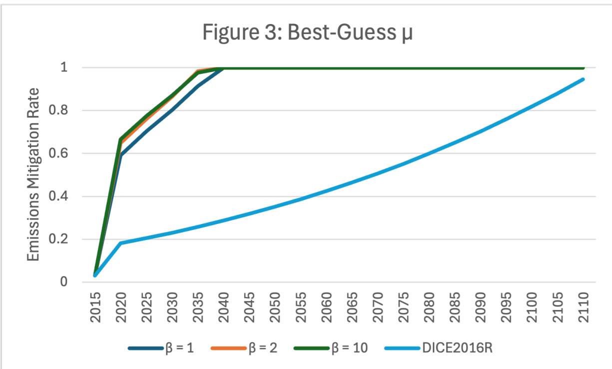


Figure 3: Best-Guess μ

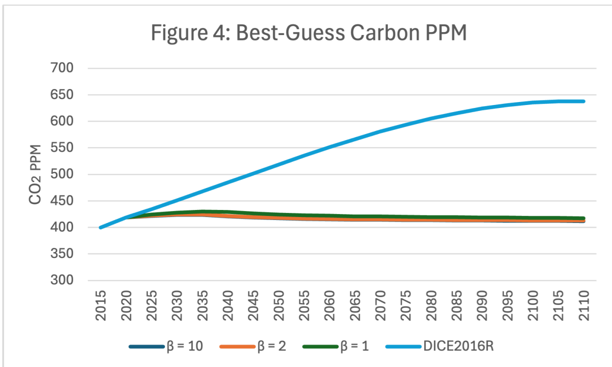


Figure 4: Best-Guess Carbon PPM

This result is unsurprising. The SCC is defined as $\frac{\partial C}{\partial E}$, the marginal cost of emissions. Tipping points cause every unit of emissions to become more costly as it risks triggering severe geophysical changes that exacerbate damages. Thus, the optimal Pigouvian tax is higher at $t^* = \frac{\partial C}{\partial E}$, so firms respond by lowering their carbon emissions until $MB = MC$. Since MB is decreasing, E^* is now lower than before and firms will heavily prioritize abatement, as shown in Figures 3 and 4.

There are, however, two interesting results worth dwelling on. First, despite aggressive carbon abatement efforts, the optimal temperature does not substantially decrease (Figure 2). This is because the DICE2016R model assumes that warming cannot be limited below 2°C (Nordhaus 2017), so if the thresholds hold to our best-guesses, we will trigger the GIS (1.5°C) and WAIS tipping points (2°C), although we barely avoid the Amazon Dieback. This explains why temperatures do not significantly decrease despite the abatement efforts, as tipping the GIS doubles equilibrium climate sensitivity. Atmospheric carbon has been more than halved, but that leads to (roughly) the same temperature increase due to the increased climate sensitivity.

Second, the specific β value does not matter much for the optimal abatement pathway. This may seem counterintuitive, as sharper "switches" should lead to harsher damages even when the temperature threshold is crossed at approximately the same time, as shown in Figure 2. But because the SCC calculates the NPV of emissions, including their future effects, every additional emissions unit still causes the same change in the geophysical system. Even though they occur slightly later, the discount rate r is not high enough for that time differential to matter.

Varying Temperature Threshold Levels

Since there remains uncertainty about *when* tipping points will be triggered, this section considers the optimal policy pathway at varying temperature thresholds. We should expect lower temperature thresholds correlating with a higher SCC since each unit of emissions brings us closer to the threshold.

The DICE2016R model starts at 0.85°C warming, which triggers the lower-bound GIS tipping point at (0.8°C). As shown in Figure 5, this leads to a higher SCC compared to the higher temperature threshold, although the difference between the best-guess and lower threshold is small. This is because the model views reaching both 0.8°C of emissions and 1.5°C of emissions as equally inevitable, and thus the damage done by each unit of emissions is equal, adjusted slightly downwards for the time differential.

