Doctorat

Dynamics and distribution of climate change impacts: insights for assessing mitigation pathways

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Short Summary

Because climate change affects economies at different scales, quantifying its impacts is particularly challenging. Yet, understanding climate change impacts is key to design appropriate mitigation and adaptation response. Damage assessment allows to set global targets and regional policies against the cost of inaction, and to prepare for adaptation by highlighting future vulnerabilities and hotspots. This thesis analyses how the dynamics and distribution of climate change impacts affects the assessment of mitigation pathways. First, I show that climate system dynamics matters to evaluate the resulting economic impacts, which increases the present value of mitigation actions. Second, using different assessments of climate change impacts aggregated at the country level, I analyse the distributional effects of different emission pathways. Finally, I study how spillovers via trade affect the distribution of climate change impacts, in the case of heat stress on labour productivity.

Résumé court

Parce que le changement climatique affecte l'économie à différentes échelles, quantifier ses impacts est particulièrement difficile. Pourtant, la compréhension de ces impacts est essentielle pour élaborer une réponse appropriée en terme d'atténuation et d'adaptation. Elle permet de fixer des objectifs régionaux et globaux à la lumière du coût de l'inaction, et de préparer l'adaptation en identifiant les vulnérabilités futures. Cette thèse s'intéresse à la façon dont la dynamique et la distribution des impacts du changement climatique affectent l'évaluation des trajectoires d'atténuation. Dans un premier temps, je montre que la dynamique du système climatique jour un rôle important pour comprendre les dommages économiques qui en résultent, ce qui peut augmenter la valeur sociale du carbone. Dans un deuxième temps, en tenant compte de l'hétérogénéité des impacts entre pays, j'étudie les effets distributifs de différentes trajectoires d'émissions. Enfin, je montre comment les effets de propagation via le commerce peuvent modifier la distribution des coûts du changement climatique du changement climatique, dans le cas des impacts sur la productivité du travail.

Contents

List of Figures

List of Tables

Chapter 1

General Introduction

Anthropogenic greenhouse gas emissions alter Earth's energy imbalance, causing changes to the climate system. These changes affect economies in complex ways. For instance, agricultural production is strongly dependant on temperatures and precipitations, and reduced yields from a changing climate can lead to food insecurity (Wheeler and Von Braun, 2013). Extreme events, such as storms or floods, whose frequency and intensity are expected to increase, destroy infrastructures and dwellings, and can have dramatic social consequences (Field et al., 2012). Sea-level rise and desertification would make a lot of places inhabitable. Climate change also has an effect on the functioning of ecosystem services, which contribute to the well-being of societies (IPBES, 2019).

From an economic point of view, climate change is an externality (Pigou, 1920). Actions of agents, who release greenhouse gas emissions into the atmosphere, cause harms to third parties, which justifies public intervention. A conventional way to solve this issue is to discourage emissions as much as they are detrimental to social welfare, by pricing them at their marginal damages. But applying this framework in the case of climate change is particularly daunting for several reasons.

First, climate change is a global externality: once in the atmosphere, emissions mix and all contribute to increase Earth's radiative forcing, causing changes all across the world. Given the diversity of biophysical impacts involved, and the complex ways in which they will affect socioeconomic systems, the possibility to reach a meaningful metrics to aggregate the impacts and quantify the marginal damage seems difficult.

Second, climate change is an intertemporal externality. Unlike with flow pollution, emissions last in the atmosphere for decades or centuries, and their consequences will be felt way into the future, so that the damage must be quantified over a long timescale. This poses a double challenge in both our ability to understand how future societies will be affected, and to give a present value to impacts hitting future generations.

Finally, the impacts from climate change are particularly uncertain. Uncertainty refers to limited knowledge about the future and limited ability to predict the outcomes from our actions (Knight, 1921; Keynes, 1921). Since the impacts will occur in the future, and we are dealing with never-seen events, climate change impacts are inherently uncertain. Besides, what economies will look like in 50 or 100 years is very uncertain, although it is key to evaluate how they will cope with climate change.

Though the quantification of impact is challenging, it is necessary as a way to reveal the benefits of mitigation actions. For instance, a decision maker can use this information when performing a cost-benefit analysis of regulations, which have an effect on emissions, or to scale the level of policy instruments meant to reduce emissions (Pearce, 2003; IAWG, 2010). Beyond the mere evaluation of marginal damages from emissions, also called the Social Cost of Carbon, being able to build high-level indicators of the future impacts from climate change is key to set long-term objectives and think about short-term mitigation strategies. For instance, what are the avoided impacts if we manage to contain global temperature increase to 2°C ? Conversely, what would be the social and economic impacts of climate change if no mitigation is undertaken? To guide decision making about how much and how soon to reduce emissions, we need to assess the impacts of climate change under different global emission pathways or temperature targets (Hallegatte et al., 2016; Edenhofer and Minx, 2014). Enriching our knowledge about future impacts can also contribute to the design of adaptation policies, which aim at minimizing the damages resulting from a given level of climate change.

Because quantifying climate change damages is complex, economists generally rely on simplified representation of damages as a way explore the performance of different mitigation strategies at the global level, and the ethical trade-offs at stake. The crude way with which damages are quantified and represented in these approaches has attracted strong criticisms, leading some to question their usefulness (Pindyck, 2013; Kaufman et al., 2020; Koomey, 2013).

In this thesis, I discuss how we can improve the representation of climate change damages to assess mitigation pathways, and whether alternative representations of damages can yield insights on the performance of different mitigation strategies. I begin by laying out the conventional way to model climate change damages to assess mitigation pathways in section 1.1. This leads me to identify the dynamics of impacts and their distribution as two areas for improvement. The following two sections discuss why these issues are key to evaluate damages, and currently insufficiently or improperly represented. Section 1.4 summarises the contribution of the different chapters of the thesis.

1.1 Damage representation as a key limitation to analyse mitigation pathways

1.1.1 Integrated Assessment Models

Nordhaus (1994) was the first to propose a simple climate-economy model with explicit modelling of climate change's feedback on the economy. He expanded a Ramsey growth model (Ramsey, 1928) to include both the possibility reduce emissions, and the consequences of these emissions via climate change. Thus, the model allows to analyse the intertemporal trade-off between the present costs of greenhouse gas reductions and their future benefits in terms of avoided impacts. The DICE model was meant to provide information about the 'optimal' mitigation pathway, i.e. the abatement level over time that would maximize discounted welfare.

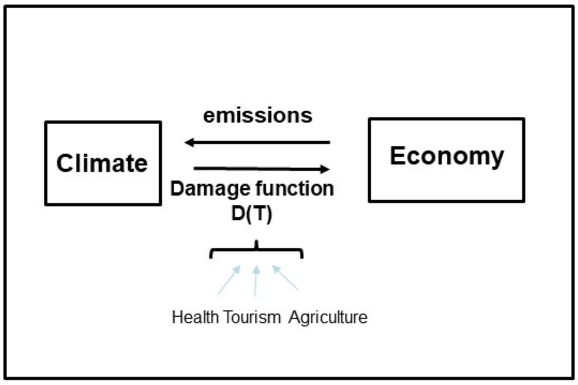


Figure 1.1 – Schematic representation of a cost-benefit Integrated Assessment Model.

DICE belongs to the category of cost-benefit Integrated Assessment Models (IAMs, see figure 1.1). They are build to model the crossed interaction between the economy and the climate system, and their evolution in the long-term, though they each make different assumptions about the climate system, mitigation costs and climate damages (Waldhoff et al., 2011; Hope, 2011; Bosetti et al., 2006). The DICE model has lead to a number of extensions, including a regional version RICE (Nordhaus and Yang, 1996). More recently, analytical IAMs allow to derive closed-form solutions for the Social Cost of Carbon and the optimal mitigation pathway (Golosov et al., 2014; Dietz and Venmans, 2019).

Because they drive the benefits from reduced emissions, it is no wonder that the way we model damages has a strong influence on the evaluation of different mitigation pathways. However, in most of these approaches, damages are modelled as losses in monetary term, subtracted from production at the aggregate level. The representation of damages is widely recognized as the weakest point of these models (Diaz and Moore, 2017; Howard, 2014; Revesz et al., 2014; Ackerman et al., 2009; Stern, 2013; Pizer et al., 2014). We summarize here the main limitations of such an approach.

1.1.2 The traditional damage function under fire

1.1.2.1 Concerns about the level of damages

A first strand of criticisms concerns our ability to produce reliable estimates of damages estimates. In many case, the damage is estimated using an enumerative method. This consists in listing a number of potential impacts, translating them in monetary terms, and summed up to obtain the total damages at a given temperature level. For instance, one can look at the value of yield losses under a given temperature change, quantify the value of assets at risk from seal-level rise, etc. Because of the diversity of climate change impacts, the estimates based can never be complete. Besides, they typically omit damages that are the most difficult to quantify, but have no reason to be negligible, such as extreme events, ocean acidification, social conflict, or impacts on ecosystems (Howard, 2014). Non-market impacts, such as mortality, biodiversity, or nature's non-use value, also raise many questions on whether and how to monetize them. Finally, aggregating different damage sources by simply adding them up exclude cross-sectoral interactions which can amplify the impacts.

Alternatives to the enumeration method also have their limitations. More recently, Computable General Equilibrium models have also produced such estimates of the economic losses under different warming levels (Roson and

Van der Mensbrugghe, 2012; Roson and Sartori, 2016; Kompas et al., 2018). They overcome criticisms about inconsistency and cross-sectoral effects, but still cannot provide complete estimates as they focus on market impacts.

Statistical approaches use past and current variation in exposition to different climates from cross-sectional or panel data to infer the effects of temperatures on aggregate variables, such as GDP or life satisfaction (Rehdanz and Maddison, 2005; Nordhaus, 2006). Recent estimates based on econometric approaches suggest larger damages than earlier assessments based on enumerative studies (Burke et al., 2015; Dell et al., 2012). Yet, it is unclear how to use these estimates to project damages at higher temperature levels. They estimated exclude many impacts, which have not yet occurred, such as sea level rise. The extrapolation of the observed damages when societies have been only confronted to modest changes is questionable, because damages are also expected to intensify. On the other hand, assuming stationarity in the relationship between climate and the economy obscures that adaptation can occur. Thus, no single method seems able to provide a satisfying approach to express the total damages.

1.1.2.2 Too aggregated damage function?

Beyond our ability to provide such estimates as the total economic damages at a given level, aggregating different sources of damages into a single monetary loss is also questionable, because it masks the dynamic processes, the distribution of damages and the uncertainty surrounding these estimates. First, by aggregating all damages sources into output losses at a given temperature change, we lose information about the processes at stake. Climate change affects many aspects of the economic system, from production inputs to well-beings, and what is affected matters. Even in the most simple setting, impacts hitting capital rather than output can interact with investment and thereby alter economic dynamics. Likewise, the mere valuation of climate change impacts on natural capital can be conditional on their relative price, so that explicitly accounting for their dynamics can change the optimal pathway (Drupp and Hänsel, 2020). Second, relying on the costs aggregated at a too high spatial level obscures that these costs will be unevenly distributed, between regions and households. Though some models rely on a dozen regions, it is still limited to identify the pathways that yield the highest welfare. Finally, because damages are uncertain, the use of a single damage function cannot shed light on the risks of different emissions pathways. Thus, evaluation of mitigation actions based on an 'average scenario,' or the best-guess damage estimates, is insufficient, and the risk dimension should be part of the decision. The value of climate change mitigation also lies in its ability to serve as a hedge against catastrophic or worst case scenarios.

In the next sections, I discuss more in depth why the conception of damages as output losses caused by temperatures at the aggregate level is inappropriate to account for the dynamics of damages and their distributional effects.

1.2 A dynamic approach to evaluate climate change damages

A static approach of the damages at a given temperature change is ill-suited to represent the dynamics of climate and that of climate damages, which can sometimes be non-linear.

1.2.1 Climate change can affect the dynamics of the economy

A key issue to evaluate the damage is whether the dynamics of the economy, or growth will be affected by climate change, for instance via reduced spending on innovation or losses to human or physical capital (Fankhauser and Tol, 2005). Indeed, if growth if affected, damages can shift economies away from their trajectory. Thus, damages accumulate over time, and even small differences in growth can lead to important losses by the end of the century. Recent econometric evidence has prompted that temperature and growth were negatively correlated (Burke et al., 2015; Dell et al., 2012). Several studies interpreted this as a loss in Total Factor Productivity (TFP) growth or accelerated depreciation rate of capital and found that much stringent mitigation would be optimal in such case (Moore and Diaz, 2015; Dietz and Stern, 2015). However, it is still unclear whether losses to output and growth perform better to explain historical losses (Newell et al., 2018). There is mixed evidence regarding the effect on TFP (Letta and Tol, 2019; Henseler and Schumacher, 2019). In addition, while econometric evidence can illustrate potential mechanisms, there are concerns about the way to interpret weather data as evidence of climate change (Auffhammer, 2018; Kolstad and Moore, 2020).

1.2.2 Climate dynamics matters

To understand how climate change affects economies, we must also come back to the nature of the biophysical changes involved. Indeed, what we call climate change covers a vast range of perturbation in the way the climate system works. The global average temperature has become a key proxy to measure the magnitude of the phenomenon, but the reality of climate change ranges from changes in temperature, precipitation patterns, or increases in the frequency and intensity of extreme events. Some of the impacts from climate change will be gradual, and evolve progressively just like global temperature. But many will come in the form of more frequent or more intense shocks.

Typically, extreme events, such as floods, hurricane, storms or heatwaves, can manifest high damages at a given year, and lower damages the next year, and we cannot predict when they will strike. Here again, relying on the evaluation of direct costs can be misleading to understand the resulting macroeconomic consequences of a shock (Hallegatte et al., 2007). The persistence of the shock or the ability of the economy to recover depends crucially on the organization of the economy, and the inputs that are affected (Piontek et al., 2019). The temporal and uncertain dimensions of shocks contrast with an approach that would consider deterministic losses gradually increasing with temperatures along an optimal growth path.

Another important dynamic aspect is that economies are not only sensitive to the level of climate change, but also to the rate at which it is occurring. For instance, species are limited in the speed at which they can adapt or migrate. Slower change gives them more time to migrate to climatically favourable places, or to adapt via genetic or behavioural adaptations. Similarly, adaptation strategies in sectors with long-lasting capital may take time, and faster rates of change may be associated with less efficient adaptation or greater losses (Hallegatte, 2009; Fankhauser and Soare, 2013). Conversely, damages won't stay at the same level once temperatures have stabilized. Some of the impacts are irreversible, while others can be reduced or even vanish once economies have adapted, for instance via investment in protective capital, behavioural changes or switch to more adapted crops. Once again, a snapshot of the losses at a given warming level may improperly capture that the dynamics of change matters to understanding economies' ability to cope with climate change.

1.2.3 Existence of non-linear dynamics of damages

Finally, thinking of damages as smoothly increasing with climate change stands in sharp contrast with its sometimes non-linear dynamics. For instance, there are thresholds effects can trigger the reinforcing of feedback loops and eventually lead entire parts of the climate system to shift. Examples of such thresholds include the collapse of the thermohaline circulation, the complete melting of the Greenland Ice Sheet, or the die-back of the Amazonian forest (Lenton et al., 2019; Steffen et al., 2018). Thus, whether we are interested in the impact of a marginal emission, or impacts along an emission trajectory it is necessary to account for the possibility of crossing such non-linear dynamics (Kopp et al., 2016).

In early approaches, the risk of tipping points or catastrophic shifts led modellers to simply increase the damage estimates. In such a setting, it is optimal to smoothly warm the climate and stop emitting when marginal damages exceed the benefits of emissions. However, this is insufficient to help decision making under such risks of non-linear behaviours, and to quantify the benefits of different mitigation pathways in terms of reducing the probability of high-impact outcomes. When these risks are integrated, mitigation strategies lead to different outcomes in different states of nature, depending on whether these thresholds are crossed or not. Thus, the evaluation of the strategy depends on how much risk we are willing to take. While some suggest that these risks are the primary contribution to the value of mitigation, and that they are too large to rely on traditional tools (Weitzman, 2009), in practice risk has been found to play a moderate role in numerical IAMs (Ackerman et al., 2013; Belaia et al., 2014).

1.3 Unraveling the distribution of climate change damages

Assessment of global climate change impacts and their being captured at a very aggregated level hides significant disparities in how they affect sectors, regions and households. However, who is affected by climate change matters. First, the same physical impacts do not lead to the same costs depending on household or regions' vulnerability, which is strongly linked to income levels. Second, who bears the cost of climate change is key to assess the fairness of different mitigation pathways (Dennig et al., 2015), in particular if the decision maker cares about the worse-off (Adler et al., 2017).

1.3.1 The poorest face higher damages

There is a growing evidence that climate change impacts will be unevenly distributed across individuals, and will disproportionately hit the poorest.

The poorest are most exposed to the various effects of climate change, such as water stress, drought intensity, heat waves or loss of agricultural yields, because of their location (Byers et al., 2018). For instance, there are disproportionate impacts on yields in low latitude regions (Rosenzweig et al., 2014), and the daily temperature extremes are expected to occur primarily in less developed areas (Harrington et al., 2016). This is also true within countries, because the poorest are more often located in risky areas (Park et al., 2018; Jongman et al., 2015).

The same physical impacts translate into greater damages for the poorest due to differences in sensitivity and adaptive capacities between countries and individuals. The poor depend more on activities that may be affected directly by climate change, have lower-quality protection infrastructures lack access to insurance mechanisms against weather shocks (Hallegatte and Rozenberg, 2017). Besides, they also face indirect impacts via for instance food price.

1.3.2 Limited quantitative studies with a global scope

Despite the evidence that the poorest will face the bulk of the damages, quantitative studies on the distribution of climate change impacts with a global scope remain limited (Rao et al., 2017). A few studies, using regional IAMs, further assume an unequal distribution of damages within regions, and show that it has a strong effect on optimal mitigation (Dennig et al., 2015; Anthoff and Emmerling, 2018). However, they typically rely on the assumption of constant income distribution, and lack strong basis for calibrating the way damages are distributed within regions.

Improving the understanding of how climate change can affect the poorest requires representing the economy at a finer scale than what economic models with a global scope typically do, to go beyond single representative household, and model the various mechanisms through which climate change impacts can affect households. This includes a deeper understanding of how the biophysical impacts from climate change will translate into changes in income, prices, or asset loss, and necessitates to include the role of cross-cutting dimensions of vulnerability such as institutions or governance (Hallegatte et al., 2011). Impacts will depend on the type of built capital or how well the impacts have been anticipated, which is strongly context-dependant. This makes it difficult to map the distribution of impacts across the world. Finally, the distribution of impacts can be challenging to assess in teleconnected economies, in which impacts at a given place propagate to other regions, along the value chain (Henriet et al., 2012; Constant and Davin, 2019) or because of indirect effects via prices.

1.4 Contribution of this thesis

To summarise, the way we conceptualize and represent damages in cost-benefit Integrated Assessment Models lead to high discrepancies in the assessment of mitigation strategies. I underlined the interest of improving how we capture the dynamic dimension of the interaction between climate and the economy, and disaggregating these damages at a finer scale. I now summarise the contributions of the different chapters of this thesis to these issues.

1.4.1 Dynamics of damages

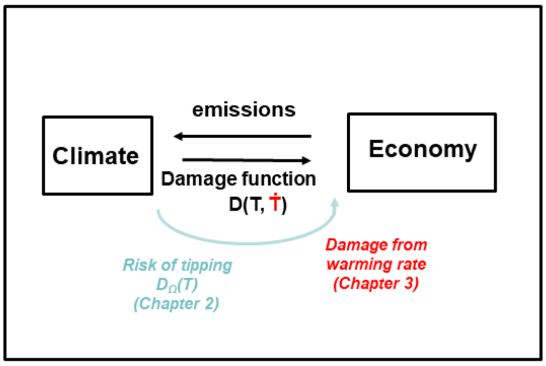
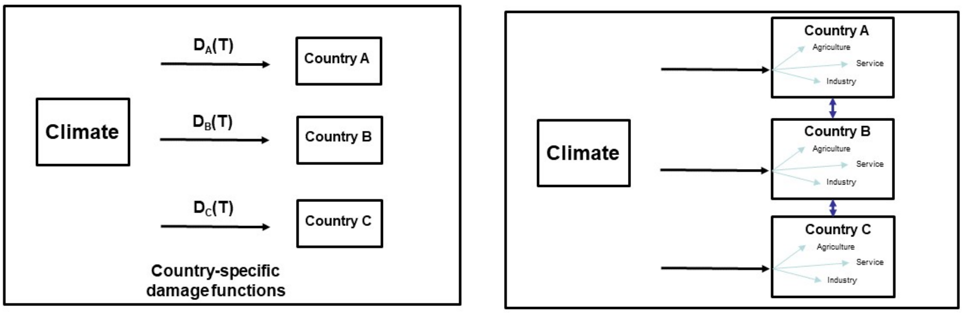


Figure 1.2 – Graphical representation of damages in the corresponding chapter

In the first part of the thesis, I explore the dynamics of impacts and compare how different modelling of climate change damages affect the welfare-maximizing path. In chapter 2, I investigate the role of risk in the case of a tipping point. I build a stochastic Integrated Assessment Model, in which the damage function exhibits a stochastic jump to account for potential tipping points in the climate-economy system. I analyse the resulting Social Cost of Carbon under different assumptions about time and risk preferences. The results suggest that a tipping point raises the Social Cost of Carbon, but mainly as a result of increased expected damages, rather than as an effect of pure risk. This allows to identify the conditions under which the 'climate premium', i.e. the willingness to pay to avoid bad outcomes, is high. It is the case under combined high damage and high risk aversion.

In chapter 3, I explore the consequences for optimal mitigation strategies when damages depend both on warming levels and warming rates, using an analytical climate-economy model. I show that when economies are also sensitive to the dynamics of warming, the Social Cost of Carbon increases, and the timing of optimal emissions is different – the same carbon budget gets spread over time in order to smooth temperature increase. Overlooking this issue leads to emission pathways in which temperatures may rise too fast given economies' ability to cope with the change.

1.4.2 Distribution of damages



(a) Chapter 5 (b) Chapter 6

Figure 1.3 – Graphical representation of damages in the corresponding chapter

The second part of the thesis deals with the intragenerational distribution of damages. I review in chapter 4 the interactions between climate change and economic inequality. While damages are unequally distributed, the richest contribute disproportionately to global emissions, both at the global and country-level. Finally, mitigation policies, depending on their design, can also be burdensome for the poorest. These issues are key to analyse the fairness of low carbon pathways, and design appropriate policy responses.

I then evaluate quantitatively the combined effects of mitigation and climate change impacts on inequality in chapter 5. I build country-by-country projections of GDP per capita account for uncertainty in socioeconomic and climate-related factors. I explore the outcomes from this scenario database using statistical methods. Uncertainty about climate change damages and socioeconomic assumptions are key to predict the value of future inequality. I also study in which conditions lower emission pathways are associated with lower inequality levels.

Finally, in chapter 6, I analyse how the distribution of direct impacts of climate change can propagate across regions due to trade, using a multi-regional multi-sectoral model. I study the case of heat stress on productivity, which has heterogeneous effects on regions and sectors, and the preliminary results suggest that final impacts can be more unevenly distributed than the direct impacts. Note that this chapter is still work in progress. Nevertheless, I chose to include it in its current form in the manuscript, because I am sure it would benefit from the perspective of the jury.

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List of publications

Chapter 2 is published as a FAERE Working Paper, and is currently under review at *Environmental and Resource Economics*.

Taconet N, Guivarch C, Pottier A. Social Cost of Carbon under stochastic tipping point: when does risk play a role? *FAERE Working Paper, 2019.11*

Chapter 3 is published as a FAERE Working Paper. This article has received the 2020 Young Economist best paper Award by the French Association of Environmental and Resource Economists.

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Chapter 4 has been published in French. The English version will be published as a book chapter.

