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The Link Between Physical and Transition Risk

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Abstract

We argue that what is usually referred to as climate 'transition risk' can be more usefully decomposed in an expectation part and a variability around this central value. We show that there is a strong inverse relationship between the expectation component of transition costs and the expectation of physical damages, and how this relationship can be estimated. Our results indicate that the uncertainty in transition costs decreases as the abatement policy becomes more aggressive (and physical damage decrease), but remains large as a fraction of the expectation component. We also show that, with the definition we provide, our transition costs match well the corresponding quantities from the benchmark IPCC scenarios.

1. Introduction

In the last decades regulators, policy makers and investors have paid a lot of attention to estimates of physical and transition climate risk. Physical risk is usually expressed as the difference in GDP at a given horizon between a world with no climate damages and a world with climate damages and a given abatement and emission schedule.[1] Since a world without climate damage is a hypothetical counterfactual, more useful estimates of physical climate risk are obtained by taking the differences in GDP associated with different abatement policies – in which case the 'business-as-usual' terms cancel out. Despite its limitations (GDP is a flow at a given point in time, and poorly conveys the cumulative welfare implications to that horizon), this definition has the great advantages of being simple and unambiguous, and of not requiring any discounting, thereby avoiding the thorny question of the appropriate discount rate.[2]

When it comes to transition risk, the definition, and the very meaning of the expression, become much less precise. In a rather narrow meaning of the term, transition risk is sometimes associated with the cumulative costs incurred by companies to manage and adapt to climate change and to the attending regulations. (See, for instance, the definition given by the United States Environmental Protection Agency in EPA (2023).) The European Central Bank (Bua, Kapp, Ramella, and Rognone (2022)) takes a somewhat broader approach, and defines transition risk as the risk that 'arises from the costly adjustment towards a low-carbon economy.' An even broader meaning to the term is conveyed by the IMF, when it states that 'transition risk results from changes in climate policy, technology, and consumer and market sentiment during the adjustment to a lower-carbon economy' (increased costs in energy are included in this definition – see Grippa, Schnuttman, and Suntheim (2019)). Some commentators then seem to give the term 'transition risk' the meaning of the additional costs of decarbonizing the economy due to a rushed transition. The idea, as Aal, Wanvick, and Dale (2022) suggest, is that a 'rapid transitions may increase [climaterelated] risks even more'. Often, it is assumed that a hard decarbonization target will be met with certainty by a certain date, and that undue delays increase these additional costs (this is the approach taken, amongst others, by Bolton and Kacperczyk (2023)). It is not clear, however, what would impel a country to reach a given decarbonization target almost at any cost, especially if the country has only morosely followed the abatement path up to the point of the sudden transition. More fundamentally, the very term 'transition risk ' is unhelpful: the word 'risk' implies variability and uncertainty; however, this variability should be superimposed on an expected transition *cost*. Distinguishing between what is expected and what uncertainty we have around this central estimate is obviously important, but rarely clearly articulated. Unfortunately, in common usage the two concepts are often conflated.

In addition, the two channels of value impairment, the physical and the transition one, are often analysed and estimated separately, and sometimes one of the two aspect is ignored altogether. Generally, more attention seems to have been devoted to transition than to physical risk – which is puzzling, since physical risk must be larger than transition costs for these costs to be incurred in the first place. Yet Bolton and Kacperczyk (2023) find that transition risk appears to be priced in traded securities, but physical risk not so. Similarly, in the popular IPCCARWGIII (2021)-sponsored SSS-RCP scenario approach,

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[1] - Sometimes physical risk is expressed as the difference in physical damages between a business-as-usual abatement and a given policy. This definition is more problematic, because it is not obvious what should be defined as a business-as-usual policy. See, in this respect, the exchange between Hausfather and Peters (2020) and Schwalm, Glendon, and Duffy (2020).

[2] - The correct-discount-rate debate goes all way the way back to Sidgwick (1907) and Ramsey (1928). A contemporary facet of this debate can be appreciated in Stern (2007) and Nordhaus and Moffat (2017). The famous 'wrinkle in time' thought experiment is presented in Nordhaus (2007).

physical risk is ignored, and agents in the underlying models do not react to higher damages by adjusting any aspect of their behaviour. At the opposite end of the spectrum, in the recent critique by Lenton, Rockstrom, and et al (2019) of the advice received by the UK pension fund trustees, only physical risk is discussed, and it is transition risk that now seems to be absent.

This state of affairs is less than satisfactory. We propose a comprehensive definition of transition costs as the total costs (understood as diversion of disposable income that could be used for consumption) needed to achieve a given level of decarbonization (emission reduction). There are several advantages from looking at transition costs in this manner. First of all, with this definition it becomes clear that physical and transition costs are two sides of the same coin, since the greater the transition effort, the more we can reduce both the expectation of and the variability of physical damages. Second, the definition makes clear that any abatement policy will have expectations of associated physical damages and of transition costs, and a substantial variability around these two central estimates. Broadly speaking, the price of a low transition effort is higher physical damages. However, even high transition costs only reduce our expectations of physical damages, but still leave considerable uncertainty. This is why it makes a lot of sense to consider these four quantities (the two central estimates and the two uncertainties) jointly.