Another unexpected result from varying temperature thresholds is that by 2100, the SCC is higher for the higher temperature threshold, despite being at a lower $TATM$ (Figure 7). Typically, SCC scales with temperature because the damage function, $\Omega(TATM) = \frac{1}{1+0.00236 \times TATM^2}$, scales exponentially as temperature increases. Thus, the cost of emissions at higher temperatures is higher because it causes more damage than at lower temperatures.

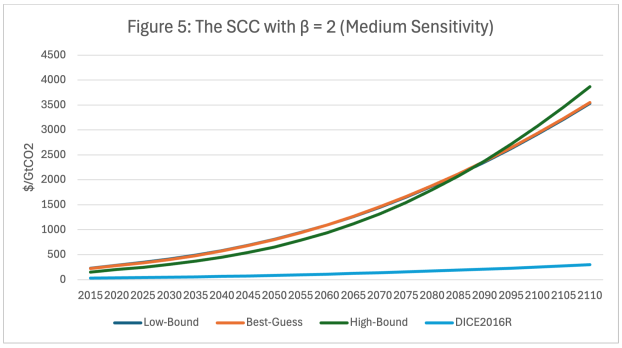


Figure 5: The SCC with β = 2 (Medium Sensitivity)

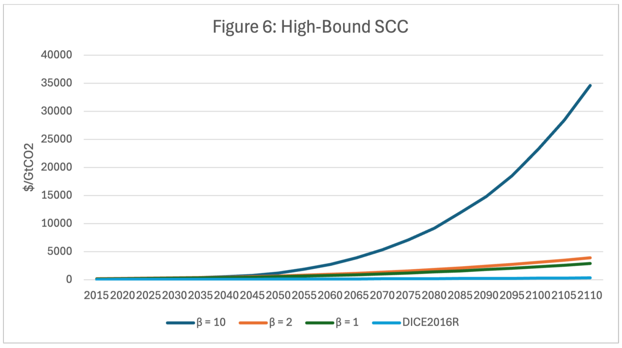


Figure 6: High-Bound SCC

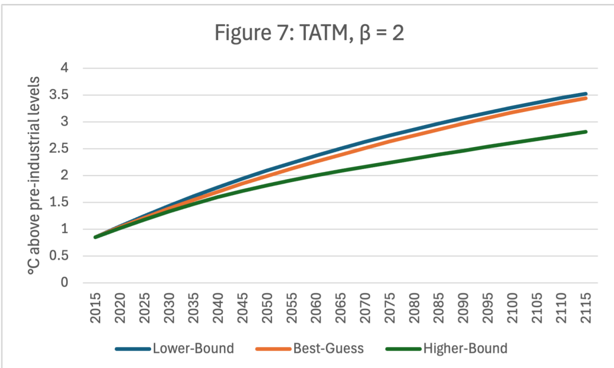


Figure 7: TATM, β = 2

But tipping points alter this relationship: the higher-bound thresholds have the lowest temperature but the highest SCC. This result occurs because the SCC is calculated marginally, that is, how much the *next* unit of emissions costs. Tipping points generally cause the next unit of emissions to be higher because of the possibility of triggering tipping points and changing to a cubic damage function. But importantly, once a tipping point has *already been triggered*, the marginal damage from an additional unit of emissions increases more slowly. While the temperatures still rise and hence SCC increases, there is no longer the risk of triggering additional damages via triggering tipping points. This is why at 2110, the SCC ordering is: high-bound > medium-bound > low-bound, in line with how many tipping points have yet to be triggered, 3 > 1 > 0. Since the high-bound has more tipping points to trigger, the marginal cost of emissions is higher as each additional unit of emissions pushes closer to the cascade.