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Chapter 5 is a reproduction of the following article:

Taconet N, Méjean A, Guivarch C (2020). Influence of climate change impacts and mitigation costs on inequality between countries. *Climatic Change* 160, 15-34

Chapter 6 reports the preliminary results of an ongoing work with PL Lostis, A Méjean and C Guivarch.

Chapter 2

Social Cost of Carbon under stochastic tipping points: when does risk play a role?

Abstract

Is climate change concerning because of its expected damages, or because of the risk that damages could be very high? Climate damages are uncertain, in particular they depend on whether the accumulation of greenhouse gas emissions will trigger a tipping point. In this chapter, we investigate how much risk contributes to the Social Cost of Carbon in the presence of a tipping point inducing a higher-damage regime. To do so, we decompose the effect of a tipping point as an increase in expected damages plus a zero-mean risk on damages. First, using a simple analytical model, we show that the SCC is primarily driven by expected damages, while the effect of pure risk is only of second order. Second, in a numerical experiment using a stochastic Integrated Assessment Model, we show that expected damages account for most of the SCC when the tipping point induces a productivity shock lower than 10%, the high end of the range commonly used in the literature. It takes both a large productivity shock and high risk aversion for pure risk to significantly contribute to the SCC. Our analysis suggests that the *risk aversion puzzle*, which is the usual finding that risk aversion has a surprisingly little effect on the SCC, occurs since the SCC is well estimated using expected damages only. However, we show that the risk aversion puzzle does not hold for large productivity shocks, as pure risk greatly contributes to the SCC in these cases.

2.1 Introduction

Climate change will induce damages in the future, although their magnitude remains uncertain (Diaz and Moore, 2017). A key uncertainty is whether emissions will trigger non-marginal or abrupt changes, often referred to as "tipping points" (Lenton et al., 2008; Alley et al., 2003; Steffen et al., 2018). Examples of large-scale regime shifts include the shutdown of thermohaline circulation, the melting of the Arctic sea-ice or the die back of the Amazonian rainforest. Such shifts could also stem from the limited ability of social and economic systems to cope with climate conditions beyond some threshold. Assessing the present social value of damages from an additional ton of CO_2 released in the atmosphere, i.e. the Social Cost of Carbon (SCC), requires to account for the risk of triggering such high-impact events as the planet warms.

Early assessments of the SCC relied on deterministic models balancing abatement costs with benefits from avoided damages, assuming they are known to the social planner (Nordhaus, 1994). They used a damage function capturing best-guess value of the level of damage for each additional degree of warming. Concerns about catastrophic damages and tipping points have first been addressed in a deterministic fashion. Many studies considered how alternative damage functions, meant to reflect that damages may be more convex or present abrupt jumps, affect the results (Pizer, 2003; Dumas and Ha-Duong, 2005; Ackerman and Stanton, 2012; Wouter Botzen and van den Bergh, 2012; Dietz and Stern, 2015; Weitzman, 2012).

More recently, studies have included in an endogenous fashion different types of climate damages risks in Integrated Assessment Models (IAMs). First, some have considered uncertainty over the damage function by representing a social planner facing a distribution of damage functions rather than a single estimate (see for instance Crost and Traeger (2013)). A second type of risks is recurring shocks or volatility in damages which hit the economy, notably as a way to reflect the occurrence of disasters (Pindyck and Wang, 2013; Bretschger and Vinogradova, 2019). There is an emerging literature on how these risks affect the SCC, also in combination with other uncertain dimensions, such as climate sensitivity or growth (Jensen and Traeger, 2016; Lemoine and Rudik, 2017; Van Den Bremer and van der Ploeg, 2018).

Tipping points belong to another category of risk. They entail that emissions can irreversibly shift the world from a low- to a high-damage regime. Pioneering works on the management of thresholds show how optimal abatement is affected by the risk that pollution may trigger a catastrophic event (Clarke and Reed, 1994; Tsur and Zemel, 1996). Studies which model tipping points as a stochastic risk in IAMs suggest that accounting for those raises the SCC (Lemoine and Traeger, 2014; Cai and Lontzek, 2019; Diaz and Keller, 2016) or near-term abatement (Keller et al., 2004; Belaia et al., 2014). These studies consider tipping points which induce either a permanent loss of productivity (Belaia et al., 2014; van der Ploeg and de Zeeuw, 2018), the destruction of most productive capacities (Bretschger and Vinogradova, 2018), or an increased damage regime (Lemoine and Traeger, 2014), and provide insightful analysis, notably on how time and risk preferences affect optimal policy.

When considering risk, one naturally wishes to compare how results differ from a risk-free situation. In financial analysis, this comparison allows to derive the risk premium of an asset. Similarly, for the SCC, the gap between a risky and a risk-free situation indicates how much risk compounds the diminution of social welfare brought by emitting carbon. This is typically done by comparing results with risk to results when all the parameters are set to their expected value (Crost and Traeger, 2013; Van Den Bremer and van der Ploeg, 2018). However, for tipping points, the standard practice is to compare the SCC with and without a tipping point. Because the additional damage a tipping point could cause does not have a zero mean, comparing cases with and without tipping points conflates the effect of increased expected damages resulting from the introduction of a tipping point, and that from the dispersion of possible damages, i.e., a zero mean risk.

In this paper, we propose a simple method to distinguish the contributions of expected damages and risk to the SCC in the case of a tipping point triggering a shift to a higher-damage regime. We decompose a tipping point on damages as an increase in expected damages plus a (zero-mean) pure risk on damages. We compare the SCC with a tipping point to the SCC under expected damages, i.e. when there is no risk and damages are set at their expected level. First, using a simplified model, we demonstrate that in the case of a stochastic tipping point, the SCC is at first order equal to the SCC under expected damage. Risk introduces a correction that is only of second order, and that is proportional to risk aversion. We then investigate numerically in an IAM the gap between the SCC with a stochastic tipping point and the SCC under expected damages. We introduce the tipping point as a stochastic risk whose hazard rate depends on temperature, leading to a permanent drop in productivity. We analyse how preferences of the social planner (i.e., risk aversion, resistance to intertemporal substitution) and the damages from the tipping point affect the comparison. We find that the SCC under expected damages closely approximates the SCC for low values of the productivity shock. Thus, risk plays a minor role when introducing a tipping point, the effect of a tipping point on SCC is due to the increase of expected damages. This result holds as long as the magnitude of the productivity shock is less than 10%. However, risk becomes important with higher productivity shocks and under high risk aversion.

Our article contributes to a wider literature on how climate damage risks affect optimal climate policies. Evidence is mixed about whether risk is a fundamental part of optimal abatement, or just a second order correction. On the one hand, some authors argue that hedging against catastrophic outcomes should be the primary driver of abatement (Weitzman, 2009; Pindyck, 2013; Dietz, 2011). However, several studies show that risk has a a surprisingly limited effect on the optimal policy – this has been called the *risk aversion puzzle*. Risk aversion, when disentangled from the elasticity of intertemporal substitution, is found to play a modest role in IAMs (Ackerman et al., 2013), even in the case of a tipping point (Belaia et al., 2014; van der Ploeg, 2016). Our contribution isolates the role of risk in the case of a stochastic tipping point, and shows under which assumptions the effect of risk is of second order. We show that risk only matters when there is possible exposure to catastrophic damages, while the SCC is primarily driven by expected damages for moderate productivity shocks triggered by the tipping point. This explains why studies find a modest role of risk aversion on the optimal policy, as productivity shocks usually considered in the literature remain below the 10% threshold. We add to this literature and provide orders of magnitude of the range of shocks and risk aversion it takes for risk aversion to significantly affect the SCC.

Our article also contributes to understand the advantages and disadvantages of different representations of climate damages. Since climate damages are the least-grounded aspect of IAMs (Diaz and Moore, 2017; Revesz et al., 2014; Howard, 2014) and have a strong impact on the SCC (as large as discounting (van den Bijgaart et al., 2016)), it is essential to build rigorous methodologies that compare how different representations of damages affect the SCC (Pottier et al., 2015; Guivarch and Pottier, 2018). Here, we compare indeed two different settings to represent a tipping point: one where tipping points are represented as a truly stochastic event, one where tipping points are represented as a mere increase in the damage function, so that it reflects expected damages. In other words, we examine how the endogenous introduction of a tipping point in an IAM compares to simply using a more convex function, i.e., the method that was first used to represent catastrophic risks in such models. Our results show in which cases the two methods lead to different outcomes.

We illustrate in section 2.2 the effects of increased expected damages and pure risk due to a tipping point in a simplified one-period model, and show that the former is the primary driver of the SCC. In section 2.3, we lay out the IAM with a stochastic tipping point we use and present how we compute the SCC under expected damages. Numerical comparison between the SCC under expected damages and the SCC with a stochastic tipping point are discussed in section 2.4. Section 2.5 concludes.

2.2 A simple model of a stochastic tipping point

We present a simple one-period model of a climate economy to highlight the intuition behind the comparison between the SCC with a stochastic tipping point, and the SCC under expected damages. We show that there is a first-order difference between the SCC with and without tipping points, difference that is captured when the SCC is calculated with damages set at their expected level. We further demonstrate that risk introduces a second-order correction, proportional to risk aversion and to the variance of damages.

Let us consider the simplest climate-economy model. The economy produces gross output Y. Gross output minus damages $d(E)$ due to emissions E and costs $c(a)$ of abatement measures a yields net output which is entirely consumed, so that aggregate consumption is given by $C(a, E) = Y - c(a) - d(E)$. With σ the (unabated) carbon intensity of production, emissions and abatement are linked by $E = \sigma Y(1-a)$. Let $u(C)$ be the social welfare function that depends only on aggregate consumption, the program of the social planner is:

$$\max_{a,E} \; u\left(C\left(a, E\right)\right), \quad s.t. \; E = \sigma Y(1 - a) \tag{2.1}$$

so that optimal abatement satisfies $c'(a^*) = \sigma Y d'(E^*)$ (we star all variables related to the optimal point).

We can define the SCC at the optimal point as the marginal social damages occurring due to an extra emission, measured in consumption units.

$$SCC = -\frac{\partial_E u(C(a,E))|_{a^*,E^*}}{\partial_C u(C)|_{C^*}} = -\frac{-u'(C^*)d'(E^*)}{u'(C^*)} = d'(E^*) \tag{2.2}$$

Note that (provided the constraints $0 \leq a \leq 1$ are not binding) the equation for optimal abatement can be written as:

$$\partial_C u|_{C^*}.(-c'(a^*)) + \partial_E u(C(a,E))|_{C^*}.(-\sigma Y) = 0 \tag{2.3}$$

so that $SCC = \frac{c'(a^*)}{\sigma Y}$: SCC is also a measure of marginal abatement costs.

2.2.1 SCC with a stochastic tipping point

We now introduce stochastic tipping points to our setting. There are several states of nature ω, depending on whether or not tipping points have been crossed. The damage function is $d_\omega(E)$ in state ω. The probability of having triggered tipping points, i.e. on being in state ω depends on aggregate emissions $p_\omega(E)$. The most common case is when there is one tipping point and two states of nature: 1 the pre-tipping point world where the damage function is the d_1, and 2 the post tipping point world that leads to a higher damage regime $d_2 \geq d_1$. The tipping point induces a jump in damages $d_2 - d_1$. The probability of being in the post-tipping world is an increasing function of the quantities of emission released $p_2(E)$. Our framework accommodates for more general formulations, such as multiple points or a single tipping point leading to different unknown post-tipping damage functions.

In the presence of tipping points, the social planner maximizes the expected social welfare, where we write $C_\omega(a,E) = Y - c(a) - d_\omega(E)$ the aggregate consumption in state ω:

$$\max_{a,E} \ \mathbb{E}_\omega \left[u(C_\omega(a,E))\right], \quad s.t.\ E = \sigma Y(1-a) \tag{2.4}$$

We note a^t, E^t the optimal abatement and emissions of this program. The SCC is the marginal social damages of an extra emission measured in consumption units, so, in this framework:

$$SCC = -\frac{\partial_E \mathbb{E}_\omega \left[u(C_\omega(a,E))\right]|_{a^t,E^t}}{\mathbb{E}_\omega \left[u'(C_\omega(a,E))\right]|_{a^t,E^t}} \tag{2.5}$$

Note that for tipping points, the probability of being in a given state of nature is endogenous to the action of the planner, in contrast with exogenous risk (for instance on the value of climate sensitivity). The optimal abatement a^t of this program solves (provided the constraints on it are not binding):

$$\mathbb{E}_\omega\left[u'(C_\omega(a,E))\right]|_{a^t,E^t}.(-c'(a^t))+(\partial_E\mathbb{E}_\omega\left[u(C_\omega(a,E))\right]|_{a^t,E^t}).(-\sigma Y)=0 \quad (2.6)$$

so that the SCC is still given by $\frac{c'(a^t)}{\sigma Y}$. Specifying to the case of a single tipping point, we have $\mathbb{E}_\omega[u(C_\omega(a,E))] = (1-p_2(E)).u(C_1(a,E))+p_2(E).u(C_2(a,E))$, and the SCC of equation (2.5) can be written as:

$$\begin{aligned} SCC = \frac{c'(a^t)}{\sigma Y} &= d_1'(E^t) \\ &+ (d_2'(E^t) - d_1'(E^t))\frac{p_2(E^t)u'(C_2(a^t))}{\mathbb{E}_\omega[u'(C_\omega(a,E))]} \\ &+ p_2'(E^t)\frac{u(C_1(a^t)) - u(C_2(a^t))}{\mathbb{E}_\omega[u'(C_\omega(a,E))]} \end{aligned} \quad (2.7)$$

As in van der Ploeg and de Zeeuw (2019), the previous equation offers a decomposition of the SCC into three terms:

- the marginal damage term, before reaching the tipping point,
- the additional marginal damage in case the tipping point is reached, weighted by the probability of tipping,
- the damage due to a marginal increase in the probability of triggering the tipping point.

Introducing tipping points in this way conflates a level effect and a risk effect. Damages are indeed increased in the same time as risk is introduced, because the effect of the tipping point is not a zero-mean risk on consumption. Indeed, compared to the situation without a tipping point, the mean additional risk of a tipping point is $(1-p(E))(d_1-d)+p(E)(d_2-d)$, which is equal to $p(E)(d_2-d_1)$ when the pre-tipping damage function is the same as the damage function without a tipping point ($d_1 = d$). As a consequence, the increase of the SCC found when a tipping point is introduced cannot be attributed to risk alone, it may be simply the effect of higher expected damages. The next subsection will investigate this point.

2.2.2 SCC under expected damages

To understand the effect of risk induced by a tipping point, we need a way to decompose the SCC so that we can disentangle what comes from expected damages from what is due to a zero-mean risk.

Let us go back to equation (2.5). We consider the expected damage function $\tilde{d}(E) = \mathbb{E}_\omega[d_\omega(E)]$. One can write: $C_\omega(a, E) = \tilde{C}(a, E) + \epsilon_\omega(E)$ with $\tilde{C}(a, E) = \mathbb{E}_\omega[C_\omega(a, E)] = Y - c(a) - \tilde{d}(E)$. This decomposes the effect of tipping point on consumption as an effect on expected damages plus a zero-mean risk $\epsilon_\omega(E) = d_\omega(E) - \tilde{d}(E)$. We note $V_\epsilon(E) = \mathbb{E}_\omega[\epsilon^2_\omega(E)]$ the variance of damages of the zero-mean risk ϵ.

In the case of a single tipping point, expected damages are $\tilde{d} = p_1 d_1 + p_2 d_2 = d_1 + p_2.(d_2 - d_1)$. The risk ϵ on consumption is $\epsilon_1 = -p_2(d_2 - d_1)$ in state 1, with probability $1 - p_2$, and $\epsilon_2 = (1 - p_2)(d_2 - d_1)$ in state 2 with probability p_2 (where all symbols are functions of emissions E). So, compared to a world without tipping points, in which the damage function is the pre-tipping damages function, introducing a tipping point increases expected damages by $p_2.(d_2 - d_1)$ and adds risk. Thus, the risk of the tipping point is that damages are less than expected if the world does not tip (state 1, pre-tipping) and that damages are above expectations if the world does tip (state 2, post-tipping). It is a zero-mean risk whose variance is $V_\epsilon(E) = p_2(1 - p_2).(d_2 - d_1)^2$. The risk is of the same order of magnitude as the jump in damages $d_2 - d_1$.

Let us assume that the risk ϵ is small and make a Taylor-expansion at the second-order in formula (2.5):

$$SCC = -\frac{\partial_E \mathbb{E}_\omega \left[u(\tilde{C}(a, E)) + u'(\tilde{C}(a, E))\epsilon_\omega(E) + u''(\tilde{C}(a, E))\frac{\epsilon^2_\omega(E)}{2} \right] \Big|_{a^t, E^t}}{\mathbb{E}_\omega \left[u'(C_\omega(a, E)) \right] \big|_{a^t, E^t}} \tag{2.8}$$

$$= \frac{u'(\tilde{C}(a^t, E^t))\tilde{d}'(E^t)}{\mathbb{E}_\omega \left[u'(C_\omega(a, E)) \right] |_{a^t, E^t}} - \frac{\partial_E \left(u''(\tilde{C}(a, E))\frac{V_\epsilon(E)}{2} \right) \Big|_{a^t, E^t}}{\mathbb{E}_\omega \left[u'(C_\omega(a, E)) \right] |_{a^t, E^t}} \tag{2.9}$$

We show in appendix 2.A that we can make a Taylor expansion also of the denominator and, after reordering, we obtain the following decomposition of the SCC (ignoring higher-than-second-order terms):

$$SCC = \tilde{d}'(E^t) + \gamma(\tilde{C}(a^t, E^t))\frac{\tilde{C}(a^t, E^t)}{2}\, \partial_E V_\epsilon(E)\big|_{E^t} \tag{2.10}$$

The SCC in the presence of a tipping point is thus shown to be the sum of marginal expected damages plus a second-order correction that is proportional to the Arrow-Pratt measure of relative risk aversion $\gamma(C) = -u''(C)/(u'(C).C)$ of the utility u, and to the marginal increase in the variance of risk $\partial_E V_\epsilon(E)$. When the effect of tipping point is split into an increase in expected damage plus a zero-mean risk, this decomposition shows that changes in expected damages drive the effect on the SCC whereas the zero-mean risk introduces only a second-order correction.

To make this statement more precise, we introduce the SCC under expected damages, that is the SCC in a deterministic model similar to equation 2.1 but with the damage function replaced by the expected damages of the tipping point $\tilde{d}$. We note a^{ed}, E^{ed} the optimal abatement and emissions of this program under expected damages. Thus SCC^{ed} the SCC under expected damages is given by:

$$SCC^{ed} = \frac{c'(a^{ed})}{\sigma Y} = \tilde{d}'(E^{ed}) \tag{2.11}$$

We call SCC with a tipping point the SCC given by (2.5) and SCC without a tipping point the SCC given by (2.2), where the damage function d is the damage function of the pre-tipping point state of the world. We have the following proposition:

Proposition 1 *The difference between SCC without a tipping point and SCC with a tipping point is proportional to the difference between expected damages and damage in the pre-tipping point state of the world. It is first-order in the magnitude of risk induced by the tipping point.*

On the contrary, the difference between SCC under expected damages and SCC with a tipping point is only second-order. It is proportional to risk aversion and the marginal increase in the variance of risk induced by the tipping point.

PROOF See appendix 2.B

To summarize, we have demonstrated that introducing a tipping point raises the SCC, compared to a SCC without a tipping point, where the damage function is given by the pre-tipping point damage function. This first order difference is explained by an increase in expected damages. Whereas comparing the SCC with and without a tipping point introduces a first-order correction in the SCC, the correction is only of second order when we compare the SCC with a tipping point and the SCC under expected damages.

This means first that it is misleading to compare the SCC with and without stochastic tipping point, and second that the increase due to the tipping point is, in this simple model, a matter of expected level rather than risk. The SCC under expected damages captures most of the value of the SCC, as long as the damage shocks are small. Risk introduces a correction that increases with risk aversion. Interestingly, this result holds under rather general conditions. We did not assume a specific form for the change in damages induced by the tipping point. Hence, it applies generally, and in particular, in the case of one tiping point, it applies when the tipping point induces a jump in damage ($d_2 - d_1$ is constant) or more convex damage, i.e. higher marginal damage ($d_2 - d_1$ is an increasing function of temperature).

The key insight of this simple one-period model is that we can think of the SCC as being composed of two parts: SCC under expected damages and a risk premium proportional to risk aversion. For small tipping point damages, the SCC under expected damages will be close to the actual SCC. In the next section, we define the SCC under expected damages for an intertemporal model and use an IAM to explore numerically the gap between both SCC.

2.3 Contributions of expected damages vs. risk in a stochastic IAM

We now use an IAM to numerically compare the SCC under a stochastic tipping point and the SCC under expected damages, in order to quantify the contribution of pure risk to the SCC. This allows us to examine whether the intuition from the simple model holds in a multi-period framework, and also for larger damages. We present in section 2.3.1 the climate-economy model and in section 2.3.2 the social welfare functions we use. We then explain how we construct in this model the SCC under expected damages (section 2.3.3), and the values we explore for the parameters of the model (section 2.3.4).

2.3.1 The climate-economy model

An IAM is meant to capture the main crossed interactions between the economy and the climate system. On the one hand, the economy, depending on growth, mitigation policies and technological choices, produces greenhouse gas emissions which interfere with the climate system. On the other, these changes in the climate system cause damages to the economy. An IAM allows to derive an optimal emission path from the point of view of a social planner balancing the costs of mitigation and damages of climate change, and to calculate the social value of intertemporal marginal damages caused by emissions – the SCC.

We use a classical DICE-like model, building on the Ramsey-Cass-Koopmans framework (Guivarch and Pottier, 2018). The economy produces a single good in quantity Q_t using two factors, capital K_t and labour L_t through a Cobb-Douglas function. The productivity is affected by climate change via a damage factor[1] Ω_t that depends on temperature T_t, so that final production Y_t writes:

$$Y_t = \Omega(T_t) A_t K_t^{\alpha} L_t^{1-\alpha} \tag{2.12}$$

Production induces emissions, which can be mitigated at a certain cost. The social planner trades off consumption, mitigation costs (which represent a share Λ_t of production), and investment in capital (share s_t of production)

$$C_t = Y_t(1 - \Lambda_t - s_t) \tag{2.13}$$

$$\Lambda_t = \theta_1(t)\mu_t^{\theta_2} \tag{2.14}$$

$$K_{t+1} - K_t = -\delta K_t + Y_t s_t \tag{2.15}$$

where δ is capital depreciation, and μ_t the abatement rate. $\theta_1(t)$ measures total mitigation costs and decreases exogenously due to technical progress.

The difference with DICE equations concerns the climate system. It has been shown that DICE's climate model implies a lag between CO_2 emissions and warming that is too long, i.e., the temperature rises too slowly in response to emissions (National Academies of Sciences, 2016; Mattauch et al., 2019) and is inconsistent at long timescales (Glotter et al., 2014). We adopt a simple linear formula linking temperature change to cumulative CO_2 emissions, as in Guivarch and Pottier (2018); Dietz and Venmans (2019). Indeed, the ratio of global temperature increase to cumulative emissions has been shown to be almost independent of time and of emission pathways in simulations of the response to a range of emission scenarios with climate models, as well as in observations (Matthews et al., 2009; Zickfeld et al., 2009, 2013; Gillett et al.,

[1] For notational convenience, we use damage factor Ω instead of damage function D. The correspondence is simply $\Omega = 1 - D$.

2013; Collins et al., 2013). There are physical explanations to this near-linear dependence between warming and cumulative carbon emissions, due to the compensating effects of oceanic uptake of heat and carbon (Solomon et al., 2009; Goodwin et al., 2015; MacDougall and Friedlingstein, 2015). There are also limitations to such a simple climate representation, for instance Leduc et al. (2015) have shown that the linear relationship between temperature change and cumulative emissions is no longer valid for high emission pathways such as the RCP 8.5.