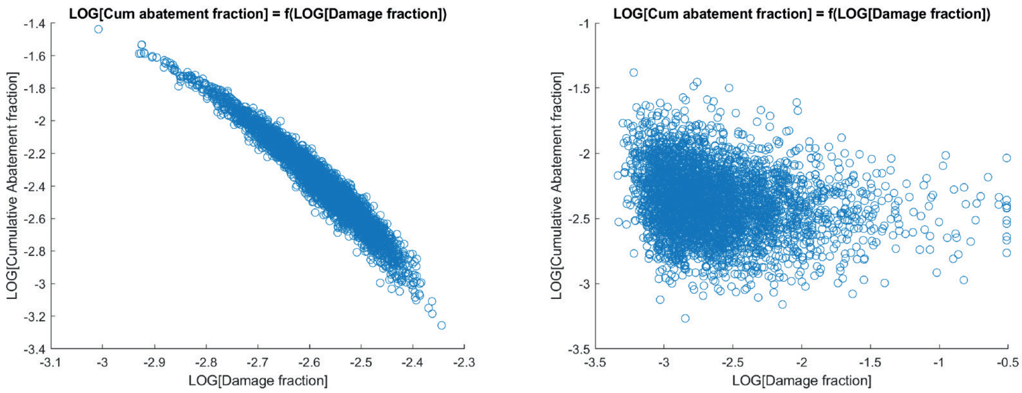
One may argue that our definition of transition risk does not answer the questions many investors and regulators ask. Transition risk, these critics may say, is often estimated in order to gauge how companies' cashflows (and hence their valuation) can be affected by the changes (technological, regulatory, etc) they have to undertake to comply with an exogenous abatement policy. This seems to be the meaning in EPA (2023), and this is the approach taken with discounted-cashflow valuation models. From this perspective, and given these goals, our definition seems too all-encompassing to be of use. However, we would argue that, to arrive at quantitative estimates of cashflow impairments, it is necessary to assess first the total transition costs, and then to estimate how these costs are spread among taxpayers (eg, via subsidies), customers (eg, via carbon taxes) and producers (eg, via quantity controls, price controls or explicit taxes). Knowing how the cake is cut is obviously important, but we would argue that knowing the size of the cake is even more so.

The approach we present can therefore be regarded as a top-down approach to estimating transition costs. Again, there are strong similarities with the analysis of physical damages, that can be carried out in a bottom-up (enumerative) manner, or following a topdown approach (say, using econometric approaches (as in Rudik (2020)), or macroeconomic methods, such as Computational General Equilibrium models). Exactly as in the case of physical damages, top-down approaches have advantages and disadvantages with respect to bottom-up methods. In a nutshell: the top-down approach that we present captures much better the global effects on equity valuation, but cannot be easily apportioned to individual firms; the bottom-up approach knows about the transition costs of the individual firms, but gives very few clues as to how these show be aggregated.

Of course, the most profitable course of action is to explore both avenues of investigation, and to ensure that the two approaches 'meet in the middle'.

In this paper we therefore try to improve on the current state of affairs in two directions: first, we define and distinguish between expectations and variability of physical and transition costs; second, we show how these quantities are related, and how the magnitude of one can be estimated given the magnitude of the other. More specifically, we use an extension of a popular Integrated Assessment Model (the Nordhaus and Sztorc (2013) DICE model) to estimate a robust relationship between physical and transition costs, and assess the degree of uncertainty associated with these estimates. To give a preview of our results, Fig 1 shows the nature of the relationship between physical and transitions costs that we manage to establish – in the case of uncertainty only in the exact pace of the abatement policy (left panel) and when the full variability of the state variables is taken into account (right panel). These figures prompt many questions: for instance, why do the physical losses in right-hand panel spread out so much to the right? And why is the explanatory power of the physical damages reduced so much in the right-hand panel? In the body of the paper we explain these features, we present how the 'clean' relationship in the left panel has been obtained, and we show how it can be justified. Already at this stage, however, the two figures clearly show how closely related physical and transition costs are, and how important it is to distinguish between expectations and variability for these quantities.

Exhibit 1: Left panel: the relationship between the logarithm of the fraction of GDP lost to physical damages (x axis) and the logarithm of the cumulative abatement fraction (y axis) when the only uncertainty is about the exact pace of the abatement policy. Right panel: The same quantities when the state variables of the problem are allowed to be stochastic.



Finally, we show in Section 3.1 that one can establish a close, quantitative correspondence between important quantities produced by the benchmark IPPC-sponsored SSP/RCP scenarios and the transaction costs we estimate. We argue that the information that can be obtained from our model is richer than what afforded by the SSP/RCP framework for two reasons: first, because, by linking physical damages and transaction costs, our approach allows a more comprehensive appreciation of the economic effects of a given abatement policy; and second, because it adds a much-needed probabilistic dimension to the outputs of the probability-agnostic SSP/RCP scenarios.

2.Definitions and Methodology

As mentioned in the introduction, we start from a popular Integrated Assessment Model (the Nordhaus and Sztorc (2013) DICE model), enriched so as to have stochastic economic output,[3] and uncertainty in the damage exponent as described in Rebonato, Dherminder, Melin, and O'Kane (2024). For reasons that we explain below, we do not use this model as an optimization tool, but simply employ its structure to link economic production to CO_2 emissions, concentrations, and increases in temperature anomalies. These are then used as input to the so-called damage function, the mapping, that is, from temperature increases to economic (physical) damages. We use for the damage function the formulation in Howard and Sterner (2017), that updates and corrects early results in the literature (as in Tol (2009), Nordhaus (1977)). The choice of the damage function is contentious, and we present our results based on this popular, but not universally accepted, functional dependence simply for illustrative purposes. If other damage functions were thought to be more suitable, the same procedure described below can still be followed. In our formulation, the damage function, $\boldsymbol{\Omega}_t$, is assumed to have the form

$$\Omega_t = a_2 T_t^{a_3} \tag{1}$$

where T_t is the time-t temperature anomaly (measured in C or K), and the exponent a_3 is referred to in the literature as the 'damage exponent'.

In the DICE model, part of the economic output is devoted to consumption and part is saved/invested, as in classic macroeconomic models. (See Appendix A for the main constitutive equations of the DICE model.) However, the agents in the model also realize that economic output contributes, through the non-decarbonized part of the economy, to CO_2 emissions, increased concentrations, temperature increases and hence (physical) damages. Therefore they decide to devote part of the output to costly abatement activities, that reduce the carbon intensity of the economy, and hence damages. When Integrated Assessment Models are used in a normative manner (by maximizing a welfare function), the abatement schedule and the savings rate are control variables, chosen so as to optimize the target welfare. In our study, we do not assume optimality, and allow for the possibility of suboptimal, politically-driven abatement policies. We are aware that this assumption flies in the face of the Lucas (1976, 1981) Rational Expectation Hypothesis, but we think that the wide divergence between the actually implemented and the theory-recommended levels of the carbon tax suggests that our assumption of non-optimality is not unreasonable. To give an example, as Litterman (2024) points out, the global emission-averaged carbon tax imposed worldwide was \$18.97/Ton in 2021, and plummeted to \$4.08/Ton in 2022, while a meta-analysis by Tol (2023) reports a median value for the optimal social cost of carbon elicited from professional economists of \$60/Ton. When it comes to climate change, in sum, agents in the real world do not appear to share what Muth (1961) calls the econometrician's model.[4] Neither choice (to allow or not to allow agents to optimize) is unproblematic, but, in the light of these considerations, and of the current glacial pace of abatement compared with the recommendations of most economists, we have preferred the no-optimization assumptions. We discuss in Section 3 how this modelling choice can affect the results.