However, this explanation is pushed to the extreme in Figure 6, where the model with the highest tipping threshold and $\beta = 10$ has an SCC of nearly \$35000/$GtCO_2$. While this is certainly partially attributable to calibration error since the model is not designed to handle tipping points, it seems unlikely that this is all that is happening. It is possible that this occurs because future damages are predicted to be much more convex when $\beta = 10$ compared to when $\beta \in 1, 2$. While previously I argued that β did not matter because the time differential between when tipping points were triggered was marginal at different sensitivities, this is not true here. Given that the model considers 3°C warming as easily avoidable, the times at which the tipping threshold is triggered vary vastly, and for the lower sensitivity values, the tipping threshold is perhaps never fully triggered. Because I have programmed the tipping indicator as a logistic sigmoid function, "partial tipping" is possible, e.g. switching to a damage function raised to the power of 2.5 instead of 3. Higher β values make partial tipping less likely (as shown before) and hence $\beta = 10$ has a higher SCC due to the risk of cascading damages that lower β values don't have as the geophysical changes occur more slowly. However, further research is certainly needed to confirm this phenomenon.

Policy Implications

In general, the model shows that including tipping points in climate models calls for a higher and faster rising carbon tax, as shown by Figure 1. Given that scientists are reasonably confident in the existence of tipping points, this supports calls from environmental economists to include tipping points and feedback loops more rigorously in IAMs, lest they become useless in policy analysis (Stern 2013; Pindyck 2013). However, concrete policy suggestions are difficult due to the degree of scientific uncertainty around tipping points: e.g., whether they are reversible, at what temperature they will occur, and how multiple tipping points interact with each other. As we obtain this knowledge, however, economists need to ensure that models can capture the depth of scientific evidence to produce policy-relevant advice (Marsden et al. 2024).

Putting these concerns to one side, one implication of the study above worth noting is that policy needs to put much more emphasis on adaptation. The optimal abatement pathway aims to avoid triggering tipping points when it can, as shown in Figure 7. However, some tipping points may be inevitable, e.g., the lower or mid-bound of the GIS and the lower-bound of the WAIS, despite aggressive mitigation efforts (Figure 4). Once these are triggered, it can make other tipping points, e.g. the Amazon Dieback, inevitable as well. In DICE2016, the technology to keep warming below 1.5°C is simply unavailable (Nordhaus 2017). But even when backstop technologies are *technically* available, it is highly unlikely that complete mitigation by 2040 will be possible. The most optimistic estimates currently predict that net-zero could be achieved by 2050 (Way et al. 2022). But even if it is technically feasible to decarbonize by 2040, such rapid decarbonization is also likely to have large human and political costs. Over 80% of the world's lithium needed for the energy transition is located on Indigenous land, and critical mineral and clean technology races by great powers are already sparking geopolitical tension (IRENA 2023). Furthermore, the energy transition itself is also carbon-intensive, averaging about 195 $GtCO_2$, and it may take all the remaining emissions available under a 1.5°C pathway (Slameršak et al. 2020). Given the challenges with mitigation, policymakers should strongly consider adaptation measures alongside mitigation. Adaptation, contrary to popular belief, is not an easy fix for failed mitigation, and maladaptation (i.e., making communities *more* vulnerable due to badly designed adaptation strategies) may be devastating in the face of tipping point damages (Schipper 2020). Therefore, adaptation policy should start earlier rather than later to ensure maladaptation does not occur.

Finally, IAMs need to accommodate uncertainty to include tipping points adequately (Marsden et al. 2024). This would ideally build on the work by Weitzman (2011) and (2014), but beyond just including uncertainty of *what* those damages will be, we also need to include uncertainty of *when* those damages will occur. The timing here matters greatly. As shown in Figures 6 and 7, when the damages occur can lead to drastically higher SCC and a difference of 0.5°C in warming. Although modelling such uncertainty will be difficult, it is necessary to fully understand the climate catastrophe knocking on our door. While a model other than MPC-DICE (or even DICE2023R) will most likely be needed to accommodate this uncertainty, policymakers should not be deterred by path dependency.

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