Our equation for temperature change is thus:

$$T_t = \beta(CE_0 + \sum_{s=0}^{t} E_s) \tag{2.16}$$

where T_t is the global temperature increase at time t, CE_0 is cumulated emissions up to the first period of the model and E_s the emissions at time s. The current stock of cumulated emissions is $S_t = CE_0 + \sum_{s=0}^{t} E_s$.

$$E_t = \sigma_t Y_t (1 - \mu_t) \tag{2.17}$$

where σ_t is the carbon content of production that decreases exogenously over time, and μ_t the abatement rate.

In our central estimates, we model the tipping point as a stochastic process with an endogenous hazard rate h_t, leading to a permanent productivity shock, in line with Cai and Lontzek (2019); van der Ploeg and de Zeeuw (2018); Belaia et al. (2014). Such a change in the damage function can potentially apply to a large range of tipping points inducing larger damages than expected. It can be direct impact on the economy, either caused by the melting of ice caps, leading to severe sea-level rise; a slowing down of thermohaline circulation; or a social tipping point beyond which adaptation is no longer possible. Before the tipping point, the damage factor is:

$$\Omega_1(T) = \frac{1}{1 + \pi T^2} \tag{2.18}$$

In our central case, once the tipping point has been reached, the damage factor writes:

$$\Omega_2(T) = \frac{1-J}{1+\pi T^2} \tag{2.19}$$

J is the magnitude of the productivity shock, ranging from 0 to 1. In this representation, the tipping point increases the level of damages, but it does not affect the convexity of the damage function. Indeed, damages go approximatively from $\approx \pi T^2$ to $\approx \pi T^2 + J$. Uncertainty about the convexity of damages may lead to greater changes than uncertainty about the level of damages (Crost and Traeger, 2013), so we also consider in the Annex the case of a tipping point increasing marginal damages.

At each period, the tipping point occurs with a hazard rate h_t which depends on the temperature level. We assume that the location of the tipping point is unknown. The initial prior is that the tipping point is uniformly distributed between $T_{\min}$ and $T_{\max}$. At each time $t-1$ with temperature T_{t-1}, the social planner learns whether the tipping point has been reached or not, as in Lemoine and Traeger (2014). If it has not been reached, this means that it can only occur when temperature is above T_{t-1}, so that the social planner updates prior for the next period. Hence the probability to reach the tipping point at t conditional to not reaching it at $t-1$ is given by:

$$h_t(T_t, T_{t-1}) = \begin{cases} 0 & \text{if } T_t \leq T_{t-1} \text{ or } T_t \leq T_{\min} \\ \frac{T_t - \max(T_{\min}, T_{t-1})}{T_{\max} - \max(T_{\min}, T_{t-1})} & \text{if } T_t > T_{t-1} \text{ and } T_{\min} \leq T_t \leq T_{\max} \\ 1 & \text{if } T_t > T_{t-1} \text{ and } T_t \geq T_{\max} \end{cases} \tag{2.20}$$

Note that the marginal hazard rate tends to increase (i.e., $\partial_2 \partial_1 h_t \geq 0$), as experienced temperatures increase. This setting differs from the representation chosen in Cai and Lontzek (2019); van der Ploeg and de Zeeuw (2018), in which the hazard rate depends solely on current temperature with no learning. In that case the tipping point is therefore unavoidable in the long term. In our setting however, the tipping point is avoided with certainty if temperature stabilizes below $T_{\min}$; it can be avoided - but with no certainty - if temperature stabilizes between $T_{\min}$ and $T_{\max}$, and it is triggered with certainty if $T_{\max}$ is exceeded. This representation does not consider possible processes where a tipping point would be triggered with some lag.

2.3.2 Social welfare functions

We study two types of social welfare functions: expected utilitarianism with Constant Relative Risk Aversion (CRRA), and an Epstein-Zin social welfare function. In the CRRA representation, time and risk preferences are embedded in a single parameter, elasticity of marginal utility, which conflates the resistance to intertemporal substitution and the risk aversion. However, the resistance to intertemporal substitution and risk aversion can have opposite effects in the presence of risk (Ha-Duong and Treich, 2004): while the former favours the consumption of present generations, the latter encourages more abatement in the present in order to lower the risk of triggering the tipping point. For this reason, we also apply Epstein-Zin preferences, which disentangle intertemporal substitution and risk aversion.

Welfare after time t, U_t, is defined recursively:

- For CRRA preferences

$$U_t = \left(1 - \frac{1}{1+\rho}\right) u_t + \frac{1}{1+\rho}\mathbb{E}[U_{t+1}] \tag{2.21}$$

where ρ is the pure time preference rate, and utility at each time step is given by:

$$u_t = L_t \frac{(C_t/L_t)^{1-\eta}}{1-\eta} \tag{2.22}$$

η is the elasticity of marginal utility.

So that we can define Bellman functions as follows:

$$V_t(x_t) = \max_{y_t} \left[u(x_t, y_t) + \frac{1}{1+\rho}\mathbb{E}[V_{t+1}(G(x_t, y_t))] \right] \tag{2.23}$$

where $x_t = (S_t, K_t)$ are state variables, $y_t = (\mu_t, s_t)$ are control variables, and $x_{t+1} = G(x_t, y_t)$ is the transfer function.

- For Epstein Zin preferences:[2]

$$U_t = \left(\left(1 - \frac{1}{1+\rho}\right) u_t + \frac{1}{1+\rho}\mathbb{E}[U_{t+1}^{1-\gamma}]^{\frac{1-\theta}{1-\gamma}} \right)^{\frac{1}{1-\theta}} \tag{2.24}$$

[2]The formula holds for $\theta<1$. Otherwise when $\theta > 1$ utility function is negative, so that $U_t = -(-(1-\frac{1}{1+\rho})u + \frac{1}{1+\rho}[\mathbb{E}_t(-U_{t+1})^{1-\gamma}]^{\frac{1-\theta}{1-\gamma}})^{\frac{1}{1-\theta}}$

$$u_t = L_t \frac{(C_t/L_t)^{1-\theta}}{1-\theta} \tag{2.25}$$

For the sake of clarity, we use different notations in the Epstein-Zin case. We denote θ the resistance to intertemporal substitution (the inverse of the elasticity of intertemporal substitution), and γ the risk aversion parameter.

We can define Bellman functions in order to solve this dynamic program: $V_t = \frac{U_t^{1-\theta}}{1-\frac{1}{1+\rho}}$.

$$V_t(x_t) = \max_{y_t}[u(x_t, y_t) + \frac{1}{1+\rho} f(V_{t+1}(G(x_t, y_t)))] \tag{2.26}$$

f accounts for the decision maker's attitude towards the risk of reaching a tipping point.[3]. $f(V_{t+1}) = [\mathbb{E}(V_{t+1}^{\frac{1-\gamma}{1-\theta}})]^{\frac{1-\theta}{1-\gamma}}$. It is the same formula as for CRRA preferences, in which $f = \mathbb{E}$.

Using dynamic programming, we first approximate Bellman functions in the post-tipping world, and then in the pre-tipping world using expectations over the temperature at which the tipping point occurs.

2.3.3 Comparing the SCC for a stochastic tipping point and the SCC under expected damages

If S is the stock of emissions (* denotes that control variables y_0 are optimally chosen given x_0.), the SCC (at initial time) under a stochastic tipping point writes:

$$SCC = -\frac{1}{1+\rho} \frac{\partial_S \mathbb{E}[V_1]|_{x_1}}{\partial_C V_0|_{(x_0, y_0^*)}} \tag{2.27}$$

We use a modified damage factor $\Omega_{ed}(T)$ to calculate the SCC under expected damages. This modified damage factor represents the expected damage factor given the prior on the temperature at which the tipping point occurs. Let us note $p(T)$ the prior probability of having reached the tipping point at temperature T. The expected damage factor writes:

$$\Omega_{ed}(T) = (1 - p(T))\Omega_1(T) + p(T)\Omega_2(T) \tag{2.28}$$

[3]when $0 < \theta < 1$, the recursive formula involves $u_t - \frac{1}{1+\rho} f(-V_{t+1})$

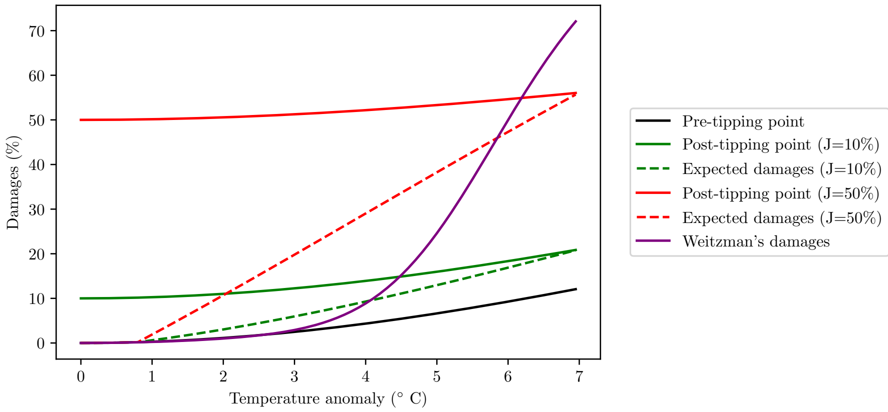


Figure 2.1 – Comparison between the two approaches. If the stochastic tipping point is triggered, the damage function jumps from pre-tipping point level (black curve) to a post-tipping point level (the green curve for a productivity shock of 10%, the red curve for a shock of 50%). The expected damage function of a tipping point is the prior expected damage level at each temperature (dashed curves), given that the tipping point is uniformly distributed between $T_{min} = 0.8°C$ and $T_{max} = 7°C$. The sextic damage function proposed in Weitzman (2012) is pictured for comparison.

Damages at a given temperature are set at their expected level given the prior knowledge on the temperature at which the tipping point occurs. Figure 2.1 shows the resulting expected damages for two productivity shocks (J = 10% and J = 50%). Even though the tipping point only affects the level of damages, the expected damage function is more convex than the pre-tipping point damage function. Indeed, whereas the tipping point changes the damage function from $\approx \pi T^2$ to $\approx \pi T^2 + J$, the expected damage function is $\approx \pi T^2 + p(T)J$, to be compared to $\approx \pi T^2$ without a tipping point.

For each computation of the SCC for a stochastic tipping SCC, we can compute the corresponding SCC under expected damages, noted SCC^{ed}, which is the SCC of a deterministic run with damages set at their expected level. The SCC in a stochastic setting represents the full effect of the tipping point, whereas we take SCC^{ed} as representing the level effect of the tipping point, absent risk. We will analyse the ratio SCC^{ed}/SCC, which is the part of the SCC that is explained by expected damages. Its complement is the part of the SCC that is due to a pure risk effect, purged of any level effect.

2.3.4 Calibration of the parameters

We summarize in table 2.1 the values and range explored for the parameters of interest. We use typical ranges of possible values for parameters related to attitudes towards risk and time. The pure rate of time preference is set at 1.5% (Nordhaus, 2008), — a lower value of 0.5% is explored in the Appendix. The elasticity of marginal utility ranges from 0.8 to 3 in the CRRA case. In the Epstein-Zin case, θ is set at 0.8, and we perform a sensitivity analysis in the Appendix. Considering the range used in the literature (Ackerman et al., 2013; Crost and Traeger, 2013; Jensen and Traeger, 2014; Cai and Lontzek, 2019), we explore risk aversion (γ) from 0.5 to 20.

For the parameters describing the tipping point, most of the published literature use impacts under a 10% decrease of productivity. Nevertheless, we acknowledge that the impacts of such a phenomenon are difficult to quantify and could be very large, so we explore a much larger window for the productivity shock J, from 0 to 50%. The temperature at which the tipping point would occur is uncertain, and we assume it is distributed between current temperature ($T_{\min} = 0.8$) and $T_{\max} = 7°$C (Lemoine and Traeger (2014) consider the upper bound for the temperature threshold between 3 and 9°C). This means for instance that there is a 19% probability of triggering a tipping point between 0.8 and 2°C. [4]

Table 2.1 – Main parameters for the stochastic tipping point numerical exercise. All other parameters are calibrated according to Guivarch and Pottier (2018)

Parameter	Value (Sensitivity test)
Pure rate of time preference (ρ)	1.5% (0.5)
Elasticity of marginal utility (η)	from 0.8 to 3
Resistance to intertemporal substitution (θ)	0.8 (0.5 and 1.5)
Risk aversion (γ)	from 0.5 to 20
Productivity shock (J)	from 0 to 50%
Minimum temperature threshold ($T_{\min}$)	0.8
Maximum temperature threshold ($T_{\max}$)	7 (10)

2.4 Results

We present the comparison between the SCC under a stochastic tipping point and the SCC under expected damages, first with CRRA preferences, then with Epstein-Zin preferences where risk aversion and resistance to intertemporal

[4] A sensitivity test using $T_{\max} = 10$ is performed in the Appendix. As said above, we also explore in the Appendix the case of a tipping point affecting the convexity of the damage function, rather than its level. Results are similar to those presented in the main text.

substitution differ. We finally discuss the significance of our results and lessons that can be drawn for the *risk aversion puzzle.*

2.4.1 With CRRA preferences

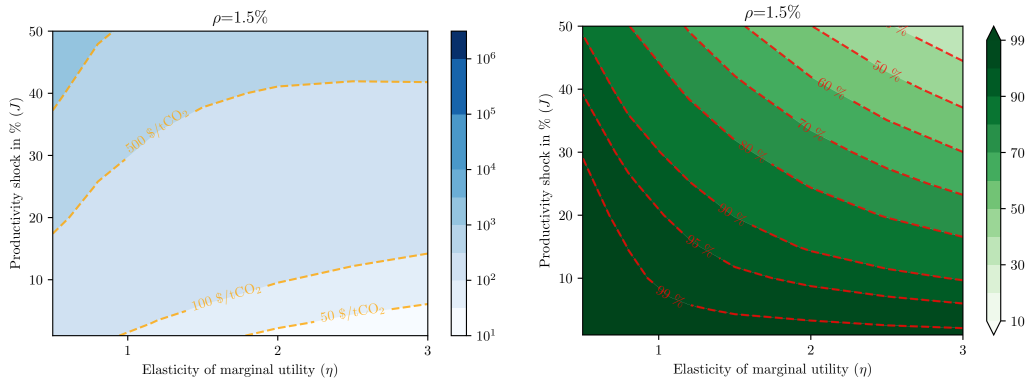
We compute the SCC for a stochastic tipping point for different values of the elasticity of marginal utility (η) and productivity shocks (J) in the range specified in section 2.3.4, as well as the SCC under expected damages SCC^{ed}.

One striking result is that the ratio SCC^{ed}/SCC is very close to one for low productivity shocks and low risk aversion (see figure 2.2, panel b), meaning that most of the SCC stems from expected damages enhanced by the tipping point rather than from the risk on damages the tipping point introduces. As J increases, aversion to the risk of high damages make the SCC rise faster than the SCC under expected damages, so that the ratio decreases.

The share of SCC due to expected damages also decreases as the elasticity of marginal utility η increases. The role of the elasticity of marginal utility η on the SCC is *a priori* ambiguous. Indeed, CRRA preferences conflate intertemporal trade-offs and risk aversion, and η has opposing effects on the SCC. On the one hand, a higher η favours present consumption relative to future consumption of wealthier generations (intertemporal substitution), which decreases the SCC. On the other hand, it encourages mitigation to reduce the risk induced by reaching a tipping point (risk aversion), which increases the SCC. In the case of SCC^{ed}, only the intertemporal substitution effect is at play, not the countervailing risk aversion effect. Thus the SCC under expected damages (SCC^{ed}) decreases faster with η than the SCC does, and the ratio SCC^{ed}/SCC decreases with η. Note that in the stochastic case, the intertemporal substitution effect outweighs the risk aversion effect: for a given productivity shock J, the SCC decreases when η increases (figure 2.2, panel a).

Though SCC varies by more than an order of magnitude with the ranges of shocks and preferences explored here, most of this variation is explained by expected damages. For example, at $\eta = 2$, introducing a tipping point with a shock of $J = 10\%$ trebles the SCC from 34 to 103 $\$/tCO_2$. However, this increase is not related to risk but to the simple fact that expected damages have increased – indeed, SCC^{ed} is 97 $\$/tCO_2$. A mere 6 percent of the SCC is due to a pure risk effect.

Numerically, it takes both a high productivity shock and a high elasticity



(a) (b)

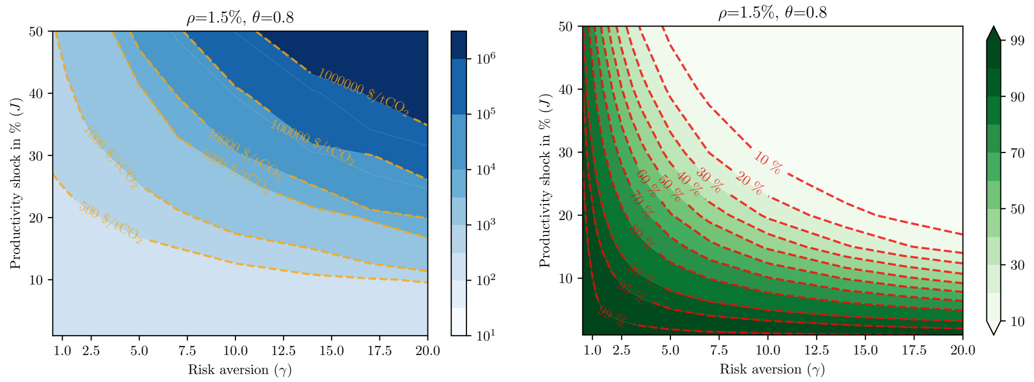
Figure 2.2 – How does the Social Cost of Carbon compare to a risk-free SCC under expected damages for CRRA preferences? Heatmap of the Social Cost of Carbon (panel a., in US$2005) and the share of its value that can be explained by expected damages (panel b., ratio SCC^{ed}/SCC). The closer the ratio to 100 %, the less risk plays a role. 90% of the SCC comes from expected damages for shocks lower than 10%, while it takes shocks greater than 40% for risk to explain at most half of the SCC.

of marginal utility for SCC^{ed} to significantly underestimate SCC. Expected damages explain more than 90% of the SCC, as long as the productivity shock is inferior to 10%, whatever the value of risk aversion in the range explored here. Only with productivity shocks higher than 40%, jointly with an elasticity of marginal utility higher than 2, does risk contribute to around half of the SCC.

The same pattern is found with a lower pure time preference rate (ρ). Though a lower ρ significantly raises the level of the SCC, it does so to the same extent in the stochastic case and under expected damages, so that the part of the SCC explained by expected damages is similar in the case of a lower ρ (see graph 2.6 in the Appendix).

2.4.2 With Epstein-Zin preferences

We perform the same exercise using Epstein-Zin preferences, i.e., disentangling preferences for risk and intertemporal substitution. We set the resistance to intertemporal substitution (θ) at 0.8, and present the results when the risk aversion γ and the productivity shock J vary in figure 2.3. The corresponding graphs for different values of resistance to intertemporal substitution and pure rate of time preference can be found in the Appendix as a sensitivity check, as



(a) (b)

Figure 2.3 – How does the Social Cost of Carbon compares to a risk-free SCC under expected damages for Epstein-Zin preferences? Heatmap of the Social Cost of Carbon (panel a., in US$2005) and the share of its value that can be explained by expected damages (panel b., ratio SCC^{ed}/SCC). The ratio decreases with risk aversion and with the magnitude of the shock, but remains above 90% for productivity shocks lower than 10%, unless risk aversion is greater than 10.

well as alternative values for $T_{\max}$.

The part of the SCC explained by expected damages has a similar pattern as in the case of CRRA preferences. As expected, the ratio SCC^{ed}/SCC decreases with risk aversion γ and productivity shock J. Values are somewhat similar to the case with CRRA preferences (with a correspondence $\eta \sim \gamma$) but as we explore a much larger range in risk aversion, the part explained by expected damages can become much lower. Interestingly, the SCC does not significantly increase with risk aversion for low values of the productivity shock (see figure 2.3, panel a.), hence the low horizontal gradient below $J = 10\%$. However, for higher productivity shocks, the SCC shows a high sensitivity to risk aversion, and a higher γ leads to SCC orders of magnitude greater. This suggests that risk aversion only matters when the economy is exposed to catastrophic risks.

For instance, for a productivity shock equal to 10%, 90% of the SCC is explained by expected damages up to a risk aversion of 4 (as in the CRRA case), but the part explained is only 60% when $\gamma = 15$. Productivity shocks higher than 25%, combined with risk aversion higher than 5, lead to the ratio SCC^{ed}/SCC below 50%. For a productivity shock equal to 40% and a risk aversion parameter equal to 5, the SCC under expected damages only makes 20% of the SCC.

The same holds for the sensitivity checks we explore in the Appendix, i.e., for alternative values of the pure time preference rate ($\rho = 0.5$) and of the elasticity of intertemporal substitution ($\theta = 0.5,\ 1.5$). A decrease in the elasticity of substitution (a higher θ) tends to decrease the SCC, but it does not affect how much the SCC is explained by expected damages. Indeed, θ plays a similar role in both deterministic and stochastic settings, as it governs the trade-off between future and present consumption. This is a strong indication that our construction of the expected damages has correctly isolated the level effect of the tipping point. It is graphically confirmed with panel b. of figure 2.4 in Appendix, where the iso-lines for the ratio SCC^{ed}/SCC are almost flat in the θ direction. For the same reason, changes in the pure time preference rate (ρ) or using a higher temperature threshold $T_{\max}$ do not affect much the shape or position of the contours of the ratio. Even when considering a tipping point affecting the convexity of the damage function, it takes both very high post-tipping point marginal damages and high risk aversion for the SCC to deviate from the value given by expected damages.

2.4.3 Significance of our findings and discussion of the *risk aversion puzzle*

A productivity shock of 10% is in the higher range of those typically considered in the literature. For instance, Lontzek et al. (2015), with a similar framework, do not consider shocks above $J = 10\%$. Belaia et al. (2014) only considers productivity shocks below 4.5% when thermohaline circulation collapses. Other modelling choices, in Lemoine and Traeger (2014), assume a tipping point induces a change from a quadratic to a sextic damage function, i.e., Weitzman's damage function that relies on an expert panel explicitly considering physical tipping points. At 4°C, this corresponds to a change of damage factor from $\Omega_1 = 0.96$ to $\Omega_2 = 0.91$ (so equivalent to a productivity shock of 5%). Our results thus suggest that the increase of SCC found in studies considering tipping points is mostly due to an increase in expected damages, rather than to the risk itself.

Identifying that most of the SCC in the presence of a small tipping point is due to expected damages and not risk sheds light on the so-called *risk aversion puzzle*. It has been found in previous work that risk aversion has a surprisingly little effect on the SCC (Ackerman et al., 2013), even in the case of a tipping point (Belaia et al., 2014). When risk aversion is higher, the SCC does not change much. This seems counter-intuitive, as risk aversion, especially after it has been disentangled from the elasticity of substitution in Epstein-Zin preferences, is expected to significantly increase the SCC.

The simple model of section 2.2 reveals why this may be the case. Indeed, the SCC is equal to the SCC under expected damages plus a risk premium proportional to risk aversion. Moreover, the smaller the tipping point, the smaller the risk premium. For instance, for a productivity shock $J = 5\%$ and a risk aversion $\gamma = 1$, the SCC under expected damages represents 99.5% of the value of the SCC. Based on the simplified model, increasing γ from 1 to 20 increases the SCC from a base $100 = 99.5 + 0.5$ to $109.5 = 99.5 + 20 \times 0.5$, i.e., an increase of less than 10%. However, for a productivity shock $J = 50\%$, the SCC under expected damages represents around 70% of the SCC at $\gamma = 1$. Setting $\gamma = 20$ increases the SCC from a base $100 = 70 + 30$ to $670 = 70 + 20 \times 30$. In our numerical results, the effects of risk turns out to be more than proportional to risk aversion, but the pattern is as described by the simple model of section 2.2.