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[3] - The stochasticity in economic output is achieved by using the Bansal and Yaron (2004) long-term risk model, as adapted to climate-change problems by Jensen and Traeger (2014).

[4] -Far from sharing the econometrician's model, Democrats and Republicans in the US do not seem to agree even on the information set on which they should condition their expectations: for instance, MacRight, Dunlap, and Xiao (2014) report that, in the wake of the unusually warm Winter of 2012, "Democrats [were] more likely than Republicans to perceive local winter temperatures as warmer than usual". And Blumenthal (2021) finds that "72% of Democrats and Democratic leaners say they have noticed extreme weather events in their area compared to just 36% of Republicans and Republican leaners."

Irrespective of whether Integrated Assessment models are used in a policy-optimization mode or not, in the model the revenues from carbon taxes are channelled towards the abatement costs that the economy accepts to bear. The key point is that, since these abatement costs reflect abatement, adaptation and carbon removal, they can be taken as a reasonable proxy for our definition of the transition costs. An Integrated Assessment Model such as DICE therefore establishes an (inverse) link between physical damages and transition costs. In its original, fully-deterministic, formulation the Nordhaus and Sztorc (2013) model gives rise to a very 'sharp' relationship between abatement and damage costs. When the state variables of the problem (say, economic growth) are instead made stochastic, the link between physical costs and abatement becomes less sharp, and this gives rise to what we call transition *risk*, ie, to uncertainty around the central expectation. In either case, an Integrated Assessment Model therefore automatically offers, alongside the physical damages on which most users have focussed their attention, also a very reasonable proxy for transition costs. In the rest of the paper we quantify the nature of the dependence between these two quantities.

To do so, we proceed as follows. First, we have to characterize the aggressiveness of the abatement policy. We do so trough a simple and powerful statistic, the effective abatement speed, κ, that controls the speed of abatement, μ_t:

$$\mu_t = \mu_0 \exp(-\kappa \cdot t) + (1 - \exp(-\kappa \cdot t)) \qquad (2)$$

(As we discuss in Appendix A, this assumption is much less restrictive than it may appear at first blush.) The speed-of-abatement function is then implicitly defined by

$$e_t = \sigma_t \cdot y_t \cdot (1 - \mu_t) \qquad (3)$$

where e_t denotes industrial CO_2 emissions, y_t the gross economic output, and σ_t is the GDP intensity (emissions per unit of GDP). The results shown below refer to the case of a deterministic GDP intensity function that decays as a deterministic function of time (as in the original DICE model), but very similar results have been obtained when the function has been endogenized.[5]

We then choose a horizon, τ, and an *expected* abatement, μ_τ, at this horizon. For instance, a policy target such as (near) complete decarbonization by 2050 would imply $\tau = 25$ and, say, $\mu_\tau = 0.95$. We allow for uncertainty in this expected horizon abatement by assigning to this quantity a truncated lognormal distribution, with percentage volatility, s, and upper an lower truncation boundaries of 0.975 and μ_0, respectively. To each of these sampled functions μ_τ we associate a horizon-dependent equivalent abatement speed, κ_T, which can be straightforwardly obtained from Equation 2 to be

$$\kappa_\tau = -\frac{1}{\tau} \log \frac{1 - \mu_\tau}{1 - \mu_0} \qquad (4)$$

Fig 2 shows in its left panel for each time from today (x axis) the abatement functions, μ_t, from the abatement speeds, κ_T, obtained from Equation 4, and shown in the right panel. The right panel shows the histogram of the abatement speeds obtained using Equation 4 for an expected time-T abatement of $\mu_\tau = 0.72$ with standard deviation of 8%.

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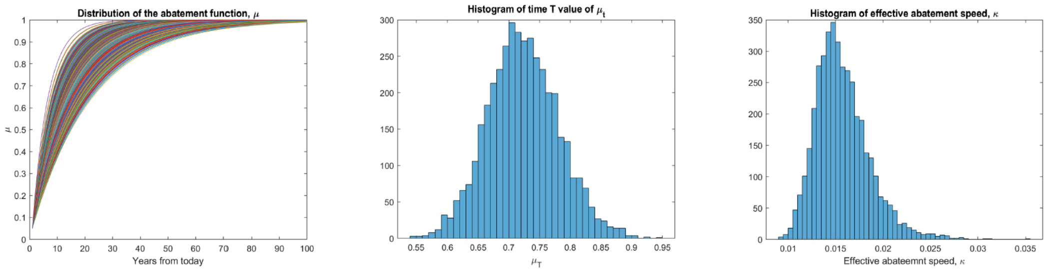
[5] - The endogenization was obtained by extracting from the original, deterministic DICE model the relationship between GDP/person and GDP intensity (the function σ) and assuming that the same relationship (plus noise) would describe the link between GDP intensity and GDP/person when the latter quantity becomes stochastic.

The histogram of the time-τ values of the abatement function, μ_t, are then shown in the middle panel.

Exhibit 2: Left panel: for each time from today (x axis) the abatement functions, μ_t, from the abatement speeds, κ_τ, obtained from Equation 4, and shown in the right panel. Middle panel: histogram of the time-τ values of the abatement function, μ_t. Right panel: histogram of the abatement speeds obtained using Equation 4 for an expected time-T abatement of μ_τ = 0.72 with standard deviation of 8%.