While the numerical results explain away the *risk aversion puzzle* for small shocks, they also show that this puzzle does not always hold. We quantify the magnitude of the shock it takes for risk aversion to play a role. Shocks leading to a minimum of a 10% drop in productivity are necessary for risk aversion to impact the SCC.

Only few studies explore the possibility of large shocks, which are required for risk aversion to significantly affect the SCC: for instance, Dietz (2011) explores damages as large as 90 % of consumption; Méjean et al. (2017) explore possible extinction, though with a very low probability. In such cases, risk aversion is expected to play a significant role.

2.5 Conclusion

When considering climate damages, one might wonder whether it is their expected level or their possible dispersion (i.e., risk) that warrants undertaking mitigation actions. This question has been studied for many types of risks, for instance regarding climate sensitivity or other critical aspects of the climate-economy system, but has not been applied to tipping points in damage functions.

Our research fills this gap. We model a tipping point as an endogenous risk, with a hazard rate increasing with temperature, leading to a permanent productivity drop. First, we demonstrate in a simple setting that the SCC with a stochastic tipping point is at the first order the SCC with damages set at their expected level. We thus isolate the effect of the increased expected damages brought by the introduction of a tipping point, so that the difference between the two methods can be attributed to the sole effect of risk. Numerically, when risk aversion is equal to resistance to intertemporal substitution (CRRA preferences), the SCC under expected damages closely approximates the SCC for a low productivity shock and a low risk aversion. Even when disentangling resistance to intertemporal substitution and risk aversion, using Epstein-Zin preferences, the share of SCC attributable to risk remains limited. For both Social Welfare Functions, risk contributes less than 10% to the SCC, as long as shocks remain below 10% of production and risk aversion is below 10. We test the robustness of our results with a number of sensitivity runs regarding the parametrization of the tipping point and preferences. In particular, the results are qualitatively unchanged when considering a tipping point that leads to more convex damages rather than higher damages.

Providing realistic values for the damage shocks triggered by tipping points is beyond the scope of the article, but we nevertheless provide orders of magnitude for the type of damages it may take for risk to play a role. This sheds light on the *risk aversion puzzle*. We show that risk aversion only plays a role when the economy is exposed to very high post-tipping damages. When low post-tipping point impacts are considered, the SCC is sensitive to expected damages, so that risk aversion plays a moderate role, in particular compared to time preferences. Thus, the low level of possible damages considered in the literature explains the *risk aversion puzzle*. However, this stresses once again that the shape of the damage function is central in IAMs. In particular, provided that the risk of triggering a tipping point increases with temperature, expected damages are more convex when considering tipping points. Thus, simply using more convex damage functions in a deterministic fashion may be a good proxy to determine the SCC, as was done for instance by Pizer (2003); Ackerman and Stanton (2012); Wouter Botzen and van den Bergh (2012); Dietz and Stern (2015); Weitzman (2012).

These results can be extended to other situations. For instance, multiple tipping points (Lemoine and Traeger, 2016b) are equivalent to a single tipping point with compounding damages. Our approach could be applied to this case, provided that these combined effects are accounted for (i.e., including the increased probability of triggering another tipping point if one is reached).

Damages affecting growth can also result into a higher SCC (Moore and Diaz, 2015), but they would make the comparison with expected damages more difficult, because of the different time profiles of damages, with losses of potential growth adding up each year (Guivarch and Pottier, 2018). Thus, we leave for future research the question of whether the risk effect plays a greater role for a tipping point affecting growth.

Because the role of preferences is critical to assess the optimal strategy under uncertainty, a direct extension of our work would be to study how the comparison between methods is affected by alternative preferences for the social planner. Epstein-Zin preferences have recently received a lot of attention in this literature, but they may violate first-order stochastic dominance (Bommier and Le Grand, 2014). Bommier et al. (2015) propose another class of preferences, which could be used in the case of catastrophic risks. The social planner may also be ambiguity averse to differing worldviews about tipping points (Berger et al., 2016; Lemoine and Traeger, 2016a). Though we have focused here on how uncertainty about the tipping points affects optimal policy, this uncertainty could be combined with other uncertainties at stake, such as climate sensitivity or the volality of growth (Cai and Lontzek, 2019; Van Den Bremer and van der Ploeg, 2018). Finally, even if the damage function is the weakest point of IAMs, they also embed a number of assumptions about the climate-economy system that may be regarded as simplistic and questionable (Pindyck, 2013).

Deterministic approaches using best-guess expected damages (together with sensitivity analyses) are currently used to set a value for the SCC for policy evaluations (IAWG, 2010), and benefit from a lower computational burden than a fully fledged stochastic model. Knowing when deterministic approaches can be used as a good proxy for computing the SCC under risk can guide policy-making. Our results show that the SCC is primarily driven by the expected level of damages, when the shock induced by a potential tipping point remains lower than 10% or so. In that case, the effects of tipping points are well captured by updating the damage function typically used to a more convex function, reflecting the increasing probability to trigger a tipping point as the Earth warms.

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2.A Proof of equation 2.10

Recall that we note $V_\epsilon(E) = \mathbb{E}_\omega[\epsilon^2_\omega(E)]$ the variance of damages of the zero-mean risk ϵ, which is of second order in $|\epsilon|$ (a norm of the risk ϵ). Let us start with Taylor expansion at second order of the term evaluated in the denominators of equation (2.8):

$$\mathbb{E}_\omega\left[u'(C_\omega(a,E))\right] = \mathbb{E}_\omega\left[u'(\tilde{C}(a,E)) + u''(\tilde{C}(a,E))\epsilon_\omega(a,E) + u'''(\tilde{C}(a,E))\frac{\epsilon^2_\omega(E)}{2} + o(|\epsilon|^2)\right] \tag{2.29}$$

$$= u'(\tilde{C}(a,E)) + u'''(\tilde{C}(a,E))\mathbb{E}_\omega\left[\frac{\epsilon^2_\omega(E)}{2}\right] + o(|\epsilon|^2) \tag{2.30}$$

$$= u'(\tilde{C}(a,E)) + u'''(\tilde{C}(a,E))\frac{V_\epsilon(E)}{2} + o(|\epsilon|^2) \tag{2.31}$$

$$\tag{2.32}$$

So the denominator is finally:

$$\mathbb{E}_\omega\left[u'(C_\omega(a,E))\right]|_{a^t,E^t} = u'(\tilde{C}(a^t,E^t)) + u'''(\tilde{C}(a^t,E^t))\frac{V_\epsilon(E^t)}{2} + o(|\epsilon|^2) \tag{2.33}$$

Let us go back to equation (2.8). It is a sum of two terms, the first one is of zero-order, whereas a second term is of second order. In this second term, we can simply replace the denominator by its zero-order approximation as any correction would induce terms with orders higher than 2. For the first term of the sum, we have to keep the full Taylor expansion of the denominator. We then reorder terms of the Taylor expansion.

$$SCC = \frac{u'(\tilde{C}(a^t,E^t))\tilde{d}'(E^t)}{\mathbb{E}_\omega\left[u'(C_\omega(a,E))\right]|_{a^t,E^t}} - \frac{\partial_E\left(u''(\tilde{C}(a,E))\frac{V_\epsilon(E)}{2}\right)\Big|_{a^t,E^t}}{\mathbb{E}_\omega\left[u'(C_\omega(a,E))\right]|_{a^t,E^t}} + o(|\epsilon|^2) \tag{2.34}$$

$$= \frac{u'(\tilde{C}(a^t,E^t))\tilde{d}'(E^t)}{u'(\tilde{C}(a^t,E^t)) + u'''(\tilde{C}(a^t,E^t))\frac{V_\epsilon(E^t)}{2}} - \frac{\partial_E\left(u''(\tilde{C}(a,E))\frac{V_\epsilon(E)}{2}\right)\Big|_{a^t,E^t}}{u'(\tilde{C}(a^t,E^t))} + o(|\epsilon|^2) \tag{2.35}$$

$$= \frac{\tilde{d}'(E^t)}{1 + \frac{u'''}{u'}\left(\tilde{C}(a^t,E^t)\right)\frac{V_\epsilon(E^t)}{2}} - \frac{u''(\tilde{C}(a^t,E^t))\,\partial_E\left(\frac{V_\epsilon(E)}{2}\right)\Big|_{E^t} - u'''(\tilde{C}(a^t,E^t))\tilde{d}'(E^t)\frac{V_\epsilon(E^t)}{2}}{u'(\tilde{C}(a^t,E^t))} + o(|\epsilon|^2) \tag{2.36}$$

$$= \tilde{d}'(E^t)\left(1 - \frac{u'''}{u'}\left(\tilde{C}(a^t,E^t)\right)\frac{V_\epsilon(E^t)}{2}\right) - \frac{u''(\tilde{C}(a^t,E^t))\,\partial_E\left(\frac{V_\epsilon(E)}{2}\right)\Big|_{E^t}}{u'(\tilde{C}(a^t,E^t))} + \frac{u'''(\tilde{C}(a^t,E^t))\tilde{d}'(E^t)\frac{V_\epsilon(E^t)}{2}}{u'(\tilde{C}(a^t,E^t))} + o(|\epsilon|^2) \tag{2.37}$$

$$= \tilde{d}'(E^t) - \frac{u''(\tilde{C}(a^t,E^t))\,\partial_E\left(\frac{V_\epsilon(E)}{2}\right)\Big|_{E^t}}{u'(\tilde{C}(a^t,E^t))} + o(|\epsilon|^2) \tag{2.38}$$

$$= \tilde{d}'(E^t) + \gamma(\tilde{C}(a^t,E^t))\frac{\tilde{C}(a^t,E^t)}{2}\,\partial_E V_\epsilon(E)|_{E^t} + o(|\epsilon|^2) \tag{2.39}$$

At the last line, we have introduced the Arrow-Pratt measure of relative risk aversion $\gamma(C) = -u''(C)/(u'(C).C)$ of the utility u to get equation (2.10).

2.B Proof of proposition 1

We are first interested in the difference between SCC with a tipping point SCC, given by equation (2.5) and SCC without a tipping point $SCC^{w/o}$, given by (2.2), with damage function d egal to damage function in the pre-tipping state of the world (we call 1 this state).

The proof is a little bit more complicated than just comparing the equations (2.2), (2.10) and (2.11). Indeed, one has to take into account not only that there are additional terms but also that these are not evaluated at the same point. This is because the planner reacts to additional damages terms and thus the optimal emissions change accordingly (it is respectively E^*, E^t, E^{ed}).

We have, at first order in the magnitude of risk ϵ, thanks to (2.10):

$$SCC - SCC^{w/o} = \tilde{d}'(E^t) - d(E^*) + o(|\epsilon|) \tag{2.40}$$

The optimal abatement and emission levels solve:

$$\frac{c'(a^*)}{\sigma Y} = d'(E^*) \tag{2.41}$$

$$\frac{c'(a^t)}{\sigma Y} = \tilde{d}'(E^t) + o(|\epsilon|) \tag{2.42}$$

Let us write $a^t = a + h$, then $E^t = E - \sigma Y h$ and assume that h is at first-order in $|\epsilon|$. We make a Taylor-expansion of the last line in h:

$$\frac{c'(a^*)}{\sigma Y} + \frac{c''(a^*)}{\sigma Y} h = \tilde{d}'(E^*) - \tilde{d}''(E^*)\sigma Y h + o(|\epsilon|) \tag{2.43}$$

Hence

$$\left(\frac{c''(a^*)}{\sigma Y} + \tilde{d}''(E^*)\sigma Y\right) h = \tilde{d}'(E^*) - d'(E^*) + o(|\epsilon|) \tag{2.44}$$

The right hand side is simply $-\epsilon_1'(E^*)$, the marginal increase in risk ϵ in state 1. Thus h is correctly at first-order in $|\epsilon|$ and the difference between the SCCs is given by:

$$SCC - SCC^{w/o} = \tilde{d}'(E^*) - d'(E^*) - d''(E^*)\sigma Y h + o(|\epsilon|) \tag{2.45}$$

$$= \left(\tilde{d}'(E^*) - d(E^*)\right) \frac{\frac{c''(a^*)}{\sigma Y}}{\frac{c''(a^*)}{\sigma Y} + \tilde{d}''(E^*)\sigma Y} + o(|\epsilon|) \tag{2.46}$$

$$= -\epsilon_1'(E^*) \frac{\frac{c''(a^*)}{\sigma Y}}{\frac{c''(a^*)}{\sigma Y} + \tilde{d}''(E^*)\sigma Y} + o(|\epsilon|) \tag{2.47}$$

This proves our first claim. We proceed similarly for the second. By definition and thanks to (2.10),

$$SCC - SCC^{ed} = \tilde{d}'(E^t) + \gamma(\tilde{C}(a^t, E^t))\frac{\tilde{C}(a^t, E^t)}{2}\ \partial_E V_\epsilon(E)|_{E^t} - \tilde{d}'(E^{ed}) + o(|\epsilon|^2) \tag{2.48}$$

The optimal abatement and emission levels solve:

$$\frac{c'(a^{ed})}{\sigma Y} = \tilde{d}'(E^{ed}) \tag{2.49}$$

$$\frac{c'(a^t)}{\sigma Y} = \tilde{d}'(E^t) + \gamma(\tilde{C}(a^t, E^t))\frac{\tilde{C}(a^t, E^t)}{2}\ \partial_E V_\epsilon(E)|_{E^t} + o(|\epsilon|^2) \tag{2.50}$$

Let us write $a^t = a^{ed} + g$, then $E^t = E^{ed} - \sigma Y g$ and assume that g is at second-order in $|\epsilon|$. We make a Taylor-expansion of the last line in g:

$$\frac{c'(a^{ed})}{\sigma Y} + \frac{c''(a^{ed})}{\sigma Y}h = \tilde{d}'(E^{ed}) - \tilde{d}''(E^{ed})\sigma Y g + \gamma(\tilde{C}(a^t, E^t))\frac{\tilde{C}(a^t, E^t)}{2}\ \partial_E V_\epsilon(E)|_{E^t} + o(|\epsilon|^2) \tag{2.51}$$

Hence:

$$\left(\frac{c''(a^{ed})}{\sigma Y} + \tilde{d}''(E^{ed})\sigma Y\right) g = \gamma(\tilde{C}(a^t, E^t))\frac{\tilde{C}(a^t, E^t)}{2}\ \partial_E V_\epsilon(E)|_{E^t} + o(|\epsilon|^2) \tag{2.52}$$

Thus g is correctly at second-order in $|\epsilon|$ (as $\partial_E V_\epsilon(E)|_{E^t}$) is) and given by:

$$g = \frac{\gamma(\tilde{C}(a^t, E^t))\frac{\tilde{C}(a^t,E^t)}{2}\ \partial_E V_\epsilon(E)|_{E^t}}{\frac{c''(a^{ed})}{\sigma Y} + \tilde{d}''(E^{ed})\sigma Y} + o(|\epsilon|^2) \tag{2.53}$$

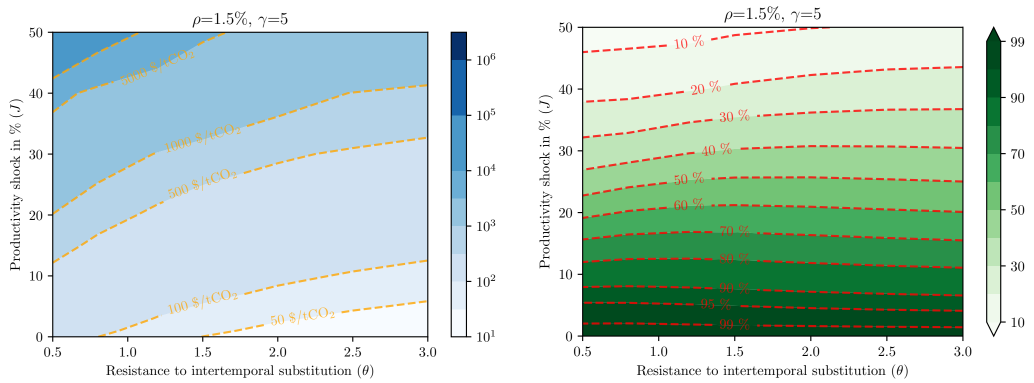
$$= \frac{\gamma(\tilde{C}(a^{ed}, E^{ed}))\frac{\tilde{C}(a^{ed},E^{ed})}{2}\ \partial_E V_\epsilon(E)|_{E^{ed}}}{\frac{c''(a^{ed})}{\sigma Y} + \tilde{d}''(E^{ed})\sigma Y} + o(|\epsilon|^2) \tag{2.54}$$

The difference between the SCCs is given by:

$$SCC - SCC^{ed} = \tilde{d}'(E^{ed}) - \tilde{d}''(E^{ed})\sigma Y g + \gamma(\tilde{C}(a^{ed}, E^{ed}))\frac{\tilde{C}(a^{ed}, E^{ed})}{2}\ \partial_E V_\epsilon(E)|_{E^{ed}} - \tilde{d}'(E^{ed}) + o(|\epsilon|^2) \tag{2.55}$$

$$= \gamma(\tilde{C}(a^{ed}, E^{ed}))\frac{\tilde{C}(a^{ed}, E^{ed})}{2}\ \partial_E V_\epsilon(E)|_{E^{ed}}\ \frac{\frac{c''(a^{ed})}{\sigma Y}}{\frac{c''(a^{ed})}{\sigma Y} + \tilde{d}''(E^{ed})\sigma Y} \tag{2.56}$$

2.C Additional graph: sensitivity to resistance to intertemporal substitution



(a) (b)

Figure 2.4 – Epstein-Zin preference: influence of the resistance to intertemporal substitution θ. Heatmap of the Social Cost of Carbon (panel a., in US\$2005) and the share of its value that can be explained by expected damages (panel b., ratio SCC_{ed}/SCC), for different values of resistance to intertemporal substitution (θ) and productivity shocks (J). Horizontal lines in panel b. indicate that preferences for intertemporal substitution does not affect the comparison between SCC and SCC under expected damage.

Two parameters are involved in welfare evaluation at each time step: risk aversion (γ) and resistance to intertemporal substitution (θ). In the main text, we have analyzed the influence of risk aversion combined with the value of the shock. On figure 2.4, we display how resistance to intertemporal substitution affects the comparison of determinsitic and stochastic methods. A change in θ does not affect the share of the SCC explained by expected damages, the contour lines on the graph are horizontal.

2.D Robustness checks

We perform a sensitivity analysis on several parameters of the model:

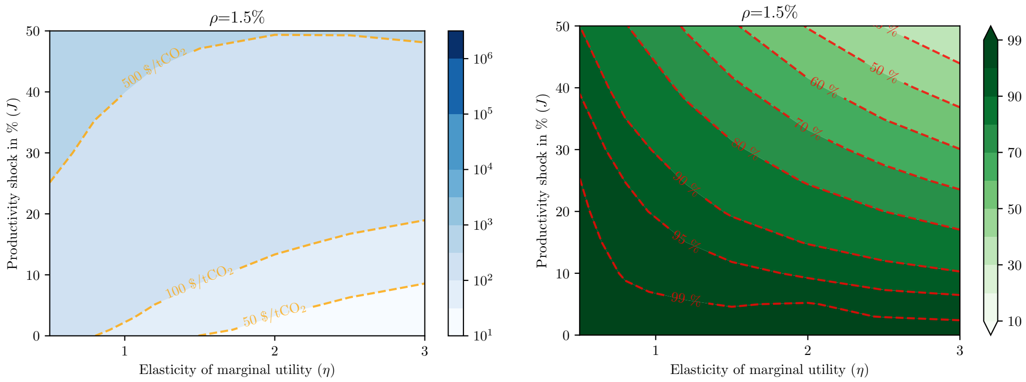
- The maximum temperature threshold for the tipping point $T_{\max}$. We look at $T_{\max} = 10$ instead of 7.

- Pure rate of time preference ρ. We run the model for lower ρ (0.5%)

- Elasticity of intertemporal substitution ($1/\theta$) in the Epstein-Zin case. We consider $\theta = 0.5$ and $\theta = 1.5$.

The graphs show that the shapes of the curves are not affected by a change in these parameters, and our finding that most of the SCC is still explained by expected damages as long as the shock remain under 10%.

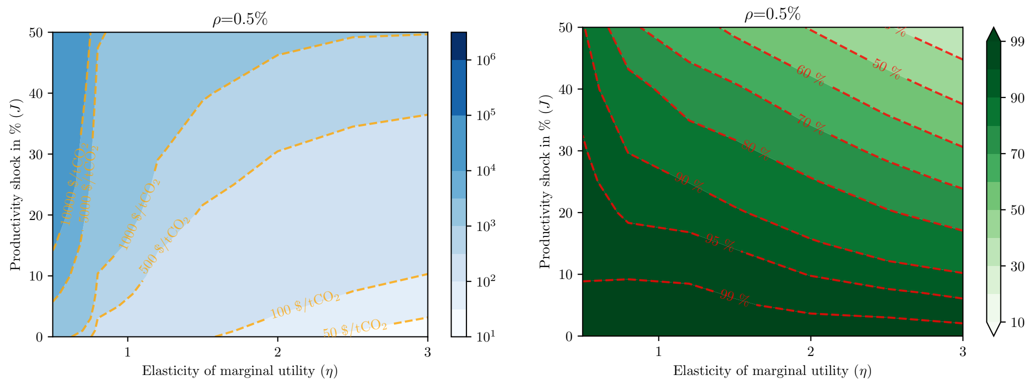
2.D.1 Parameter $T_{\max}$



(a) (b)

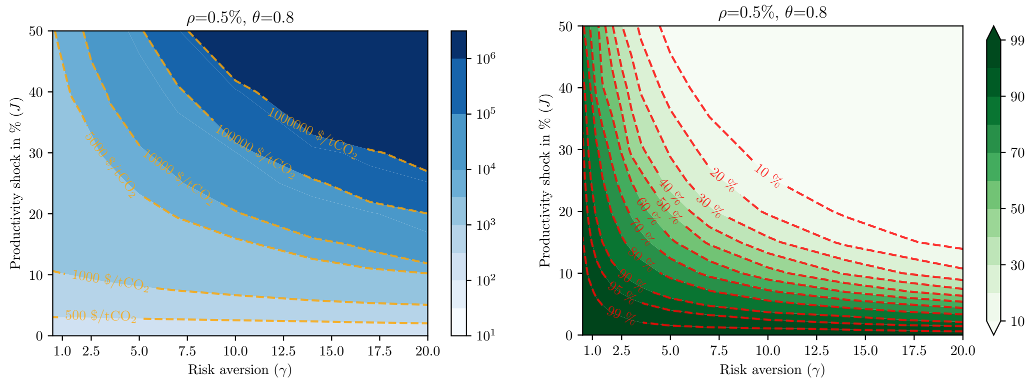
Figure 2.5 – Sensitivity analysis for $T_{\max} = 10°C$ (CRRA preferences). Heatmap of the Social Cost of Carbon (panel a., in US\$2005) and the share of its value that can be explained by expected damages (panel b., ratio SCC_{ed}/SCC).

2.D.2 Parameter ρ



(a) (b)

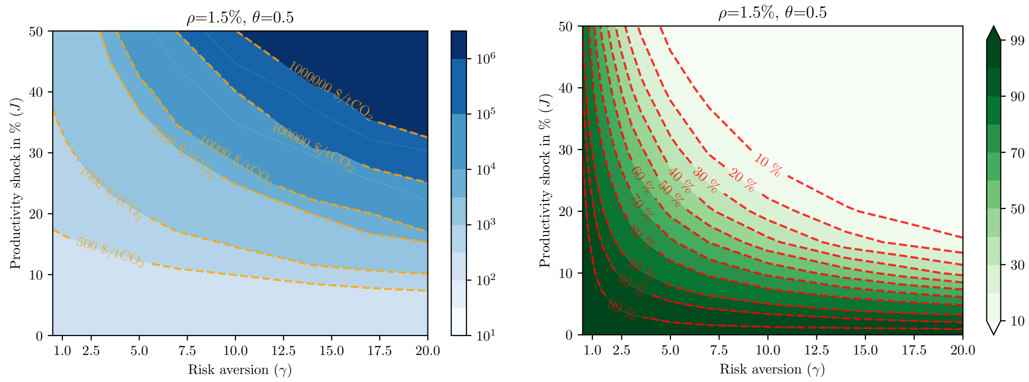
Figure 2.6 – Sensitivity analysis for $\rho = 0.5\%$ (CRRA preferences). Social Cost of Carbon under Epstein-Zin preferences. Heatmap of the Social Cost of Carbon (panel a., in US\$2005) and the share of its value that can be explained by expected damages (panel b., ratio SCC_{ed}/SCC).



(a) (b)

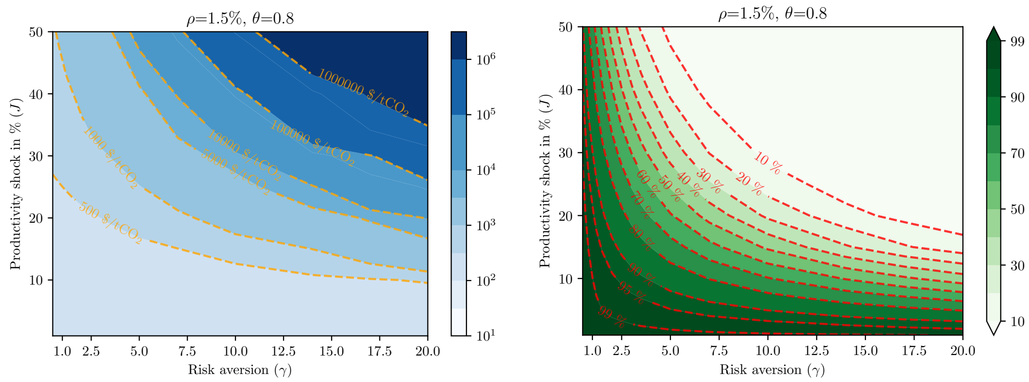
Figure 2.7 – Sensitivity analysis for $\rho = 0.5\%$ (Epstein-Zin preferences). Heatmap of the Social Cost of Carbon (panel a., in US\$2005) and the share of its value that can be explained by expected damages (panel b., ratio SCC_{ed}/SCC).

2.D.3 Parameter θ



(a) (b)

Figure 2.8 – Sensitivity analysis for $\theta = 0.5$ (Epstein-Zin preferences). Heatmap of the Social Cost of Carbon (panel a., in US\$2005) and the share of its value that can be explained by expected damages (panel b., ratio SCC_{ed}/SCC).



(a) (b)

Figure 2.9 – Sensitivity analysis for $\theta = 1.5$ (Epstein-Zin preferences). Heatmap of the Social Cost of Carbon (panel a., in US\$2005) and the share of its value that can be explained by expected damages (panel b., ratio SCC_{ed}/SCC).

2.D.4 A tipping point affecting the convexity of damages

We plot the same graphs when the tipping point affects the convexity of the damage function. Thus, the tipping point increases marginal damages rather solely damage level. We assume that the coefficient π in the damage factor $\Omega = \frac{1}{1+\pi T^2}$ can jump from its initial value (π_1=0.00028) to a higher value π_2 (see figure 2.10 for an illustration of the effect on the damage function)

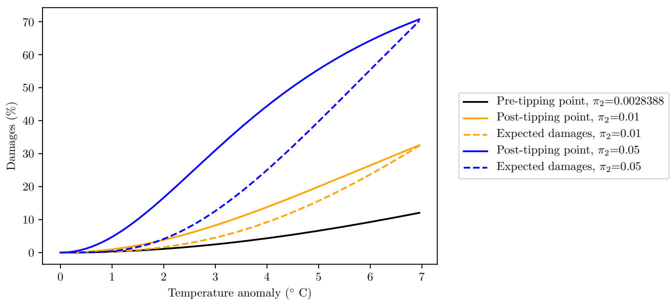


Figure 2.10 – Comparison between stochastic damage function and expected damages approaches, for a tipping point which affects π.

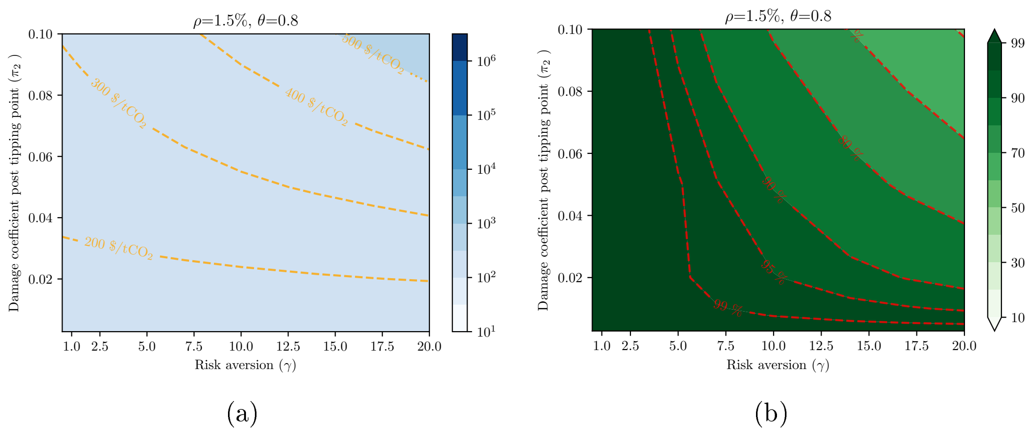


Figure 2.11 – Sensitivity analysis for a tipping point affecting the convexity of the damage function. Heatmap of the Social Cost of Carbon (panel a., in US\$2005) and the share of its value that can be explained by expected damages (panel b., ratio SCC_{ed}/SCC).

Chapter 3

Optimal climate policy when warming rate matters

Abstract

Studies of the Social Cost of Carbon assume climate change is a stock externality for which damages stem from warming level. However, economic and natural systems are also sensitive to the *rate at which warming occurs*. In this paper, I study the optimal carbon tax when such a feature is accounted for. Damages caused by warming rates do not affect optimal long-term warming, but they delay the use of the same carbon budget. They also make carbon price less sensitive to discounting assumptions. Numerically, when controlling for the welfare loss from climate change, the more damages stem from warming rates rather than warming levels, the higher the initial carbon price. This suggests that mitigation strategies that overlook this issue might lead to too rapidly increasing temperature pathways.

3.1 Introduction

Many human activities, in particular the burning of fossil fuels, release greenhouse gases that warm up the atmosphere and cause damage to the economy. These damages in economic analysis are typically considered to be a stock externality, driven by temperature anomaly, or the stock of atmospheric carbon dioxide, that is the "level" of climate change. However, economic and natural systems are not only sensitive to the level of change, but also to *the rate at which it occurs*, for instance because rapid changes constrain adaptation and thus induce greater damages. Failing to account for this sensitivity to warming rate may favor emission pathways for which global temperature increases too fast, given economies' ability to cope with the change.

There is evidence that the speed of change plays a key role in the way ecological, climate and human systems will be affected by temperature change. If ecosystems have been confronted to different climatic conditions in the past, what makes climate change so concerning is the never-seen rate at which it is occurring. More rapid rates of change limit the ability of natural systems to adapt (LoPresti et al., 2015; Hoegh-Guldberg et al., 2007; Gilman et al., 2008; Maynard et al., 2008; Malhi et al., 2009; Thackeray et al., 2010). Conversely, slower rates of change give ecosystem the time to adapt to new environmental conditions (either through behavioral or genetic changes) or to migrate in search for more favourable climates. A study suggests that for 30% of Earth, plant species would not be able to migrate to keep pace with projected climate change (Loarie et al., 2009). The importance of the rate of change holds in particular for systems with significant inertia, such as vegetation or soil carbon stores (Jones et al., 2009; Sihi et al., 2018). Coral reefs may also not be able to adapt to rapid rates of change (Maynard et al., 2008; Hoegh-Guldberg, 2009), because the rate of carbon absorption by the deep ocean is limited (Lenton et al., 2008).

Rapid rates of change can also contribute to trigger non-linear dynamics in the climate system, also referred to as 'tipping points' (Lenton, 2012; Levermann and Born, 2007; Steffen et al., 2018; Wieczorek et al., 2011). For instance, the stability of thermohaline circulation, as it involves water circulation flow and thus the melting rate of glacier, is sensitive to both warming level and rate of change (Stocker and Schmittner, 1997; Marotzke, 1996). A warming of 0.3 °C per decade sustained over a century could lead to a collapse in thermohaline circulation, while the same warming of 3°C reached with slower rates of change would only lead to a slowdown.

For economies too, climate damages may stem both from a changed climate and from a changing climate. Faster changes induce greater costs or less efficient adaptation (Huntingford et al., 2008; Stafford Smith et al., 2011; New et al., 2011; Smit and Wandel, 2006). For decisions involving long timescales, such as urbanisation plans, tranportation, building, or forestry, faster rates of change imply that infrastructures will be confronted to a larger range of climate conditions, which makes their design more difficult and construction more expensive (Hallegatte, 2009; Fankhauser and Soare, 2013). Slower rates of change also allow for more sequential decision making and to use capital more efficiently, while rapid change would force economies to retire productive capital sooner. Conversely, some of the damages may be reduced once the climate has stabilized, and that economies have adapted to new climate conditions, for instance, through the use of air conditioners, changes in crop varieties or behavioral adaptations such as changes in work hours. This is consistent with recent empirical analysis suggesting that economic damage is driven by a deviation from experienced temperatures in past decades, rather than by temperatures themselves (Kahn et al., 2019; Kalkuhl and Wenz, 2020), and thus may fade away once temperatures have stabilized. Finally, institutional barriers may also limit the ability of societies to react efficiently to rapid changes. Damages from warming rates reflect transitional adaptation costs of a changing climate, while damages from warming levels are persistent losses due to a changed climate.

It has been argued in the scientific literature that climate change action should also seek to constrain the rate of change (O'Neill and Oppenheimer, 2004; Bowerman et al., 2011; Kallbekken et al., 2009). In the economic literature on climate change however, the role of the rate of change is rarely accounted for. Environmental externalities are usually considered as either a stock or a flow externality (Farzin, 1996; Ulph and Ulph, 1994; Van Der Ploeg and Withagen, 1991), with climate change belonging to the former category.

Both DICE, the most widely used numerical Integrated Assessment Model (IAM), and recent analytical models of the climate and the economy all assume that damages stem from the level of warming or the stock of atmospheric carbon dioxide (Golosov et al., 2014; Gerlagh and Liski, 2018; Dietz and Venmans, 2019), leaving aside the influence of the speed of warming. In other numerical IAMs, such as FUND (Tol, 1996) or PAGE (Hope et al., 1993), damage depend both on level and rate of change in some sectors, but the authors did not analyse how the combination of both types of damages affected the outcomes. A few studies in the 1990s have compared damage from warming level and warming rates, either in a numerical IAM (Peck and Teisberg, 1994) or in an analytical model (Tahvonen, 1995; Hoel and Isaksen, 1995), suggesting that both types of damages require different optimal climate policies. However, they do not look at the case of damages being caused by a combination of level and rate of change.

In this paper, I analyse how damage caused by both warming level and warming rate affect optimal climate policy. To do so, I use an analytical model of the climate and the economy building on Dietz and Venmans (2019), in which I add the feature that damage also depend on warming rate. I show that accounting for damages from warming rate does not change the long-term optimal temperature, compared to the case when damages depend solely on the warming level. However, it warrants different emission trajectories. When damages from warming rates are factored in, carbon price is greater, but increase less rapidly. Then, I explore combination of parameters for both types of damage leading to the same welfare loss from climate change. Less damage coming from the level of change results in higher long-term temperature. However, the effect on carbon price in the short run is offset by the countervailing influence of higher damages from warming rate, which provides incentives to slow down the warming. Thus, even when controlling for the welfare loss, in the short-run, damages from warming rates lead to higher carbon price.

In section 3.2, I present the model and derive optimal climate policy. In section 3.3, I explore numerically how damages from warming rate and warming level affect the outcomes. Section 3.4 discusses implications, perspectives and concludes.

3.2 Model

I build upon the model in Dietz and Venmans (2019) to analyze optimal climate policy when the warming rate induces damage. This choice is motivated by their representation of the climate system, which is in line with recent results from the climate science that after a short adjustement period of ten years, the ratio of warming on cumulated emissions is independent of both time and cumulated emissions (Matthews et al., 2009; Solomon et al., 2009; Mattauch et al., 2019).

3.2.1 Setting

Let us assume an economy, producing Q using three inputs, capital K, labour L and emissions E. Labour and total factor productivity grow exogenously, respectively at rate n and g. Warming T caused by emissions reduces production. In addition to the exponential quadratic-damage function of warming levels T, I consider a symmetrical damage factor capturing that warming rate $\dot{T}$ reduces output.

$$Q = e^{(n+g)t} f(K) exp\left(-\frac{\gamma}{2}T^2 - \frac{\alpha}{2}\dot{T}^2\right) exp\left(\Phi E - \frac{\varphi}{2}E^2\right) \tag{3.1}$$

α and γ determine the sensitivity of economies repectively to warming level and warming rate. The case $\alpha = 0$ is the special case of economies only affected by warming levels considered in Dietz and Venmans (2019), and more generally in the climate-economy literature.

Agents derive utility from their consumption $u(c)$, and the social planer, assumed to be utilitarian, seeks to maximize the present discounted social welfare, written as follows:

$$max_{c,E} W = \int_0^\infty e^{(n-\rho)t} u(c) dt \tag{3.2}$$

Where ρ is the rate of pure time preference, at which future utility is discounted, and utility is isoelastic, given by:

$$u(c) = \frac{c^{1-\eta}}{1-\eta} \tag{3.3}$$

η is the resistance to intertemporal substitution, which drives intergenerational inequality aversion.

As discussed above, in line with recent scientific findings, I assume quasi-linearity between cumulative emissions and warming:

$$\dot{T} = \epsilon(\zeta S - T) \tag{3.4}$$

where ϵ is the initial pulse-adjustment timescale, and ζ reflects the Transient Climate Response to Cumulative Carbon Emissions.

The part of production that is not consumed adds up to the capital stock k, but the stock also depreciates at rate δ. Thus, following the convention to write variables divided by effective labour $e^{(n+g)t}$ with a hat, capital follows the dynamical equation:

$$\dot{\hat{k}} = \hat{q} - \hat{c} - (\delta + n + g)\hat{k} \tag{3.5}$$

As in Dietz and Venmans (2019), it is reasonable, given the orders of magnitude at stake, to consider that the economy is on a balanced growth path with constant growth of output per capita as long as the damage from warming rates has a small effect on the growth rate.

3.2.2 Optimal path

To determine the evolution of optimal abatement, we can write the Hamiltonian of the welfare maximization problem:

$$H = \frac{\hat{c}^{1-\eta}}{1-\eta} - \lambda^S E - \lambda^T \epsilon(\zeta S - T) + \lambda^{\hat{k}} \left[\hat{q}(\hat{k}, E, T) - \hat{c} - (\delta + n + g)\hat{k}\right] \tag{3.6}$$

Optimality conditions lead to:

$$\lambda^S = \hat{c}^{-\eta}\hat{q}(\Phi - \varphi E) \tag{3.7}$$

$$\dot{\lambda}^S = (\rho - n + g(\eta - 1))\lambda^S - \epsilon\zeta\lambda^T - \hat{c}^{-\eta}\hat{q}\alpha\epsilon^2\zeta(\zeta S - T) \tag{3.8}$$

$$\dot{\lambda}^T = (\rho - n + g(\eta - 1) + \epsilon)\lambda^T - \hat{c}^{-\eta}\hat{q}(\gamma T - \alpha\epsilon^2(\zeta S - T)) \tag{3.9}$$

$$\hat{q}_{\hat{k}} - \delta = \eta(\frac{\dot{\hat{c}}}{\hat{c}} + g) + \rho \tag{3.10}$$

Integrating equation 3.9 gives:

$$\lambda^T = \int_t^\infty e^{-(\rho - n + g(\eta-1)+\epsilon)(u-t)}\hat{c}^{-\eta}\hat{q}(\gamma T - \alpha\epsilon^2(\zeta S - T))du \tag{3.11}$$

Given that the climate system adjusts quickly to emissions ($\epsilon \approx 0.5$), the discount rate applied to the marginal disutility of temperature change is high (around 50%). Thus, we can consider that the integral is dominated by the short-term of a few years, and over this period, $\hat{c}^{-\eta}\hat{q}(\gamma T - \alpha\epsilon^2(\zeta S - T))$ is constant:

$$\lambda^T \approx \frac{\hat{c}^{-\eta}\hat{q}(\gamma T - \alpha\epsilon^2(\zeta S - T))}{\rho - n + \epsilon + g(\eta - 1)} \tag{3.12}$$

Coming back to equation 3.8

$$\dot{\lambda}^S = (\rho - n + g(\eta - 1))\lambda^S - \epsilon\zeta\frac{\hat{c}^{-\eta}\hat{q}(\gamma T - \alpha\epsilon^2(\zeta S - T))}{\rho - n + \epsilon + g(\eta - 1)} - \hat{c}^{-\eta}\hat{q}\alpha\epsilon^2\zeta(\zeta S - T) \tag{3.13}$$

Deriving the equation in λ^S, together with the assumption of a balanced growth paths, lead to:

$$\dot{\lambda}^S = (-\eta\frac{\dot{\tilde{c}}}{\tilde{c}} + \frac{\dot{\tilde{q}}}{\tilde{q}} - \frac{\varphi\dot{E}}{\Phi - \varphi E})\lambda^S \tag{3.14}$$

$$\dot{E} = [\rho - n + (\eta - 1)g]\,(E - \Phi/\varphi) + \epsilon\frac{\zeta}{\varphi}\frac{(\gamma T - \alpha\epsilon^2(\zeta S - T))}{\rho - n + \epsilon + g(\eta - 1)} + \frac{\alpha}{\varphi}\epsilon^2\zeta(\zeta S - T) \tag{3.15}$$

The climate system adjusts quickly to CO2, so I treat the growth rate of cumulative emissions as constant in the short run, $\theta = \dot{S}/S$, and I can approximate temperature as follows:

$$T \approx \frac{\epsilon}{\epsilon + \theta}\zeta S \tag{3.16}$$

Substituting into the equation in $\dot{E}$:

$$\dot{E} = [\rho - n + (\eta - 1)g]\,(E - \Phi/\varphi) + \frac{\zeta^2 S\epsilon^2}{\varphi(\epsilon + \theta)}\left(\frac{\gamma - \alpha\epsilon\theta}{\rho - n + \epsilon + g(\eta - 1)} + \alpha\theta\right) \tag{3.17}$$

Finally, since $\dot{S} = E$, we can write:

$$\ddot{S} = [\rho - n + (\eta - 1)g]\,\dot{S} + \frac{\zeta^2\epsilon^2}{\varphi(\epsilon + \theta)}\frac{\gamma + \alpha\theta(\rho - n + g(\eta - 1))}{\rho - n + \epsilon + g(\eta - 1)}S - [\rho - n + (\eta - 1)g]\,\frac{\Phi}{\varphi} \tag{3.18}$$

I obtain a second-order differential equation for cumulative emissions. $\rho - n + (\eta - 1)g$ is the discount rate applied to the marginal damages as a proportion of output. Compared to the case of level-only damages, the only coefficient that is different is the one before S.

In the long-term, $\theta = 0$, so it is clear that the optimal cumulative emission and optimal peak warming is unchanged compared to a case where only level damage matter $S^* = c/b = S^*_{level}$. It follows that optimal temperature levels are also identical:

$$T^* = T^*_{level} = \frac{\rho - n + \epsilon + g(\eta - 1)}{\epsilon} \frac{(\rho - n + (\eta - 1)g)\Phi}{\zeta\gamma} \tag{3.19}$$

However, the dynamics of abatement changes when economies are also affected by warming rates. The factor in $\alpha\theta$ slows down the convergence to the long-term equilibrium, reflecting damages from warming rates as long as temperature changes.

In order to compare dynamics between our case and the classical case of damages depending solely on temperature level, I assume linearity between cumulative emissions and temperature in the next section.

3.2.3 Closed-form solution assuming no climate delay

In this section, I assume that temperature responds instantaneously to cumulative emissions, in order to obtain closed-form solutions. This simplifications rests on the fact that the climate system adjusts rapidly (within 10 years) to changes in cumulated emissions ($\epsilon = 0.5$). There is also evidence that the maximum of emissions levels is linked to the maximum warming rate (Bowerman et al., 2011), so a linear model could be an acceptable first-order representation for our purpose. $T = \zeta S$.

The damage factor describing the sensitivity of production to warming rate writes: $exp(-\frac{\alpha}{2}\dot{T}^2) = exp(-\frac{\alpha}{2}\zeta^2 E^2)$.

$$Q = e^{n+g} f(\hat{k}) exp(-\frac{\gamma}{2}T^2 - \frac{\alpha\zeta^2 + \varphi}{2}E^2 + \Phi E) \tag{3.20}$$

Appendix 3.A demonstrates that the stock of carbon follows:

$$\ddot{S} = (\rho - n + (\eta - 1)g)\dot{S} + \frac{\zeta^2\gamma}{\varphi + \alpha\zeta^2} S - (\rho - n + (\eta - 1)g)\frac{\Phi}{\varphi + \alpha\zeta^2} \tag{3.21}$$

Writing the equation as $\ddot{S} = a\dot{S} + bS - c$, and comparing it the case of level-only damages, we have: $a = a_{level}$, $b = b_{level}\varphi/(\varphi + \alpha\zeta^2)$, and $c = c_{level}\varphi/(\varphi + \alpha\zeta^2)$. As expected, S convergences towards the same equilibrium, the time profile of cumulative emission is given by:

$$S_t = (S_0 - c/b)exp\frac{1}{2}t(a - \sqrt{a^2 + 4b}) + c/b \tag{3.22}$$

Thus, emissions write:

$$E_t = (c/b - S_0)\frac{1}{2}(\sqrt{a^2 + 4b} - a)exp\frac{1}{2}t(a - \sqrt{a^2 + 4b}) \tag{3.23}$$

The optimal carbon price is the optimal marginal abatement cost for producers, which do not internalize the climate change externality:

$$p^* = Q_0 e^{(\tilde{g}+n)t}(\Phi - \varphi E) \tag{3.24}$$

Initially the carbon price is given by:

$$p_0^* = Q_0 \left(\Phi - \varphi((\rho - n + (\eta - 1)g)\frac{\Phi}{\zeta^2 \gamma} - S_0)\frac{\sqrt{(\rho - n + (\eta-1)g)^2 + 4\frac{\zeta^2\gamma}{\varphi + \alpha\zeta^2}} - (\rho - n + (\eta - 1)g)}{2} \right) \tag{3.25}$$

Since $b < b_{level}$, initially, carbon price is higher than in the level-only case. However, it increases less rapidly to reach the same long-term trajectory as in the level-only case. The reverse occurs for emissions, with a lower start but slowlier decrease, so that the same carbon budget is just spread over time.

This result comes from the fact that damages from warming reduce the rate at which marginal productivity of emissions decreases (formally equivalent to a change in φ), because of the flow externality they represent. However, they do not change the marginal productivity of the first emission. Alternatively, if the damage factor was an exponential-linear function of the warming rate, it would decrease the marginal productivity of the first emission (akin to a change in Φ). Under such assumption, optimal long-term temperature would be lower.

To put things into perspective we can compare the dynamics of the carbon price to other models. In Golosov et al. (2014), with an exponential-linear level damage, carbon price grows as fast as the economy. With exponential-quadratic level damages, Dietz and Venmans (2019) find that this growth is enhanced in the short-run. Further assuming, as we do, that damages also depend on warming rate tends to raise initial carbon price, but moderate the short-term growth.