Since we have uncertainty in the horizon value of the abatement function, the time-T physical damages will have a distribution, with an expected value and a variance. Two reasonable functions of physical damage are then the change in GDP between a world without climate damages and a world with climate damages and a certain abatement schedule, or the change in GDP growth between the two worlds. If we denote GDP growth with and without climate change by $\tilde{g}_{GDP}$ and g_{GDP}, respectively, we then show in Appendix 10 that the ratio of these two latter quantities is given by

$$\frac{\tilde{g}_{GDP}}{g_{GDP}} = 1 - \gamma \cdot \frac{\Omega_t + \Lambda_t}{K} \tag{5}$$

As for the ratio of the GDP with and without climate damages, $G\tilde{D}P_t$ and GDP_t, we have

$$\frac{G\tilde{D}P_t}{GDP_t} = 1 - \Omega_t - \Lambda_t \tag{6}$$

Whichever the chosen measure of economic loss, the expectation of this loss is therefore a function of the expected value of the abatement (transition) costs and physical damages. In addition, there will an uncertainty in this economic loss, which will be a function of the uncertainty in the physical damages and transition costs, and of the correlation between these two quantities. Intuitively, we expect that, the greater the abatement effort (the transition cost), the smaller the physical damage. It is this precise dependence that we set out to estimate.

3. The Dependence of Ω_t on Λ_t

As discussed above, both both the loss in GDP (with respect to a reference case) and The drop in GDP grow are reasonable measures of economic damage. Since we show in Appendix B that both these quantities can be linearly related to physical damages, $\mathbf{\Omega}_t$, and abatement costs, $\mathbf{\Lambda}_t$, we focus on the joint estimates of of $\mathbf{\Omega}_t$ and $\mathbf{\Lambda}_t$, and leave the choice of the value-loss metric to the reader.

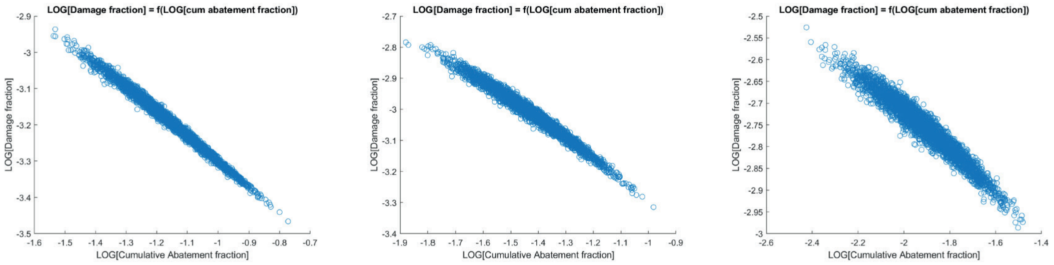
We make the assumption that the damages at time t, $\mathbf{\Omega}_t$ should be a function of the cumulative abatement effort out to the same horizon, plus some residual noise:

$$\log \Omega_t = \log \left(\int_0^t \Lambda(s) ds \right) + \epsilon_t \tag{7}$$

From our calibrated Integrated Assessment we compute, for a given abatement schedule μ_t characterized by an equivalent abatement speed, κ, (see Appendix A) the discretized version of Equation 7. We carry out this calculation for two cases:
1. when the expectation of the abatement schedule known, there is uncertainty about the horizon value of μ_T, but all state variables are deterministic;
2. when the expectation of the abatement schedule known, there is uncertainty about the horizon value of μ_T, and economic output and the damage exponent are stochastic.

When we do so, we obtain the clear relationship displayed in Fig 3, which shows the logarithm of the damage function at the horizon, $T = 2100$ (y axis) as a function of the logarithm of the cumulative abatement fraction out to the same horizon (x axis), for the cases of expected abatements at the chosen horizon of $\mu_T = 0.72$ (left panel), $\mu_T = 0.60$ (middle panel) and $\mu_T = 0.45$ (right panel) fort the case where all the state variables are assumed to be deterministic. The three cases correspond to an equivalent abatement speed of $\kappa = 0.0156, 0.0109, 0.0069$ (see Appendix A for a precise definition of the equivalent abatement speed), and with half lives of 44, 63 and 100 years, respectively.

Exhibit 3: The logarithm of the damage fraction at the horizon, T = 2100, (y axis) as a function of the logarithm of the cumulative abatement fraction out to the same horizon (x axis), for the cases of expected abatements for an expected decarbonization target of $\mu_\tau = 0.72$ (left panel), $\mu_\tau = 0.60$ (middle panel) and $\mu_\tau = 0.45$ (right panel) for $\tau = 2050$, and when all the state variables are assumed to be deterministic.

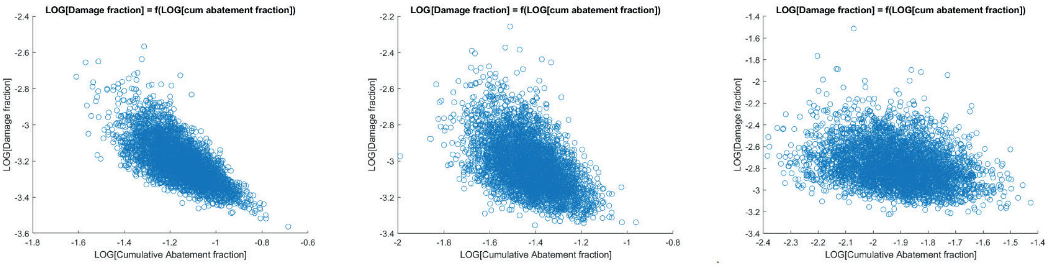


As these figures show, there is a clear dependence between the cumulative abatement effort (that we take as a proxy for the transition cost) and the damages. Clearly, the stronger the abatement, the greater the transition cost. We also note for future reference that in this deterministic setting not only the expectation, but also the dispersion of the cumulative abatement costs increases as the abatement speed decreases.