3.3 Application

3.3.1 Illustrative pathways

In this section, I propose a numerical application of the model, to evaluate the size of the effect. Assessing future level-damages is a challenging exercize, because of the diversity of impacts that climate change will induce and the many uncertainties surrounding them (Diaz and Moore, 2017; Auffhammer, 2018). The same limitation applies to the assessment of rate-dependent damages. The difficulty is compounded because impact assessments are typically based on damages at a given temperature level (see for instance recent review of impact estimates (Nordhaus and Moffat, 2017; Howard and Sterner, 2016; Tol, 2018)), and thus do not quantify the effect of the rate of change. However, we can use results from Kahn et al. (2019) to illustrate possible orders of magnitude. In the study, the impacts come from temperature deviation from its average in past decades, so it is equivalent to assuming that there is only a rate effect ($\gamma = 0$). In the central projections, output losses in 2100 due to a warming rate of 0.01 and 0.04 °C/year are respectively 1.1% and 7.2%. This is respectively consistent with α of 93 and 221. Note that the values of losses from warming rates considered in Peck and Teisberg (1994) correspond to α in the same order of magnitude, between 60 (a 2% loss brought by 0.015°C/year increase) and 180 (a 2% loss brought by a 0.025°C/year).

Figure 3.1 illustrates the influence of parameters specifying rate and level-damages on the optimal carbon price. Unless specified otherwise, all other parameters are calibrated as in Dietz and Venmans (2019). Figure 3.2 compares the temporal evolution of carbon prices to the case of damages solely based on warming levels (α=0). As we have seen, damage from warming level determine optimal long-term temperature, while damage stemming from warming rates affects the optimal path to reach the temperature. For the illustrative values proposed here, adding damages from warming rate raises initial carbon price by 25 to 55%, but the carbon price increases slowlier than in the case of level-only damage, so that both trajectories cross between 2200 and 2300. Thus, rate-damage lead to a significant delay in the use of the carbon budget to reach the same temperature target. Importantly, the temporal dynamics of impacts differ between both types of damages. The stock externality from level impacts rises over time as temperature increases. On the contrary, damages from warming rates hit economies early on and vanish as temperatures stabilize. Damages from warming rates therefore make carbon price less sensitive to discounting assumptions (see figure 3.3). For instance, for the central value of γ, when there is no damage from warming rates, moving the pure rate of time preference from 1 to 3% leads to a threefold reduction in carbon prices. However, if we assume $\alpha = 100$, the same change in time preference only leads to a 30% reduction of carbon prices.

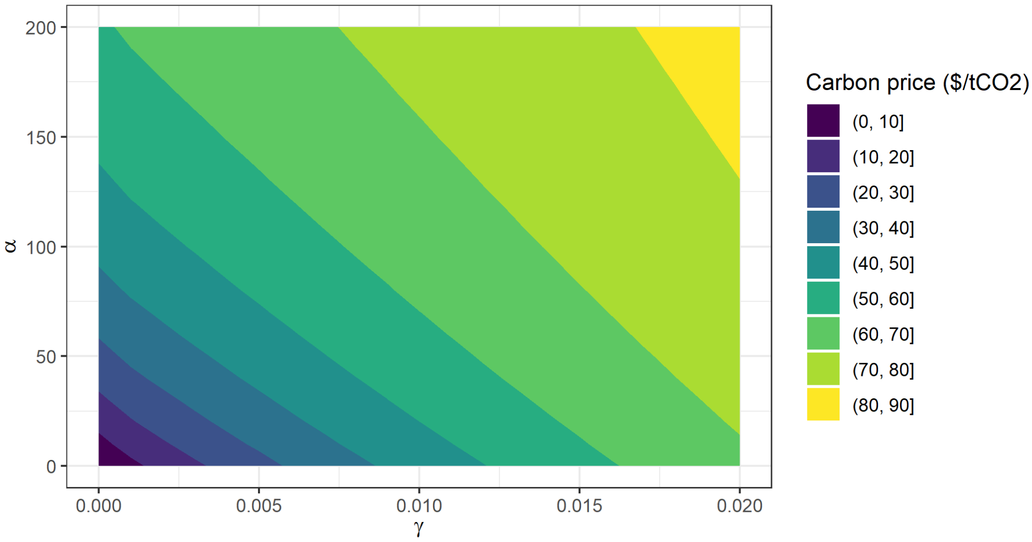


Figure 3.1 – Carbon price for different values of parameters defining damages from warming level (γ), and warming rate (α)

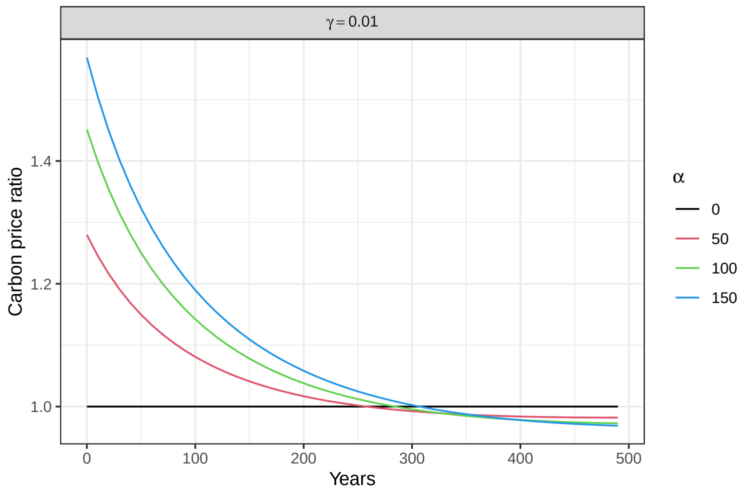


Figure 3.2 – Evolution of carbon price for different values of parameters defining damages from warming level (γ), and warming rate (α)

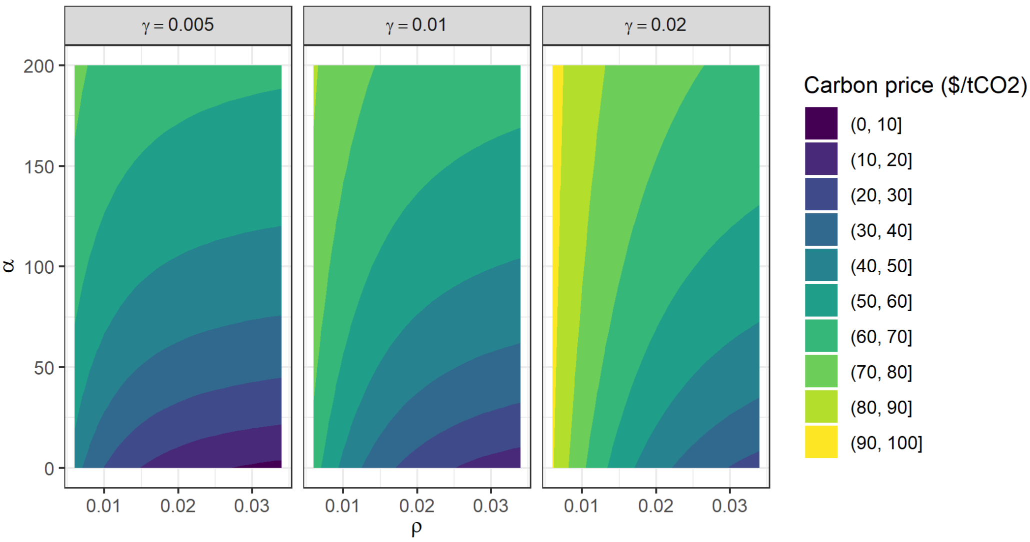


Figure 3.3 – Evolution of carbon price for different values of parameters defining damages from warming level (γ), and warming rate (α)

3.3.2 Level vs Rate damages: a controlled comparison

To highlight how the balance between the two channels of damage influence the outcome of the model, I explore the results under combinations of damage parameters leading to the same welfare loss under a *laissez-faire* scenario. This allows to explore how the sensitivity of the economy to the level and speed of warming optimal policy affect optimal policy, keeping the damage strength constant. This metric is used notably in Stern (2007), and applied in Guivarch and Pottier (2018) to compare the effect of damage falling on GDP level and GDP growth. Welfare losses need to be assessed in a laissez-faire scenario so they only reflect damage, and not mitigation costs.

I compute values of α and γ leading to the same welfare loss. I consider three damage strengths corresponding to the case of damages from warming level γ in 0.005, 0.01,0.02. These values make climate damages correspond to a loss of consumption, now and forever, of respectively around 1% (low),2% (medium) and 4% (high). Note that attributing losses to warming rates in the low and medium damage case correspond to values of α of respectively 100 and 200, which are consistent with the orders of magnitude from Kahn et al. (2019).

In the long-term carbon prices are always lower when damages stem from warming levels (a higher α combined with a lower γ). Indeed, as emissions decrease and temperature gradually stabilize, the level effect dominates (see

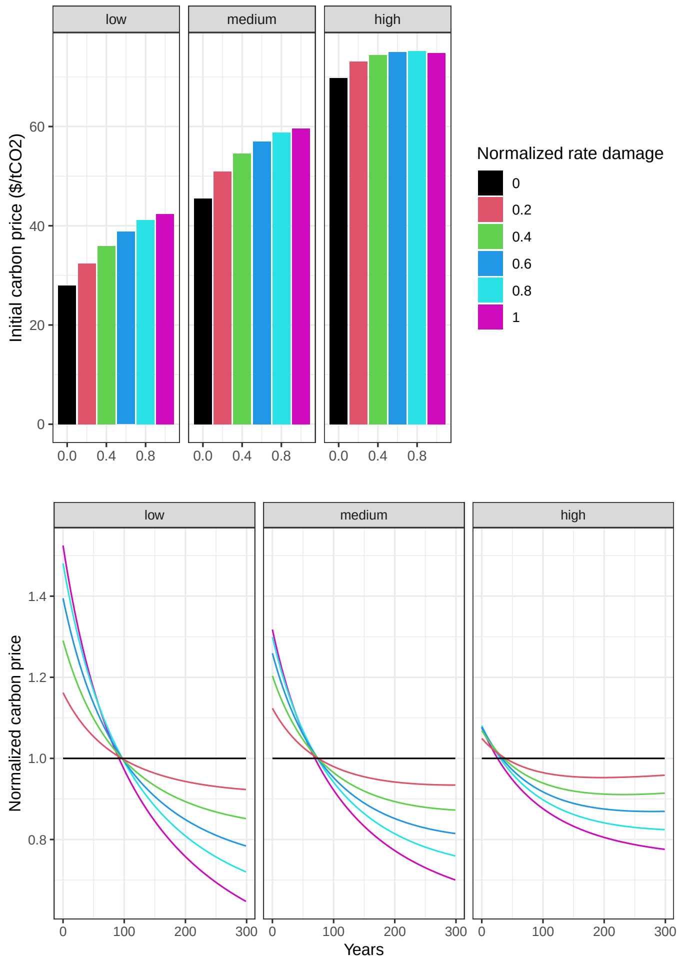


Figure 3.4 – Initial value and evolution of carbon price for a given level of welfare loss (low, medium, or high). The normalized rate damage is the ratio of α over its value in the case of welfare losses only caused by warming rates: it quantifies how much welfare losses come from the rate of change (0 for level-only damages, 1 for rate-only damages). For the evolution of the carbon price over time, the carbon price is normalized by its value in the case of damages only coming from warming levels.

figure 3.4). This is directly linked to the fact that damages from warming rates generate a flow externality and are transitional, while damages from warming levels are permanent and so lead to more stringent long-term targets.

However, in the short run, the balance between level and rate damage is *a priori* ambiguous on the carbon price, because α and γ both increase the carbon price. A lower γ is associated with a greater carbon budget, which decreases carbon price. However, a greater α gives more incentives to reduce emissions in the short-run. In the range of values considered, the rate-effect dominates, and thus more damages from warming rates lead to greater carbon price in the short-run. The balance between both types of damages matters more when the damage strength is low, with discrepancies reaching 45% of the value for the initial carbon price. Conversely, whether damages come from warming rates or warming levels only leads to 10% differences in initial carbon price under the assumption of high damage strength. Indeed, under strong welfare impacts, there is a strong incentive to limiting emissions in the short-run, which also limits the rate of warming in the short-run. On the other hand, if the welfare losses from climate damages are rather low, there can be a strong discrepancy between the case of level-only damages (in which warming increases pretty fast in the short-run), and the case of rate-only damages (in which warming rate is contained).

3.4 Perspective and conclusion

In this article, I argue that the rate of warming plays an important role in assessing damages from climate change. I review the literature to show that both natural and economic systems have limited ability to adapt to rapid changes, thus suggesting that damages depend not only on warming levels, but also on warming rates.

Using an analytical model of the climate and the economy, I show that the damages from the rate of change do not affect optimal long-term temperature change, compared to a case when damages only depend on warming level. This is due to the marginal productivity of the first emission being unchanged under exponential-quadratic damages from the rate of warming. However, the use of the same carbon budget is spread over time, and damages from warming rate warrant higher carbon price in the short-run. I show that damages from warming rate also require higher carbon price in the short run than damages from warming levels, when controlling for the welfare losses under a business as usual scenario. Damages from warming rate lead to higher temperature levels, but emissions should still be constrained to limit the speed of warming in the short-term.

This suggests that mitigation strategies only seeking to contain global temperatures below a certain level, as specified by the Paris Agreement, overlook crucial issues on the timing at which the target should be reached to minimize damages. Although damages from warming rate are only transitional, compared to permanent 'level damages', they are crucial to understand optimal mitigation in the short run. This opens up research avenues to further refine the representation of how different warming rates affect economic and natural systems. I acknowledge that both the functional form of damages and the calibration I use is questionable. For instance, as stated above, assuming that the damage factor from warming rates is exponential-linear, rather than exponential-quadratic, reduces optimal long-term warming. In the formulation I use, warming rate affects output in the next period, while the effects could be more persistent.

Accounting for the sensitivity of economies to warming rate has crucial implications for other climate policy questions, which the simplicity of the model I use does not allow me to deal with. First, the possibility to rely on negative emissions in the future raises the question of assessing overshoot temperature trajectories, in which Earth warms up to a peak before decreasing significantly (Bowerman et al., 2011). Overshoot trajectories have a very different temperature dynamics, in particular with a strong rate of temperature change in the short-term. Thus, accounting for damages from warming rates would probably affect the evaluation of such pathways. Second, given that different greenhouse gas have different lifetimes in the atmosphere, rate-dependent damages can change the trade-off between greenhouse gas (Manne and Richels, 2001), and would provide a stronger case for abating short-lived atmospheric components in the near-term, in order to slow warming rates.

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3.A Solution for the no-delay

The Hamiltonian of the welfare maximization problem, with this time only two state variables and two control variables is:

$$H = \frac{\hat{c}^{1-\eta}}{1-\eta} - \lambda^S E + \lambda^{\hat{k}} \left[\hat{q}(\hat{k}, E, S) - \hat{c} - (\delta + n + g)\hat{k} \right] \tag{3.26}$$

Optimality conditions give us:

$$\lambda^S = \hat{c}^{-\eta}\hat{q}(\Phi - (\varphi + \alpha\zeta^2)E) \tag{3.27}$$

$$\dot{\lambda}^S = (\rho - n + g(\eta - 1))\lambda^S - \hat{c}^{-\eta}\hat{q}\gamma\zeta^2 S \tag{3.28}$$

Derivating the expression in λ^S:

$$\dot{E} = (\rho - n + (\eta - 1)g)(E - \frac{\Phi}{\varphi + \alpha\zeta^2}) + \zeta^2\gamma S/(\varphi + \alpha\zeta^2) \tag{3.29}$$

$\dot{S} = E$ leads to the differential equation.

Chapter 4

Global inequalities and climate change

Abstract

In this chapter, we synthesize recent works on the links between climate change and inequality to show how climate change impacts and mitigation affect inequalities, both between countries and between individuals. First, we analyse inequalities in exposure and vulnerability to climate change. Second, we study inequality in the contribution to greenhouse gas emissions between countries and individuals. Finally, we show how inequality can shed light on the fairness of actions to fight climate change.

Introduction

Recent decades have seen economic convergence between countries, driven in particular by the rapid development of India and China, although GDP growth rates remain low in some African countries (Firebaugh, 2015; Milanovic, 2016). In contrast, income inequalities within countries have increased over the same period (Alvaredo et al., 2018). For example, in the United States, the incomes of the poorest 10% have stagnated since the 1980s when those of the richest 1% have grown by an average of 2% per year (Thomas Piketty, Saez, and Zucman 2018). Considering both inter-country and intra-country inequalities, income growth since 1990 has been very unevenly distributed among the different income deciles worldwide, as shown by the so-called "elephant curve" (Milanovic, 2016; Alvaredo et al., 2018). At both ends of the distribution, the poorest have benefited little from this growth, while the richest 1% have experienced strong income growth. In between, the increase in the incomes of a large part of the population in emerging economies contrasts with the decline of the middle class in developed countries.

At the same time, global greenhouse gas emissions have increased, and there is already an average global warming of 1,1°C compared to the pre-industrial era, with significant consequences for income inequality. Indeed, climate and inequality are closely linked for several reasons. The climatic and environmental conditions enjoyed by countries partly explain differences in their economic performance (Mellinger et al., 2000). Moreover, both at the country and individual levels, it is generally the less wealthy who are most vulnerable to the impacts of climate change. The various effects of climate change (heat waves, droughts, sea level rise, etc.) disproportionately affect the less wealthy. They could slow down the expected convergence between countries, and make it more difficult to reduce inequality within countries.

In addition, economic inequalities are reflected in the differences in the contribution to greenhouse gas emissions on a global scale. Developed countries, and the richest individuals, by their level of consumption, contributed disproportionately to the increase in temperature. This is a double penalty: those who are most likely to suffer the consequences of climate change contribute the least to the problem (Roberts, 2001; Althor et al., 2016) (Roberts 2001; Althor, Watson, and Fuller 2016) (IPCC Special Report 1.5, Chapter 3), and conversely the most responsible countries are also the least vulnerable (Figure 4.1).

Emergence-Index ratio

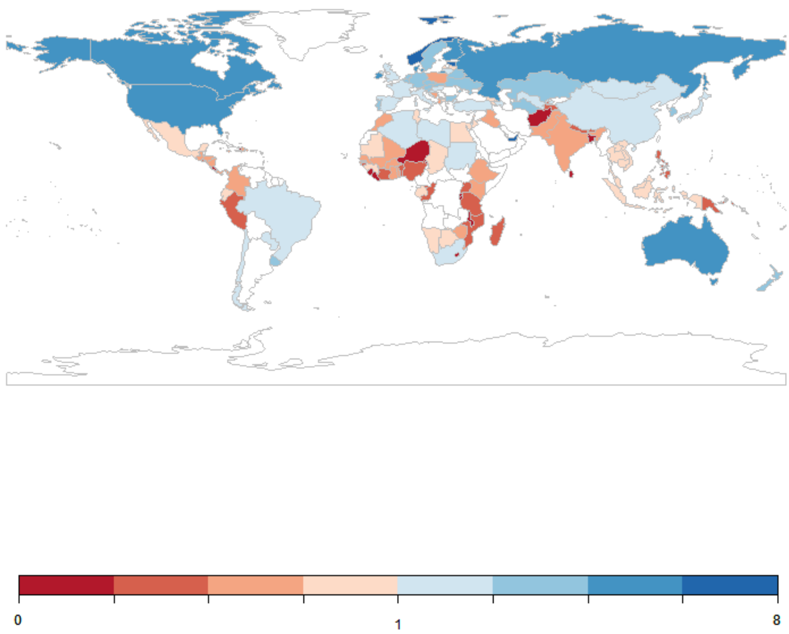

Figure 4.1 – Emergence-Index ratio (logarithmic scale), which quantifies contribution to climate change over future impacts. A value above 1 means that a country is relatively more responsible for climate change than impacted by it (Data from Frame et al. (2019)). See Figure 4.2 and 4.3.

Finally, the design and implementation of climate policies to reduce greenhouse gas emissions and adapt to a changing climate also poses questions in terms of inequalities between and within countries. Between countries, it raises the issue of equity in the distribution of mitigation and adaptation actions and their financing. Within countries, climate policies can affect inequalities when their costs weigh more heavily on the most modest or when certain social categories are excluded from their benefits. For example, mitigation policies may increase energy or food prices, with the risk that the poorest would face a decline in their standard of living, and that poor countries would slow their development (IPCC Special Report 1.5, Chapter 5). On the other hand, climate policies may also reduce inequalities, depending on the policy design. It is thus a matter of understanding under which conditions climate policy can be reconciled with the achievement of development objectives, the reduction of poverty and inequality.

In this article, we summarize recent literature on the links between climate change and inequality, to show how issues related to climate change impacts and mitigation affect inequalities, both between countries and between individuals. First, we analyze the inequalities in exposure and vulnerability to the impacts of climate change. Then, we look at the inequalities in the contribution to greenhouse gas emissions between countries and between individuals. Finally, we show how inequalities in the face of climate change can shed light on the equity of the distribution of actions to combat climate change.

Box 1. Defining inequalities

The study of inequalities focuses on how certain benefits are distributed within a society (distributive justice) and on the fairness of processes by which these benefits are distributed (procedural justice). In the economic sense of the term, inequality is often understood as the extent to which income is unequally distributed among individuals in a population or between countries. It can be measured using indicators such as the Gini index, which measures the gap between the observed distribution of income and an ideal egalitarian distribution where every individual would receive the same income. It is also possible to analyse the situation of a given proportion of the poorest households and compare it with the situation of the richest. However, income provides a limited view of economic inequalities: wealth, both land and financial assets, is often more concentrated than income, and is therefore an important source of inequality between individuals. Wealth inequalities have generally increased in recent decades, and the share of wealth held by the richest 1% has risen from 28% in 1980 to 33% in 2017 (Alvaredo et al., 2018).

Moreover, inequalities are not limited to purely economic aspects, and are often multidimensional (see IPCC, Fifth Assessment Report, Group 2, Chapter 13). Other types of social inequalities can strongly influence people's living conditions and opportunities
Moreover, inequalities are not limited to purely economic aspects, and are often multidimensional (see IPCC, Fifth Assessment Report, Group 2, Chapter 13). Other types of social inequalities can strongly influence people's living conditions and opportunities
(Crow et al., 2009; Sen, 1997), such as access to health, education, participation in decision-making, as well as racial or gender inequalities, which can exclude social groups from access to jobs or social services. Finally, inequalities can be of an environmental nature, through differentiated access to certain natural resources, services provided by nature, or through exposure to pollution externalities.

Box 2: Typology of inequalities linked to climate change

We can distinguish different types of inequalities related to the environment (Laurent, 2011):

- *Exposure and access inequalities* deals with the unequal distribution of environmental quality different individual and social groups, whether negatively (exposure to environmental nuisance or hazard) or positively (access to environmental amenities). In the case of climate change, individual and countries are are and will be unequally affected by the consequences of climate change (see section 4.1) ;
- *Impact inequalities* reflect the differential contribution to environmental degratation, for instance in greenhouse gas emissions which are responsible for climate change (see section 4.2) ;
- *Policy effect inequalities* occur when environmental policies are implemented. Mitigation or adaptation actions can amplify inequalities, for example because their costs may weigh more on the poorest households or because certain categories may be excluded from their benefits. (see section 4.3) ;
- *Policy-making inequalities* may exist because of unequal involvement and empowerment of individuals and groups in decisions regarding their environment.

4.1 Poor countries and poor households are the most vulnerable to the impacts of climate change

Inequalities exist outside of any consideration related to climate change. Yet, like many factors such as institutions, education, labour market or social structures, climate plays a role in people's living conditions, since it affects some sources of income (especially from agriculture), can lead to the destruction of homes or physical capital, and has an impact on well-being and health. Not all individuals are affected in the same way by climate change: the physical impacts will be different from one region to another. In addition, economic impacts depend on the socio-economic vulnerability of individuals and countries. In general, poor countries and poor individuals are the most vulnerable to the impacts of climate change: they are more exposed, more sensitive, and have a lesser ability to adapt (see figure 4.2). Climate change is already exacerbating inequalities and may exacerbate them further.