These figures give a first indication of the variability in transition costs, but they still significantly underestimate the uncertainty in this quantity that materializes when the main stochastic drivers of the problem (linked to the uncertainty in economic output and in the damage exponent) are switched on. This is clearly shown in Fig 4, which displays the same quantities presented in Fig 3, but for the case where the economic output and the damage exponent are assumed to be stochastic.

Why is the explanatory power of the cumulative abatement costs (as captured, say, by the R^2 of the regression) so much lower? The answer lies in the large uncertainty about the damage function, which is the component of the economic modelling about which there is greatest uncertainty (see Kainth (2023) for a discussion). The resolution of this uncertainty over time is independent of the abatement policy, and therefore a great part of the dispersion in the damages for a given level of cumulative abatement depends on whether a high or a low damage exponent is revealed to be true.[6] In practice, this means that, *for a fixed abatement path*, damages can be much higher if a high damage exponent is revealed to be true, but abatement costs are not affected by this discovery. Since, as mentioned, there is great uncertainty in the damage function (particularly so, as Lenton, Held, Kriegler, Hall, Lucht, Rahmstorf, and Schellnhuber (2008) points out, in the presence of tipping points),[7] this reduces the explanatory power of damages to account for transition costs.

Exhibit 4: The logarithm of the damage function at the horizon, T = 2100, (y axis) as a function of the logarithm of the cumulative abatement fraction out to the same horizon (x axis), for the cases of expected abatements for an expected decarbonization target of $\mu_\tau = 0.72$ (left panel), $\mu_\tau = 0.60$ (middle panel) and $\mu_\tau = 0.45$ (right panel) for $\tau = 2050$, and when the economic output and the damage exponent are assumed to be stochastic.



Given the dependence of the cumulative abatement costs on the abatement speed, and our choice of proxying transition costs by this quantity, we can ask another interesting question: what is the (equivalent) abatement speed required for the transition costs to be below a certain value at a given confidence level? There two competing effects at play: first, the higher the abatement speed (the horizon abatement, κ_τ), the greater the abatement costs: the whole distribution will therefore shift upwards with increasing κ_τ; however, a higher speed of abatement reduces the dispersion around the expectation (reduces the pure transition *risk*), and therefore a high percentile does not grow as fast as the expected transition cost. Figure 5, which displays the expectation and the 90th percentile of the horizon-time distribution of cumulative abatement costs as a function of the terminal abatement, μ_τ, shows that this is indeed the case, but that the upward shift in the distribution due to increase in abatement speed dominates.

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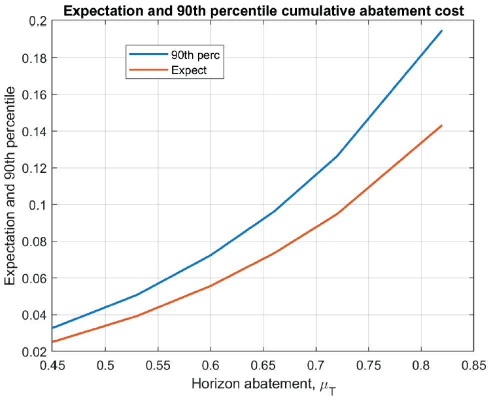
[6] - In our simulations we have capped GDP losses at 60%: this explain the 'ceiling' visible at the top of the three graphs.
[7] - As Alley, Marotzke, Nordahus, and et al (2003) clearly point out, '[u]npredictability exhibited near climate thresholds in simple models shows that some uncertainty will always be associated with projections.' Unfortunately, this means in practice that we may only conclusively know the location of the threshold of a tipping point once we have crossed it.

3.1 Links with the SSP/RCP scenarios

Our approach to estimating physical and transition costs allows a very interesting link with the popular IPCC-sponsored SSP/RCP scenarios (see IPCCARWGIII (2021) and van Vuurem et al (2011)). With this approach the qualitative narratives described in five Shared Socioeconomic Pathways (SSPs) are matched with a number of Representative Carbon Pathways (RCPs). The latter describe the forcing (in W/m^2) at the end of the century.[8] Since this quantity is a function of the CO_2 emissions and concentrations, and these in turn can be linked to temperatures, the SSP/RCP approach links socioeconomic narratives with end-of-century temperatures. Quantitatively, the link is carried out through Process-Based Integrated Assessment Models (PB IAMs), whose internal degrees of freedom are set so as to mimic as closely as possible the chosen narrative. (Despite their rather vivid descriptions, narratives ultimately specify the path of population, technological and economic growth: this is what makes their mappings to the parameters of the PB IAMs relatively easy). Once the parameters of the model have been set to reflect the narrative, a single degree of freedom is left to achieve the desired temperature (forcing) target: the carbon tax. In the RCP/SSP approach, all the carbon tax transfer is assumed to be channelled to abatement activities, chosen on the basis of cost minimization from the marginal cost curves. It is important to note that, since PB IAMs are cost-minimizing but not welfare-optimizing models, there is no notion of climate damages in the approach.

Exhibit 5: The expectation and the 90th percentile of the horizon-time distribution of cumulative abatement costs as a function of the terminal abatement, μ_T.



The conceptual similarity between the SSP/RCP setup and the approach we have proposed in this paper is transparent. In particular, the cumulative abatement cost in our approach is the exact counterpart of the cumulative carbon tax levied in the SSP/RCP approach to hit a particular forcing target.Our model adds two important components: a link between the transition and the physical-damage cost; and an appreciation of the variability around these estimates. This can be seen more precisely as follows.

We most commonly used RCPs correspond to forcings ranging from 1.9 to 6.0 W/m^2.

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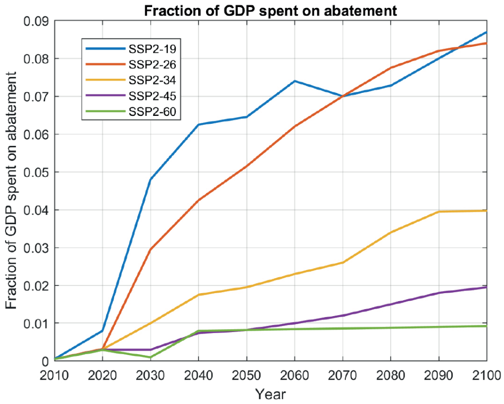
[8] - Forcing is the balance between energy in and energy out per unit time and per unit area.

Exhibit 6: Model-implied carbon tax transfer for the SSP2 ("Middle of the Road") narrative and forcings at T = 2100 equal to 1.9, 2.6, 3.4, 4.5 and 6.0 W/m2 (top to bottom).



We make use of a simple but reasonable linear mapping between forcings, F, and expected temperature, ET, of the form[9]

$$ET = 0.5653 + 0.459 \cdot F \tag{8}$$

With this relationship the forcings of 1.9, 2.6, 3.4, 4.5 and 6.0 W/m^{2}map into temperatures of 1.4, 1.8, 2.1, 2.6 and 3.3 C, respectively (all the figures refer to a end-of-century horizon). Given these targets, we can then easily calibrate the average abatement speed in our model to obtain any desired temperature. The abatement costs in our model are the equivalent of the carbon taxes in the SSP/RCP framework. Welfare-optimization studies invariably find that carbon taxes should grow over time (and this is what the cost-minimization SSP/RCP approach obtains as well). We therefore make the simplest assumption that the carbon tax as a percentage of GDP will grow linearly from today to the final horizon. A glance at Fig6 suggest that the assumption is not unreasonable.

We are now in a position to compare the projections of abatement costs produced by the SSP/RCP framework and by our model. For illustrative purposes, we focus on year-2100 temperatures of 1.8 and 2.6 C (corresponding to forcings of 2.6 and 4.5 W/m^2, respectively). When we look at the high-temperature, low-abatement RCP4.5 case, we find that the cumulative abatement cost (carbon tax) ranges from approximately 4% to 11%. With our assumption of linear increase in taxation, this corresponds to a year-2100 taxation level ranging between 0.57% and 1.57%. These values compare well with the terminal value of the corresponding curve in Fig 6 (second curve from the bottom).

We can repeat the exercise for the case of a 1.8 C temperature by year 2100 (which corresponds to an RCP of 2.6 W/m^2). This is a low-temperature, high-abatement, highcost case. Indeed, we find that the cumulative abatement cost (carbon tax) is now much higher, ranging as it does from approximately 35% to 55%. This corresponds to a year-2100 taxation level ranging between 5.0% and 7.9%. Again, this compares reasonably well with the value of a bit more than 8% obtained using the SSP/RCP framework, as one can read from Fig 6 (second curve from the top).

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9 - The linear mapping has an R^2 of 0.9811

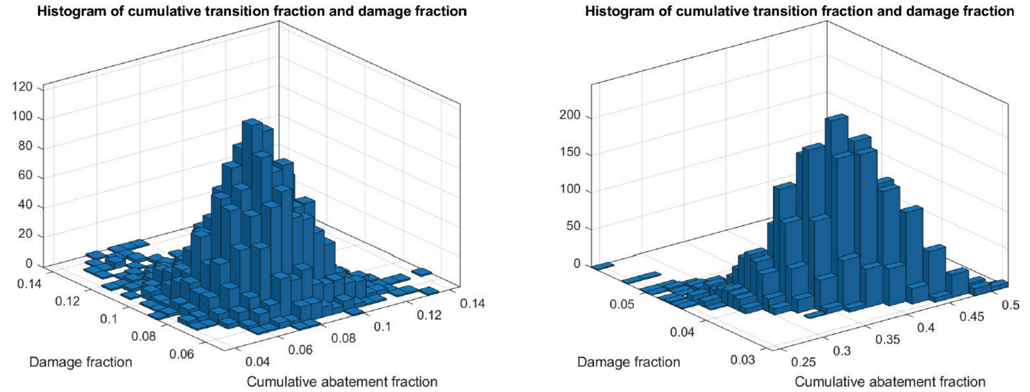
We note that in our case we have a distribution of outcomes (corresponding to the different possible values for economic growth and damage exponent), while Fig 6 shows only *the* one value per RCP associated to the chosen narrative (SSP2 in the figure). Adding the values associated with the other narratives would of course create a spread of tax schedules also in the SSP/RCP case. However, this spread could not be interpreted as a distribution, because the SSP narratives are by design not associated with any probability. If one believes that the distribution of the state variables used in our version of the DICE model conveys reasonable probabilistic information, with our approach one can also estimate the likelihood of the different transition cost outcomes.

There is another important advantage associated with our approach: by making use of the information in Figs 3 and 4, one can now associate a distribution of physical damages to each transition cost, and obtain a more meaningful picture of the overall costs and damages associated with any chosen abatement policy. Again, a probabilistic dimension can be added to this combination, as shown in Fig 7 that displays the empirical joint distribution of the damage fraction and cumulative abatement fraction for the low- and high-temperature cases analysed above. Apart from the obvious shift in opposite directions for the distribution of damages and costs when a slower abatement schedule is chosen, note how the correlation between physical damages and transition costs increases with the aggressiveness of the abatement policy (ie, moving from the left to the right panel). A world with a strong abatement policy, in other words, is more predictable not just in the outcomes, but also in the link between physical damages and transition costs. The residual variability comes, in our model, from the significant uncertainty in economic growth produced by the Bansal and Yaron (2004) model – a variability that is by design absent in the output from the SSP/RCP scenarios.

4. Discussion, Limitations and Conclusions

We have decomposed the transition costs associated with a given pace of decarbonization into an expectation component and an uncertainty term (and reserved the term 'transition risk' to this latter quantity). We have also shown that, at least within the confines of a relatively stylized model, there is a clear and strong inverse relationship between reasonable measures of economic damages (physical damages) and the associated transition costs. More generally, we have found that there are clear relationships between the first two moments of both distributions: the expectation of the physical damage costs, for instance, has an impact not only on the expectation of transaction costs, but also on their variability. This suggests that the analysis of transition and physical costs should be most profitably carried out in a joint manner, rather than in isolation, as it has mainly been done so far.

Exhibit 7: The empirical joint distribution of the damage fraction and cumulative abatement fraction. Left panel: year-2100 temperature = 2.6, right panel = year-2100 temperature = 1.8.