The physical impacts are already greater in poor countries and they will be even more so in the future (IPCC, Special Report 1.5, Chapter 3). Because of their location, poor contries are more exposed to the various effects of climate change : water stress, drought intensity, heat waves, loss of agricultural yields or degradation of natural habits. Some authors estimate, using indicators that take into account these effects of climate change, that 90% of exposure to climate risks falls on Africa and Southeast Asia (Byers et al., 2018), and the poorest individuals within these regions are the most at risk

For the agricultural sector, studies show that the impacts of climate change are negative overall, particularly in the low latitude regions in which developing countries are concentrated (Rosenzweig et al., 2014). The differentiated effect between countries has already been observed : although climate change has reduced agricultural yields in most regions (Lobell et al., 2011), some developed countries, notably in Europe, have benefited from this warming, for example the United Kingdom (Jaggard et al., 2007), Scotland (Gregory and Marshall, 2012), and other Northern European countries (Supit et al., 2010).

Various indicators also illustrate this unequal distribution of physical impacts. The daily temperature extremes expected as a result of climate change are located in less developed areas (Harrington et al., 2016). While there is uncertainty at the global level about the evolution of water resources due to climate change, the regions in which water stress is expected to increase are disavantaged areas, particularly in North Africa (Gosling and Arnell, 2016). Ecosystems are also disproportionately affected in poor areas. Tropical ecosystems are usually adapted to narrow ecological conditions when those in temperate zones can adapt to greater climate variations, which they experience during the year. Tropical ecosystems are therefore threatened by smaller temparature variations. For this reason, limiting the global temperature increase to 1.5°C rather than 2°C would benefit the poorest countries (King and Harrington, 2018).

Within countries, poor communities or households are also located in areas wih higher climate risk, for which land is often more afforable or because they

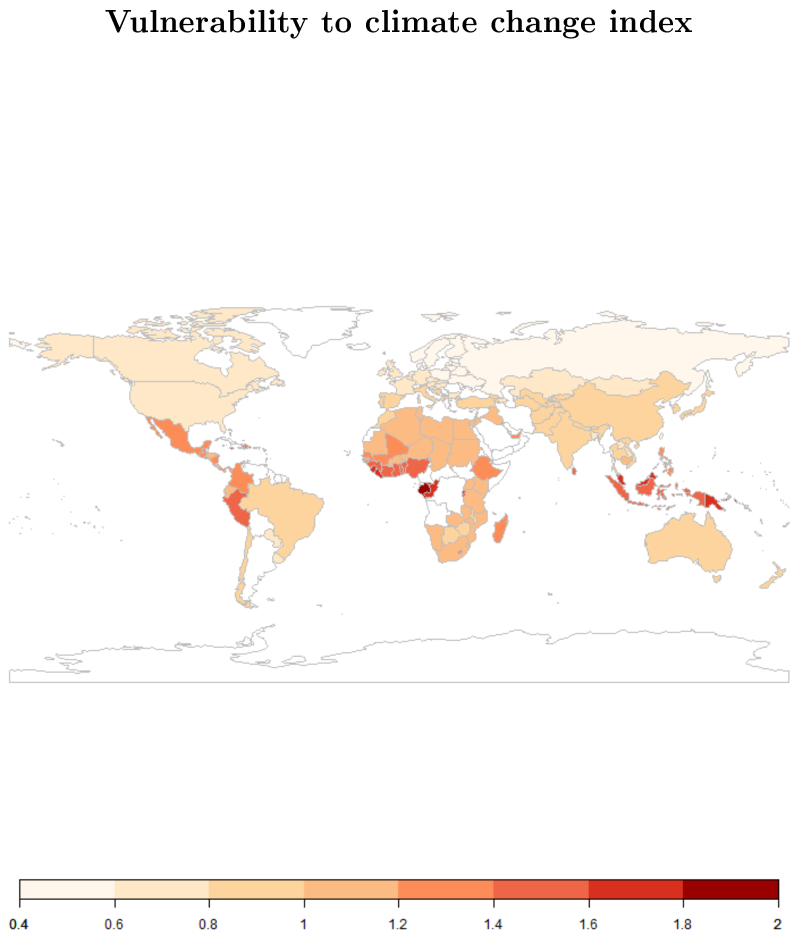

Figure 4.2 – Vulnerability to climate change index, using normalized "Signal-to-noise" ratio. The ratio indicates how much temperature will increase compared to observed historical variability, and thus the sensitivity to climate change. Countries for which data is missing are left blank. Note that we removed values for the Central African Republic due to an apparent error in the data. Data from Frame et al. (2019)

offer opportunities in terms of access to employement, education or health. They may be forced to live in flood-prone areas, or in risky delta areas (Brouwer et al., 2007) [1]. In cities, informal settlements are frequently located in areas subject to climatic hazards, for example in Dhaka (Braun and Aßheuer, 2011), or on slopes likely to experience mudslides, as in South America Painter (2007). In particular, the poorest are disproportiontely located in areas at risk of urban flooding or drought, and the number of people exposed to such risk could increase by about 10% in 2030 in the absence of emission reductions (Jongman et al., 2015). The same is true for exposure to extremes of heat, as in warm countries, the poorest tend to concentrate in areas with higher

[1]See also World's 15 Countries with the Most People Exposed to River Floods

temperatures (Park et al., 2018).

Moreover, the same physical impacts do not result in the same damage, due to differences in sensitivity and adaptive capacities between countries and between individuals. The greater sensitivity of poor countries to the impacts of climate change is due in part to the importance of the agricultural, forestry and fishing sectors in the economy. A significant proportion of the population is directly dependent on activities that may be affected by climate change, particularly the poorest whose survival depends on natural capital at hand rather than on physical or human capital (Huq et al., 2010), and who benefit from many services provided by nature (Noack et al., 2015), which may be threatened by climate change.

The poorest are also highly vulnerable to extreme events such as natural disasters, which are likely to increase with climate change. They live in lower-quality homes and are therefore more sensitive to climatic hazards. Cumulative repair costs can represent a larger share of their income than for wealthier households, as was the case following the Mumbai floors in 2005 (Patankar, 2015). Although the number of natural disasters between low- and high-income countries has been equivalent since the 1970s, the number of deaths is 10 times higher in the poorest countries (Strömberg, 2007). Beyond income, institutions also play an important role in protecting people from natural disasters (Kahn, 2005). The difference in vulnerability between rich and poor countries is decreasing but still remains considerable : for the period 2007-2016, the mortality rate due to natural disasters is about 4 times higher in poor countries (Formetta and Feyen, 2019).

Finally, poorest households are at risk of suffering from the various health effects of climate change, via heat waves (Ahmadalipour et al., 2019) or the spread of diseases (malaria, dengue). Heat waves affect unevenly different social groups. During the 2003 heat wave in Europe, beyond the demographic factor (90% of deaths were above 65 years old), mortality was higher for the lowest social categories (Borrell et al., 2006). This heat wave could be an average summer at the end of the century in high emission scenarios.

The poorest also face indirect impacts, such as higher food prices resulting from lower agricultural yields or extreme weather events (Hallegatte and Rozenberg, 2017). They are particularly sensitive to changes in these prices, since they spend a large share of their income on food. Rising prices could threaten food security in some regions, particularly in sub-Saharan Africa or South Asia, which would increase poverty in these regions (Hertel, 2015). Income can also be affected when labour productivity declines due to high temperatures, particularly for outdoor work Deryugina and Hsiang (2014); Heal and Park (2016).

For all these impacts, the poorest have lower adaptive capacities, and climate change exacerbates pre-existing difficulties. Most of the time, they do not benefit from insurance mechanisms, or access to basic health services that can mitigate price or income shocks. In the case of damage caused by a natural disaster, such as a storm or flood, they must draw on their own assets. With fewer assets, it is more difficult for them to cope with risk. Their assets are also less diversified : for poor urban households, housing consitutes the bulk of their assets (Moser, 2007), and is at risk in case of extreme events. For poor rural households, their capital lies mostly in herds, and they may be lost during a drought (Nkedianye et al., 2011). In the event of climatic hazards, the poorest are also more affected by diseases such as malaria, or waterborne diseases (Hallegatte et al., 2015). An environmental shock results in long-term effects, increasing their changes of falling into poverty traps (Carter et al., 2007). Thus, climate change acts as a risk amplifier for the poorest.

Box 3. Hurricane Harvey

The case of Hurricane Harvey, which hit Texas in 2017, shows that developed countries are also vulnerable to extreme weather events. The hurricane and its torrential rains killed about 100 people and caused damage estimated at about $100 billion. The poorest suffered most of the damage, as low-income households were concentrated in flood-prone areas (Reeves, 2017). It was also more difficult for them to relocate (Boustan et al., 2017). Most did not have insurance, which can push them into poverty in an enduring way.

According to the IPCC, hurricane intensity is likely to increase with climate change. In particular, the annual probability of Texas experiencing rainfall comparable to Hurricane Harvey would increase to 18% by the end of the 21st century in the most pessimistic greenhouse gas emission scenario, compared to only 1% for the period 1980-2000 (Emanuel, 2017).

These inequalities in vulnerabilities are linked to other socio-economic dynamics, both at the level of social groups and at the country level. Vulnerability is multidimensional, and can be accentuated by different forms of discrimination against certain groups, based on gender, race or class. In many developig countries, women are responsible for collecting water and firewood, making them vulnerable to the effect of global warming (Egeru et al., 2014)(IPCC, Fifth Assessment Report, Working Group II, Chapter 13). Beyond the dimension of income, race, family structure or level of education play a role in how individuals are affected by natural disasters, as it was the case during Hurricane Katrina (Elliott and Pais, 2006; Logan, 2006; Masozera et al., 2007; Myers et al., 2008). This situation is reinforced by the fact that disadvantaged groups have less decision making power, and thus may benefit less from public resources.

Climate change is therefore likely to exacerbate existing inequalities. Greater impact from climate change for the poorest can already be measured at all scales. Climate change has increased inequalities between countries, and one study suggests that the ratio between the last and first deciles would be 25% lower if there had been no climate change (Diffenbaugh and Burke, 2019). The impact of climate change disproportionately affects the most disadvantaged within countries between different regions, and within cities. Without action to limit climate change, its impacts would continue to amplify inequalities - between and within countries – and could undermine development and poverty eradication (King and Harrington, 2018; Bathiany et al., 2018; Hallegatte and Rozenberg, 2017). A World Bank report estimates that an additional 100 million people could fall into poverty in 2030 as a result of climate change (Hallegatte et al., 2015). Managing global warming is there a prerequisite for sustainable improvement in living conditions.

4.2 Rich countries and individuals contribute disproportionately to climate change

While the poorest countries and individuals are the most vulnerable to the impacts of climate change, it is the richest who are responsible for the majority of greenhouse gas emissions, whose accumulation in the atmosphere causes climate change.

While some emerging countries have begun to overtake developed countries in terms of current total emissions – China is by now the largest emitter of carbon dioxide (Quéré et al., 2018) - there remains a disparity between developed and developing countries in terms of emissions per capita and total historical emissions, and thus contributions to observed global warming. Territorial greenhouse gas emissions remain today mainly linked to the level of wealth and development of countries: relative to population, emissions in the United States reach nearly 20 tCO2-eq/person/year, those in the European Union and China are close to 8 tCO2-eq/person/year, those in India just over 2 tCO2-eq/person/year and those in Senegal or Burkina Fasso, for example, are between 1 and 2 tCO2-eq/person/year (Ritchie and Roser, 2017).

If emissions from the production of goods are reallocated to countries where the goods are consumed, the gap between developed and developing countries widens further (Peters et al., 2011; Karstensen et al., 2013; Caro et al., 2014). Developed countries are indeed net importers of emissions "incorporated" into trade, and emerging and developing countries are exporters.

Finally, if we try to attribute to countries the historical responsibility for the additional radiative forcing or global warming observed today (Figure 4.3), the contribution of developed countries is greater than it is based solely on current emissions, because, having been the first to initiate the industrial revolution, they have caused the accumulation of greenhouse gases in the atmosphere for longer. Depending on the choice of year from which to start accounting for emissions, inclusion or exclusion of emissions from land-use change (including deforestation) and gases other than CO2, countries relative contributions change significantly (Höhne et al., 2011; Den Elzen et al., 2013; Matthews et al., 2014; Matthews, 2016). Nevertheless, it appears that the historical responsibility for the observed warming is mainly borne by industrialized countries (which account for more than 55% of cumulative emissions since 1850), but also by countries with high levels of deforestation. The share of historical responsibility attributable to emerging and developing countries is gradually increasing, particularly those of China and India, and could exceed that of developed countries by 2030 (Ward and Mahowald, 2014).

Within countries, there are also large disparities in the carbon footprint of households. If an individual's level of wealth is not the only determinant of his emissions (the other determinants being his urban/rural location, age, etc.), it remains the first. This has been shown in particular for European (Ivanova et al., 2017; Sommer and Kratena, 2017), American (Jorgenson et al., 2017) and Chinese (Wiedenhofer et al., 2017; Chen et al., 2019) households. In France, households from the highest decile emit almost 3 times more than households from the lowest decile (Figure 4.4). The analysis of the Palma "carbon" index - i.e. the ratio of emissions of the 10% of the most emitting individuals to those of the 40% least emitting - shows that this ratio is higher in

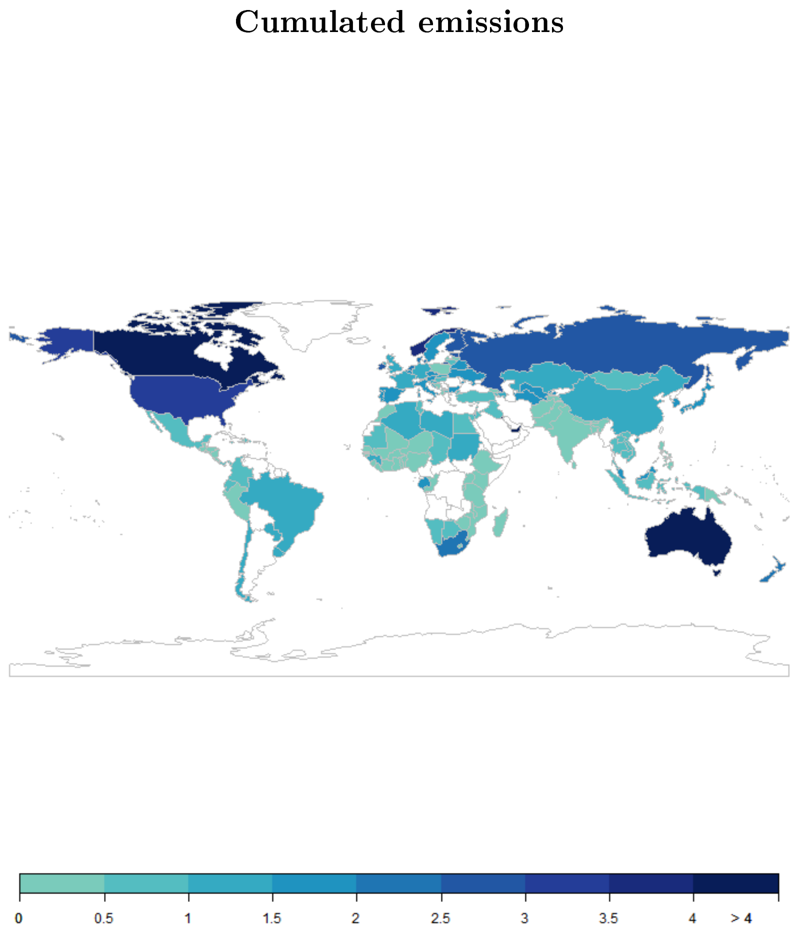

Figure 4.3 – Normalized cumulated per capita emissions for the 130 countries for which population is larger than 1 million. Data from Frame et al. (2019). This index quantifies countries' historical responsability in global warming.

developing countries than in developed countries (Pan et al., 2019). Globally, the Palma Carbon Index is higher than within any country, reflecting a very marked inequality when considering individual emissions beyond territorial boundaries. The rapid development of China and other emerging countries has reduced emissions inequalities between countries in recent decades, but this movement has been accompanied by an increase in emissions inequalities within countries. Thus, today, on a global scale, the 10% of the most emitting households are responsible for about 40% of greenhouse gas emissions, while the 40% that emit the least represent less than 8% of emissions (Piketty and Chancel, 2015).

Moreover, not all emissions can be equated from an ethical point of view. Among the emissions, it is indeed necessary to distinguish those linked to basic needs from those that constitute a "luxury" (Shue, 1993, 2019). For

French households' carbon footprint by income decile

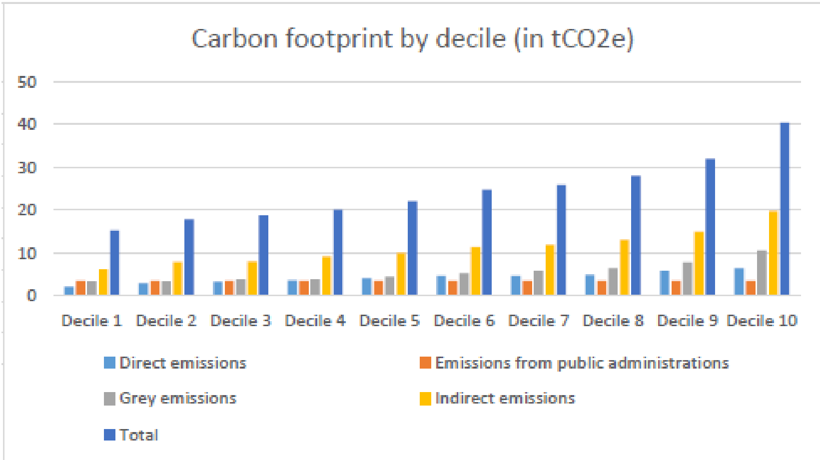

Figure 4.4 – Carbon footprint by income decile. The footprint is composed of direct emissions (emitted at the moment of consumptions), indirect emissions (emitted during production of the goods or services), grey emissions (occurring upstream from the value chain), et emissions from Public Administrations. Footprint are calculated at the household level to account for composition effect. When the analysis is done at the individual level, the increase in footprint with income is slightly reduced. Source: ADEME, 2019, "La fiscalité carbone aux frontières"

example, can we consider that a ton of CO2 emitted to travel to a distant holiday destination and a ton of CO2 emitted to produce staple food are to be considered on the same level? It relates to the principle of equity, which has been present in the texts of international climate negotiations since the 1992 United Nations Framework Convention on Climate Change and is reflected in the Paris Agreement, which stresses that "action and response to climate change and the effects of climate change are intrinsically linked to equitable access to sustainable development and poverty eradication."

Based on the capacity and basic needs approach, some authors (Rao and Baer, 2012; Rao and Min, 2018a; O'Neill et al., 2018) have interpreted this principle of equitable access to sustainable development by defining a set of universal, irreducible and essential material conditions for achieving basic human well-being, as well as associated indicators and quantitative thresholds. They define a "decent living standard" (Rao and Baer, 2012; Rao and Min, 2018a) or a " safe and just" development space (O'Neill et al., 2018), through indicators measuring the satisfaction of basic human needs (adequate nutrition, housing, access to health care, education, etc.). They then quantify the energy needs and emissions associated with these indicators. There is a consensus that the eradication of extreme poverty or universal access to energy can be achieved without representing significant greenhouse gas emissions (Tait and Winkler, 2012; Pachauri, 2014; Chakravarty and Tavoni, 2013; Rao et al., 2014; Pachauri et al., 2013). However, studies give divergent results on the direction of the effect of a reduction in inequality on emissions, leading to an increase or decrease in emissions (Hubacek et al., 2017; Grunewald et al., 2017; Rao and Min, 2018b). However, the absolute effect remains moderate: Rao and Min (2018b) limit to 8% the maximum plausible increase in emissions that would accompany the reduction of the global Gini coefficient from its current level of 0.55 to a level of 0.3.

Finally, several studies conclude that reaching higher income levels, beyond exiting extreme poverty, and achieving more qualitative social objectives are associated with higher emissions (Hubacek et al., 2017; Scherer et al., 2018; O'Neill et al., 2018). This requires policies that can take into account both mitigation and inequality reduction objectives, including focusing on the carbon intensity of lifestyles (Scherer et al., 2018), attention to sufficiency and equity (O'Neill et al., 2018) and targeting people at the other end of the social scale - the super-rich (Otto et al., 2019).

4.3 Distributional effects and equity in actions to respond to climate change

Given the strong ties between climate change and inequality which have been mentioned, it is essential to articulate policies to reduce greenhouse gas emissions with their effects on current and future inequalities. Taking into account the distributional effects of mitigation, both in terms of distribution effects of benefits due to avoided climate change impacts, and the distribution of mitigation costs, can help clarify the level of ambition of climate policies and the fairness of mitigation actions and their financing between different countries. Mitigation and adaptation policies can indeed have regressive or progressive effects, increase or decrease inequalities and poverty, depending on how they are designed and implemented.

The disproportionate impacts of future climate damages warrant more ambitious mitigation policies. Reducing emissions today limits future risks for the most vulnerable to experience extreme events or impacts on their health.

The reduction of future inequalities can thus be seen as a " co-benefit " of mitigation. This benefit can be measured using an economic analysis tool called the Social Cost of Carbon, which correspond to the discounted value of the avoided damages, but also to the value to be given to mitigation actions. This value is used in particular to carry out cost-benefit analysis of public policies, public investment projects or to design a carbon tax. Determining this value raises philosophical and ethical questions about how risk is taken into account and how inequalities are valued (Fleurbaey et al., 2019), but the fact that the impacts fall more heavily on the lowest income groups gives them more weight. This can increase the value of attenuation by a factor of between 2 and 10 (Dennig et al., 2015; Anthoff and Emmerling, 2018) (see figure 4.5). The magnitude of this effect may be limited when the costs of mitigation disproportionately affect the most vulnerable (Budolfson et al., 2017). However, even when costs are shared regressively between countries, mitigation can still reduce inequalities in the long-term in many socioeconomic scenarios (Taconet et al., 2020).

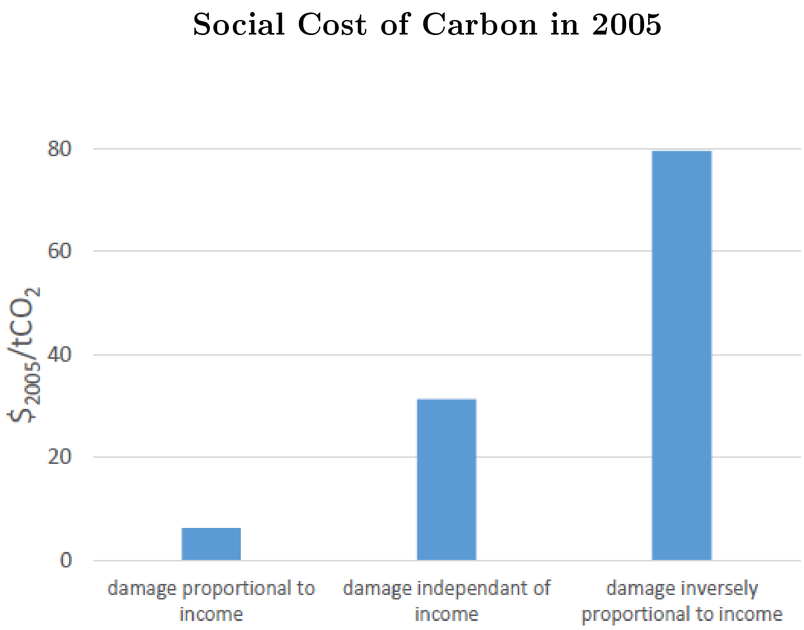

Figure 4.5 – Social Cost of Carbon in 2005, depending on the assumption made on the relationship between climate change damage and income. Source: Dennig et al. (2015)

Defining the fair distribution of mitigation actions, and their financing between countries is difficult, both because of the difficulty of taking into account the different levels of interactions between inequality and climate, and given different word views on what is fair (Pottier et al., 2017). In the climate negotiations, countries have sought during the various COPs to define the equitable distribution of emission reductions between countries and international financing obligations, respecting both countries' historical responsibility and their different capacities. This has notably led to the adoption of the principle of " Common But Differentiated Responsability " first in the United Nations Framework Convention on Climate Change (UNFCCC), and then in the Kyoto Protocol. But many questions arise to make this concept operational. Should we compensate countries that will be more affected by climate change (Cian et al., 2016)? How to take into account the need for development while limiting the temperature increase to 2°C (Winkler et al., 2013) ? How to assign responsibility for emissions between production and consumption ? Should priority be given to the poorest and how can exemptions be created for emissions to meet the basic needs of the poorest (Rao, 2014; Chakravarty et al., 2009)? Should inequalities due to carbon externality be treated with those outside the climate issue (Gosseries, 2005)?