We have also shown that our approach produces transition costs that are closely aligned with the carbon taxation burden derived by the benchmark SSP-RCP scenarios. Since the transition risk in the restricted, company-specific sense of EPA (2023) depends in great part on how this taxation levy is spread between companies, consumers and present and future taxpayers, the quantification of the cumulative carbon tax is an essential piece of information for a top-down analysis. Our approach offers the added advantage that, unlike the output from the SP/RCP scenarios, it produces not only an estimate of the transition costs, but also their variability, and (the distribution of) the associated physical damages.

We stress that our estimates of the transition costs should be understood as a lower bound, because in our analysis we have assumed that the agents in our economy deploy their abatement resources in the most efficient way, by careful examination of the marginal cost curves of different abatement and removal technologies, as discussed for instance in Rebonato, Dherminder, Melin, and O'Kane (2024). Unfortunately, there are many examples of inefficient allocation of abatement resources, of which the case of ethanol subsidies, discussed in detail in Chapter 14 of Richter (2014), is only one example amongst many. Deviations form cost minimization would necessarily increase transition costs. Also, a 'rushed' transition – as situation, that is, where an emission target must be met by a central date, but abatement policies are delayed until the last moment, causing a sudden catch-up of abatement initiatives – would plausibly increase transition costs.

We have provided some numerical results, but our contribution should be seen as mainly methodological: we have provided what we believe are reasonable results for our version of the popular DICE model, but we have not discussed in detail the precise choice of many of its components, such as the damage function. Different users can, of course, make different choices for the various modules of their Integrated Assessment Model, and these choices will obviously affect the quantitative results. However, the general idea of establishing a link between the distributions of physical damages and transition costs retains its validity for any *integrated* assessment model.

Definitions, *qua* definitions, are neither right nor wrong. They can, however, be more or less helpful. We have therefore proposed to distinguish clearly between the expectation of transaction costs, and the uncertainty associated with this central estimate, and to reserve the term 'transition risk' to this latter quantity. Apart from definitional issues, the fact remains that we have quantified the links between what has so far been called physical and transition risk, and we have shown that, when the uncertainty in the main drivers of the joint climate/economy system is taken into account, there is substantial variability in the costs associated even with a fixed schedule of decarbonization of the economy – the more so, the slower the chosen abatement speed. These conclusions should be of interest both to policymakers and to investors.

A. Deriving the Equivalent Abatement Speed

In this appendix we define and derive an expression for the equivalent abatement speed that appears in Equation 2.

In the DICE approach the build-up of CO_2 concentrations and the reabsorption of emissions are modelled by means of a three-box climate model, with the three boxes describing the atmosphere, the upper ocean and the lower ocean. The concentration in the three layers can be described by a vector, m_t:

$$m_t = \begin{bmatrix} m_t^{at} \\ m_t^{up} \\ m_t^{lo} \end{bmatrix} \tag{9}$$

In discrete time, the evolution of the the concentration vector is given by

$$e_1 \neq 0\text{:}\;\; e_t = [e_t^{atm}, 0, 0]' \tag{10}$$

with b a 3 × 3 matrix and e_t a 3 × 1 emission vector with only $m_{t+1} = [b \cdot m_t + e_t]dt$. Equation 10 can be rewritten as

$$m_{t+1} - m_t = [(b - I)m_t + e_t]dt \rightarrow \frac{dm_{t+1}}{dt} = (b - I)m_t + e_t \tag{11}$$

This can be expressed as

$$\frac{dm_{t+1}}{dt} = (b - I)m_t + e_t = -\xi \cdot m_t + e_t \tag{12}$$

with

$$\xi = I - b \tag{13}$$

The solution of the associated homogenous ODE is given by

$$m_t = \exp(-\xi t) \cdot m_0 \tag{14}$$

where $\exp(-\xi t)$ is the exponent of a matrix, and is itself a 3 × 3 matrix.

When e_t is a generic function, finding a solution to the inhomogeneous ODE is difficult. Let's discretize the problem. We have

$$m_1 = \exp(-\xi \Delta t)m_0 + e_1 \tag{15}$$

$$m_2 = \exp(-2\xi \Delta t)m_0 + \exp(-\xi \Delta t)e_1 + e_2 \tag{16}$$

$$m_3 = \exp(-3\xi \Delta t)m_0 + \exp(-2\xi \Delta t)e_1 + \exp(-\xi \Delta t)e_2 + e_3 \tag{17}$$

$$\dots \tag{18}$$

$$m_n = \exp(-\xi \cdot n\Delta t)m_0 + \sum_{i=1}^{n} \exp(-(n-i) \cdot \xi \Delta t)e_i \tag{19}$$

or, in continuous time,

$$m_t = \exp(-\xi \cdot t)m_0 + \int_0^t \exp[-\xi(t-s)]e(s)ds \tag{20}$$

So, the infinity of emission pattern for which the integral, $\int_0^t \exp[-(t-s)]e(s)ds$, has the same value produce exactly the same terminal (time-t) CO_2 concentration.

The results so far have been expressed in terms of equivalent emissions. However, in IAMs it is customary to use as control variable the abatement function , μt, implicitly defined by the equation

$$e_t = \sigma_t(1 - \mu_t)y_t \tag{21}$$

with σ_t the emission intensity of GDP (GDP/emissions), and yt the gross economic output.

This shows that emissions depend not only on the abatement schedule, but also on the GDP growth and on the rate of decline of the emission intensity. To express the horizon concentration in terms of of abatement schedule, we can proceed as follows. First, for simplicity,[10] let's set

$$\sigma_s = \sigma_0 \exp[-h \cdot s] \tag{22}$$

$$y_s = y_0 \exp[g \cdot s] \tag{23}$$

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[10] It is conceptually easy to extend the treatment to the case when the growth rates, *h* and *g*, are functions of time.

One gets

$$m_t^{atm} = \exp(-\xi t) \cdot m_0 + \sigma_0 \cdot y_0 \int_0^t \exp[-\xi(t-s)]\zeta(s)ds \tag{24}$$

with the vector $\zeta(s)$ given by

$$\zeta(s) = [\exp[(g-h)s](1-\mu_s), 0, 0]' \tag{25}$$

Consider now the particular emission schedule given by

$$\mu_t = \exp(-\kappa \cdot)\mu_0 + (1 - \exp(-\kappa \cdot t)) = 1 + \exp(-\kappa \cdot t)(\mu_0 - 1) \tag{26}$$

Then, for this particular abatement schedule, the vector ζ has the expression

$$\zeta(s)^* = (1-\mu_0)[\exp[(g-h-\kappa)s], 0, 0]' \tag{27}$$

It then follows that the infinity of abatement schedules, μ_t, for which the integrals $\int_0^t \exp[-\xi(t-s)]\zeta(s)ds$ and $\int_0^t \exp[-\xi(t-s)]\zeta(s)^* ds$ have the same values produce the same atmospheric concentration. The constant κ is called the *equivalent abatement speed*.

B. Relating Physical Damages to Ω_t and Λ_t

In this appendix we derive the links between plausible measures of economic losses and the damages (Ω_t) and abatement costs (Λ_t) that appears in DICE-like Integrated Assessment Models.

In the DICE model the equations that link the economic and climate variables of the problem can be summarized as follows:

$$Y_g(t) = A(t)K(t)^{\gamma}L(t)^{1-\gamma} \tag{28}$$

$$Y_n(t) = \frac{Y_g(t)}{1-\Omega(t)-\Lambda(t)} \tag{29}$$

$$inv(t) = Y_n(t)savrate(t) \tag{30}$$

$$c(t) = Y_n(t) - inv(t) \tag{31}$$

$$K(t+1) = K(t)(1-\delta\Delta t) + inv(t) * \Delta t \tag{32}$$

$$g_c(t+1) = \log\left(\frac{c(t+1)}{c(t)}\right) \tag{33}$$

where Y_g denotes gross output, Y_n net output, $A(t)$ the total factor productivity, *inv* investment, $\Omega(t)$ the fraction of gross output lost to climate damages, Λ the fraction of gross output spent on abatement, $K(t)$ capital, c consumption, δ the depreciation per unit time, g_c consumption growth and Δt the time interval. These equations must be complemented by initial values for capital, labour and the total value of production: these we take from the latest value of the DICE model.

We can then start from Eq (3.13) in Neal (2023):

$$GDP_{t+1} = GDP_t \cdot (1 + g_t^{GDP}) \rightarrow \frac{GDP_{t+1}}{GDP_t} = (1 + g_t^{GDP}) \tag{34}$$

Consider a Cobb-Douglas economy without damages:

$$Y_t = A_t \cdot K_t^{\gamma} \cdot L_t^{1-\gamma} \tag{35}$$

The quantity Y_t in the Cobb-Douglas Equation 35 is the GDP in Equation 34. We then have:

$$c_t = Y_t - sav_t \rightarrow sav_t = Y_t - c_t \tag{36}$$

and

$$K_{t+1} = K_t \cdot (1 - \delta) + sav_t = K_t \cdot (1 - \delta) + (Y_t - c_t) \tag{37}$$

where δ is the depreciation rate. Therefore

$$Y_{t+1} = A_{t+1} \cdot K_{t+1}^{\gamma} \cdot L_{t+1}^{1-\gamma} \tag{38}$$

If, for simplicity, for assume constant growth for the population, L, and the total factor productivity, al, one has

$$L_{t+1} = L_t \cdot (1 + g_L) \tag{39}$$

and

$$A_{t+1} = A_t \cdot (1 + g_A) \tag{40}$$

Since $\frac{GDP_{t+1}}{GDP_t} = \frac{Y_{t+1}}{Y_t}$, one obtains for $\frac{Y_{t+1}}{Y_t}$:

$$\frac{Y_{t+1}}{Y_t} = \frac{A_{t+1} \cdot K_{t+1}^{\gamma} \cdot L_{t+1}^{1-\gamma}}{A_t \cdot K_t^{\gamma} \cdot L_t^{1-\gamma}} \tag{41}$$

Substituting, we have

$$\frac{Y_{t+1}}{Y_t} = (1 + g_a) \cdot (1 + g_L)^{1-\gamma} \left(\frac{K_{t+1}}{K_t} \right)^{\gamma} \tag{42}$$

and

$$\frac{K_{t+1}}{K_t} = (1 - \delta) + \frac{Y_t - c_t}{K_t} = 1 + w_t \tag{43}$$

with

$$w_t \equiv \frac{Y_t - c_t}{K_t} - \delta \tag{44}$$

From this one obtains

$$\frac{Y_{t+1}}{Y_t} = (1+g_a)\cdot(1+g_L)^{1-\gamma}\,(1+w)^{\gamma} \tag{45}$$

Using the expansion

$$(1+t)^n \approxeq 1+nt \tag{46}$$

we get

$$\frac{Y_{t+1}}{Y_t} = (1+g_a)\cdot(1+(1-\gamma)\cdot g_L)\,(1+\gamma\cdot w)\,. \tag{47}$$

Neglecting terms with products of percentage growths, this gives:

$$\frac{Y_{t+1}}{Y_t} = 1+g_a+(1-\gamma)\cdot g_L+\gamma\cdot w \tag{48}$$

Finally, from Equation 34 we get

$$g_{t,GDP} = g_{t,a}+(1-\gamma)\cdot g_{t,L}+\gamma\cdot\left(\frac{Y_t-c_t}{K_t}-\delta_t\right) \tag{49}$$

This refers to a world with no climate damages. If we included the effects of abatement costs, Λ, and of climate damages, Ω, we would get

$$\tilde{g}_{t,GDP} = g_{t,a}+(1-\gamma)\cdot g_{t,L}+\gamma\cdot\left(\frac{[Y_t(1-\Omega_t-\Lambda_t)]-c_t}{K_t}-\delta_t\right) \tag{50}$$

The result is that GDP growth can be approximated by an affine function of damages, Ω_t, and abatement costs, Λ_t.

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