The recognition of the historical responsibility of developed countries led the Kyoto Protocol to impose emission reductions only on so-called Annex 1 countries, and to propose North-South financing mechanisms, such as the Clean Development Mechanism, and technology transfer. The Kyoto Protocol was to be a first step towards a universal emissions reduction agreement, which was to enter into force after 2012. The top-down approach of emission reductions burden-sharing was abandoned after the Copenhagen COP (2009), due to the impossibility of agreeing on a fair share for all. Under the Paris Agreement, it is up to each country to define its contribution to emission reductions through Nationally Determined Contributions (NDCs). If NDCs were exactly achieved, they would contribute to a reduction in per capita emissions inequalities between countries by 2030, with a reduction for the main OECD countries and an increase for emerging and developing countries (Benveniste et al., 2018) (Figure 4.6). Nevertheless, the resulting emissions in 2030 would be too high to be compatible with the Paris Agreement objective of containing the increase in global average temperature well below +2°C compared to pre-industrial levels. Compared to a more ambitious short-term emission reduction scenario, NDCs are unfavourable in terms of intergenerational equity, but also in terms of future intra-generational equity because future generations would have to bear the cost of very rapid emission reductions after 2030 and/or greater impacts of climate change – these impact hitting primarily the poorest (Liu et al., 2016).

In view of the revision of the NDCs, which should lead to increased ambition, several studies (Robiou du Pont et al., 2017; Kartha et al., 2018; van den Berg et al., 2019) have assessed the current NDCs against the main proposed mitigation burden sharing criteria (convergence of emissions per capital, equality of cumulative emissions per capita, capacity to pay. . .) The emissions that would be allocated to a given country vary widely across criteria, and some criteria lead to negative emissions budgets for developed countries (see for instance http://www.ccalc.ethz.ch ou parisequity-check.org).

The question of equity and fairness of the ambition for the NDCs will keep on playing a role in international negotiations, and the long term objective set by the Paris Agreement requires each country to move towards carbon neutrality, at a pace that depends on its specific capacities. Equity is now more about financing (Holz et al., 2018).

Evolution of per capita emissions

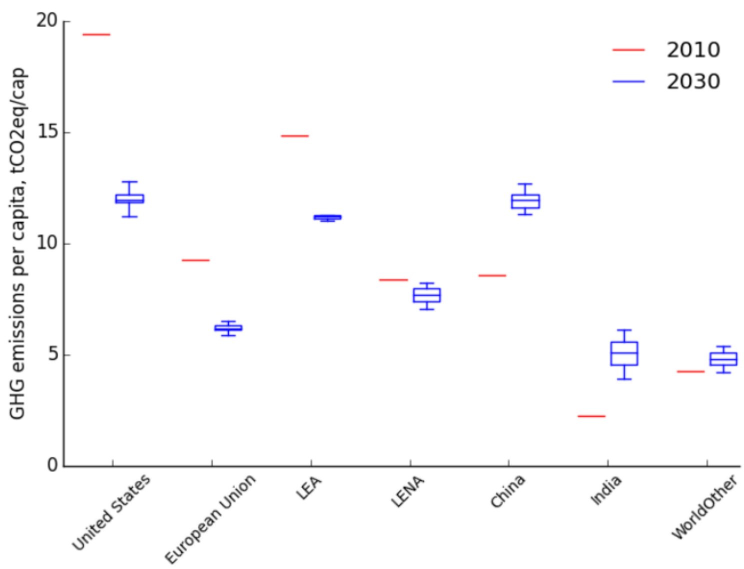

Figure 4.6 – Evolution of per capita greenhouse gas emissions (in tCO2-eq per capita), between 2010 (in red) and 2030 based on exact realization of NDCs (blue) for different countries or groups of countries. The uncertainty range for 2030 are presented with 5th percentile, 1st quartile, median, 3rd quartile and 95th percentile. LEA stands for Large Emitters which have NDCs with Absolute reduction compared to a reference year (Australia, Brazil, Canada, Japan, Kazakhstan, Russia and Ukraine). LENA is for Large Emitters which have NDCs with No Absolute targets (Egypt, Indonesia, Iran, South Korea, Malaysia, Mexico, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates). Figure from Supplementary Material from Benveniste et al. (2018).

Finally, actions to reduce greenhouse gas emissions and adapt to a changing climate must not overlook their own impact on inequality and on poverty. Climate policies induce costs and benefits for different individuals within a country. These policies can be regressive, i.e. the cost expressed as a share of income is greater for the poorest (Bento, 2013). Indeed, these policies raise the prices of emissions-intensive goods, which account for a larger share of the poorest people's spendings. The shift to cleaner technologies, which are sometimes more capital intensive, also affects income. These effects depend both on the type of policy instrument and how they are implemented.

For example, emissions taxation induces important distributive effects. These effects are more significant in some sectors such as transport, and in developed countries than in developing countries, where energy consumption by low-income households is low (Dorband et al., 2019; Ohlendorf et al., 2018). The impact of a tax also depends on the effects on labour and capital income (Goulder et al., 2019), on how consumers react to price changes, and to income changes over the course of their lifetimes (Ohlendorf et al., 2018). In France, a carbon tax on the transport and housing sectors was introduced in 2014 and its level is to increase each year, with a risk for car-dependent households or living in poorly insulated housing. The effect of a tax at 30 euros per CO2t (its 2017 level) thus increases the number of people in fuel poverty by about 6% (Berry, 2019). However, the introduction of a tax is accompanied by additional tax revenues, the use of which determines its fairness (see figure 4.7). The increase in fuel poverty induced by the carbon tax can be offset by redistributing part of the revenues to households: it is sufficient to use 15% of the revenue to cancel out the effect on fuel poverty. Although the lowest 10% of households can on average benefit from redistribution, there is still a large proportion of households whose situation is deteriorating due to great heterogeneity within deciles (Douenne, 2020). Likewise, the effect of emissions permits depend on the allocation rules – with free allocation favoring owners of polluting companies (Dinan and Rogers, 2002; Parry, 2004). Finally, tax reforms to remove replace fossil fuel subsidies can be beneficial if they are replaced by direct transfers (Durand-Lasserve et al., 2015; Vogt-Schilb et al., 2019).

Other public policies aimed at reducing eissions can have a negative effect on the poorest. Energy efficiency standards for vehicles, while saving emissions, also increase the cost of purchasing vehicles (Levinson 2016). To reach the same emission reduction, standards can be more regressive than taxes

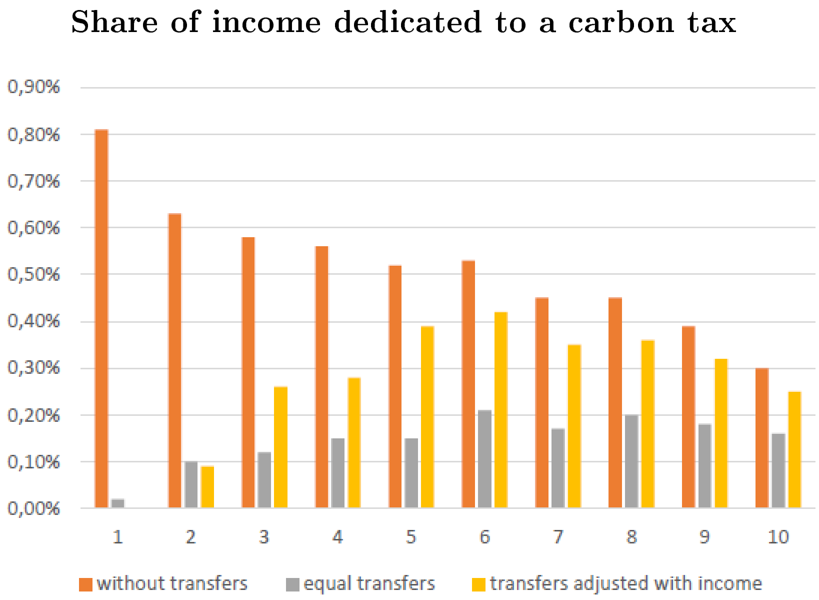

Figure 4.7 – Without transfert is average share of income from French household, by decile, spent on carbon tax. The other cases correspond to the share after redistribution of part of the revenues to compensate the regressivity generated by the tax (regressivity is based on Suits index) : either on an equal per household basis (in such a case, 59% of revenues need to be redistributed), or with transfers inversely proportional to income (in such a case, only 33% of revenues need to be distributed). Source: Berry (2019)

(Fullerton, 2017). Similarly, energy efficiency standards in the construction sector in California have had a negative effect on the poorest, and have resulted in a reduction in the surface area of their homes Bruegge et al. (2018). The distributional effect of subsidies for renewable energies vary according to their design, in particular on the way prices are set in the electricity market, and the ability of producers to pass on costs to consumers (Reguant, 2018). Finally, tax credits for the installation of solar panels or the purchase of electric vehicles can benefit the richest. In the United States, 60% of the different "green" tax credits between 2006 and 2013 went to the richest 20% (Borenstein and Davis, 2016).

Some mitigation policies affect the poorest through effects on food prices. For instance, the development of biofuel can have a detrimental effect on food security (Hasegawa et al., 2018; Fujimori et al., 2019). The use of land for biofuel production raises food prices, and can have negative impacts, particularly in low-income regions such as sub-Saharan Africa and South Asia. It could also lead to deforestation and dispossess communities of their land.

Conversely, some mitigation policies have co-benefits for the most vulnerable. Indeed, the combustion of fossil fuels releases local pollutants such as fine particles, or nitrogen oxides that cause cardiorespiratory diseases (Smith et al., 2013). The socially disadvantaged communities are the most exposed to these global health risks (Hajat et al., 2015). They could therefore benefit from the reduction in internal combustion engine vehicles or restrictions on coal use. Similarly, the use of more efficient furnaces reduces greenhouse gas emissions while improving air quality, and thus the health of users (Rao et al., 2013).

Adaptation policies faces analogous challenges and can have important effects on low-income households. Some adaptation actions can reduce the vulnerability of the poorest to climate hazards, such as conversion to more resilient crops. The development of financial services for the most vulnerable, from which they are often excluded, improves their ability to cope with unforeseen events, particularly climatic ones. Indexation of cash transfers to food prices could also help households during food prices spikes (Hallegatte et al., 2015). However, adaptation spendings focus sometimes more on protecting physical capital than people at risk (Georgeson et al., 2016). As such, some public decision-making tools such as cost-benefit analysis, which only take into account future benefits and not how they are distributed, may favour projections with the highest monetary benefits to the detriment of those that provide better protection for the most vulnerable. Taking into account welfare effects, not just absolute monetary benefits would better insure that projects that protect the poorest are financed.

Conclusion

Climate change acts as an inequality amplifier by disproportionally affecting the most disadvantaged at all scales, who are both more exposed and more vulnerable to the impacts of climate change. Taking into account these inequalities in impact gives more value to actions to mitigate greenhouse gas emissions and should lead to more ambitious mitigation policies.

To the extent that emission levels differ between countries and individuals, that the costs of reducing emissions and the benefits of avoided impacts are unequally distributed among individuals and between countries, equity issues within each generation are essential to define fair low-carbon pathways that respect the needs of present generations and the interests of future generations (Klinsky et al., 2017; Klinsky and Winkler, 2018).

Emission reduction policies can also have impacts for the poorest. At the international level, the aim is to reduce emissions without impeding access to development, particularly in the least developed countries, and to support poverty eradication. Within a country, reducing emissions raises the question of a just transition. Depending on the type of public policies that are put in place, the most modest can be disproportionately affected, or on the contrary benefit from the policies.

Studies on the subject show that climate and equality do not necessarily oppose one another, and that there are ways to articulate climate policies and social justice. This requires first recognizing potential conflicts between social justice and climate policies, and second setting up supporting and compensation mechanisms.

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Chapter 5

Influence of climate change impacts and mitigation costs on inequality between countries

Abstract

Climate change affects inequalities between countries in two ways. On the one hand, rising temperatures from greenhouse gas accumulation cause impacts that fall more heavily on low-income countries. On the other hand, the costs of mitigating climate change through reduced emissions could slow down the economic catch-up of poor countries. Whether, and how much the recent decline in between-country inequalities will continue in the twenty-first century is uncertain, and the existing projections rarely account for climate factors. In this study, we build scenarios that account for the joint effects of mitigation costs and climate damages on inequality. We compute the evolution of country-by-country GDP, considering uncertainty in socioeconomic assumptions, emission pathways, mitigation costs, temperature response, and climate damages. We analyze the resulting 3408 scenarios using exploratory analysis tools. We show that the uncertainties associated with socioeconomic assumptions and damage estimates are the main drivers of future inequalities. We investigate under which conditions the cascading effects of these uncertainties can counterbalance the projected convergence of countries' incomes. We also compare inequality levels across emission pathways, and analyze when the effect of climate damages on inequality outweigh that of mitigation costs. We stress the divide between IAM- and econometrics-based damage functions in

terms of their effect on inequality. If climate damages are as regressive as the latter suggest, climate mitigation policies are key to limit the rise of future inequalities between countries.

5.1 Introduction

Income inequalities between countries have declined in recent decades notably as a result of rapid economic growth in China and India (Firebaugh, 2015; Milanovic, 2016). Most projections see inequalities continuing along this dwindling path throughout the twenty-first century (Hellebrandt and Mauro, 2015; Riahi et al., 2017; OECD, 2018; Rodrik, 2011; Hawksworth and Tiwari, 2011; Spence, 2011). However, they do not consider the impact of climate change on inequalities. Indeed, climate change will induce impacts that hit primarily the poorest countries (Oppenheimer et al., 2014; Burke et al., 2015; Nordhaus, 2014; Mendelsohn et al., 2006; Stern, 2007; Tol, 2018), which may slow or even reverse the expected convergence of per capita national incomes. Limiting these impacts through greenhouse gas reduction policies also bears consequences for inequalities, as mitigation policies could be a hurdle to development. How the distributional effects of reduced climate change damages compare with those of mitigation costs and how they weigh against other socioeconomic factors have not been analyzed. Our paper bridges this gap.

We analyze how climate change affects future inequalities between countries via joint impacts and mitigation costs. We build country-by-country GDP trajectories up to 2100, exploring the uncertainty around 6 dimensions: (1) socioeconomic assumptions, (2) emission pathways, (3) mitigation costs, (4) regressivity of mitigation costs, (5) temperature response, (6) climate change damages. The different combinations of uncertainties lead us to explore 3408 scenarios, for which we analyze between-country inequality as measured by the Gini coefficient, as well as the first income decile. We perform a statistical analysis of the outcomes to identify the main drivers of future inequality. We find that the burden of climate damages on poor countries is sufficiently large to lead to a reversal in the declining inequality trend in some combinations of socioeconomic pathways and damage estimates. We also analyze inequality levels of various emission pathways, showing that lower emissions are associated with a lower level of inequalities under the strongest damage estimates. If damage estimates are low, mitigation can still reduce inequalities in some combinations of assumptions regarding socioeconomic evolution, the level of mitigation cost and the distribution of these costs.

We discuss the drivers of future inequality in Section 5.2. We then present the methodology used to build scenarios in Section 5.3. We analyze the results of the projections in Section 5.4. We discuss limitations and conclude in Section

5.5.

5.2 Drivers of future inequality

We consider two types of factors affecting future economic growth: climate-related and socioeconomic factors. Climate change affects between-country inequality in two ways: through uneven climate damages and through differentiated mitigation costs.

First, climate change is expected to reduce future income, through direct production and capital losses and lower economic growth. It is also expected to increase investment needs for adaptation. These climate damages will be shared unevenly among countries, because physical impacts may differ, and because the vulnerability to climate change and the ability to adapt vary widely across countries. For instance, some countries are more dependent than others on sectors that will be affected by climate change, such as the agricultural sector. Damage evaluation is a perilous exercise: it is very difficult, if not impossible, to predict how each country will be impacted by climate change. However, an extensive literature suggests that overall damages of climate change will be greater in poorer countries (Oppenheimer et al., 2014; Tol et al., 2004; Mendelsohn et al., 2006; Burke et al., 2015; Nordhaus and Yang, 1996; Hallegatte and Rozenberg, 2017; Dell et al., 2012), and the Intergovernmental Panel on Climate Change lists the distribution of impacts as one of the five "Reasons for Concern" about climate change.

Second, the cost of greenhouse gas emission reductions will affect countries' future income, with the costs depending on local contexts. For instance, current carbon intensities differ widely across countries, as do their potentials for the development of renewable energy. Mitigation policies can be more burdensome for low-income countries than for rich countries, meaning that poor regions may lose a greater share of GDP than rich regions for the same amount of abated emissions (Krey, 2014; Edenhofer et al., 2014). Indeed, low-income economies are often characterized by higher energy and carbon intensities. By raising the price of energy, mitigation policies could thus hamper their ability to develop. Higher costs in low-income countries can also arise due to term of trade effects of climate policy (Leimbach et al., 2010). Some mitigation strategies, notably using biofuels, could also threaten food security in the poorest regions (Hasegawa et al., 2018; Fujimori et al., 2019). However, the actual regressivity of mitigation costs will depend on the way the burden of the emission reduction effort is shared among countries in the post-COP21 agenda (Aldy et al., 2017; Liu et al., 2016) and on the feasibility of international transfers (Fujimori et al., 2016).

Climate damages and the economic impacts of mitigation policies are closely intertwined, as the greater the emission reductions through mitigation policies, the smaller the damages. Thus, while greenhouse gas emission reduction may place a greater burden on poor countries, it also reduces future damages that fall disproportionately on them, so that the resulting effect of mitigation is ambiguous in terms of inequality: avoided climate change may reduce inequality only if mitigation costs do not fall too heavily on the poorest countries. Yet, no study has brought both sides of the issue together to study future inequalities. Here, we analyze inequalities between countries for different emission pathways.

Climate-related factors are only one piece of the future inequality puzzle, as other socioeconomic factors affect the gap between rich and poor countries, such as demographics, technological progress, education, and institutions (Barro and Sala-i Martin, 2004). A key question concerns the ability of low income countries to mimic China and India's rapid economic catch-up. Whether convergence is just a question of time, occurs only regionally or is country-specific is the subject of intense debates in the development literature (Milanovic, 2006; Rodrik, 2011), and how fast the income of different countries can converge in the twenty-first century remains deeply uncertain.

5.3 Methodology

5.3.1 Building the scenarios

We build scenarios to explore future inequalities between countries, accounting for socioeconomic and climate-related factors. We model 6 dimensions of uncertainties: (1) socioeconomic assumptions, (2) emission pathways, (3) mitigation cost estimates, (4) regressivity of mitigation costs, (5) temperature response, (6) climate change damages. A summary of the uncertainties and sources considered is provided in table 5.2.

Table 5.1 – The Shared Socioeconomic Pathways (SSP)

SSP	Name
1	Sustainability
2	Middle of the Road
3	Regional Rivalry
4	Inequality
5	Fossil-fueled Development

5.3.1.1 Socioeconomic assumptions

We use shared socioeconomic pathways (SSP) scenarios to explore possible evolutions of socioeconomic factors in the twenty-first century (Riahi et al., 2017). SSPs consist of five pathways (SSPs 1 to 5) that reflect combined and consistent hypotheses on demographics, technological progress, and socioeconomic evolutions (see table 5.1). SSPs project economic growth for all countries based on future population, technological progress, physical and human capital, as well as energy and fossil resources (Dellink et al., 2017). While SSPs 1 and 5 depict sustained growth and convergence of income levels by the end of the century, in SSPs 3 and 4 poor prospects for developing countries and lack of cooperation lead to much slower reduction of inequality. SSP 2 lies in between, with moderate growth and convergence. For each country, initial GDP per capita levels in 2015 are set using the latest World Development Indicators (WDI 2017, May), and economic growth is set based on SSP trajectories.[1]

5.3.1.2 Emission pathways

The SSP growth projections for all countries assume there are no climate policy and no climate change impacts. We build on these projections to compute projections for different mitigation pathways with radiative forcing targets corresponding to representative concentration pathways (RCPs). The radiative forcing levels reached in the baseline case in 2100 differ across SSPs, with the highest — SSP 5 — being the only one above RCP 8.5, while the lowest — SSP 1 — is below RCP 6.0 (Riahi et al., 2017). Thus, we leave aside RCP 8.5, and only keep RCPs 2.6, 4.5, and 6.0, to which we add the intermediary radiative forcing target of 3.4 W/m^2 from the SSP database. Of these, only RCP 2.6 is likely to meet the target of limiting global mean temperature increase below 2°C compared with pre-industrial levels (Stocker et al., 2013). For all

[1] SSP trajectories are available at SSP Database (Version 2.0).

mitigation scenarios, we account for mitigation costs to meet the target and for the economic impacts from a changing climate.

5.3.1.3 Mitigation costs

We compute mitigation costs based on regional projections from the SSP database, which provides the results from six different integrated assessment models (IAMs) for scenarios spanning the SSP-RCP matrix. We use mitigation costs calculated by the IAMs that include an endogenous growth module (AIM/GCE, MESSAGE-GLOBIUM, REMIND-M, and WITCH). Other IAMs in the SSP database (IMAGE and GCAM) assume exogenous GDP growth pathways that are not affected by mitigation policies and thus do not change according to the RCP. We exclude the results from these models, as they do not represent the effect of mitigation on growth. Of the four models, some have not run all SSPs, so we have between 2 and 4 estimates for each combination of SSP/RCP. A clear advantage of using the mitigation costs from the SSP database is that they are consistent with the storylines of the SSPs. Thus, the same target is more difficult to reach in a scenario where baseline emissions are large or technical progress is slow. However, the cost projections rely on a least-cost approach, which brings two caveats. First, the actual cost of reaching the target may in fact be higher due to real-world market imperfections, for instance if there is inertia or imperfect foresight (Waisman et al., 2012). Second, emission reductions are supposed to take place in the region where they are the cheapest, regardless of equity considerations. Given the limited cooperation and policy harmonization across countries on climate change issues at present, the distribution of costs may differ from those assumed in the SSP database. To account for different effort-sharing schemes, we use two variants of mitigation cost distribution: first, we distribute the regional costs from the IAMs within each region proportionally to each country's income. Second, we look at the more regressive case of equally-shared costs within a region. As we explain in section 5.5.1, more progressive distributions could be envisaged that would reflect different burden sharing approaches under international negotiations. Such distribution would strengthen the impact of climate damages on inequality relative to mitigation cost.

5.3.1.4 Temperature response

There is great variability in the evolution of temperature at the country level for a given RCP as given by climate models (Stocker et al., 2013). Therefore, we consider values for temperature changes corresponding to the mean, and the 10th and 90th percentile of outcomes. Temperature changes in 2100 are taken from the Climate Intercomparison Model Project CMIP5[2]. CMIP5 provides national mean annual temperature changes in 2100 for RCPs 2.6, 4.5, 6.0 and 8.5. When the radiative forcing in 2100 of a scenario falls between two values provided by CIMP5, we perform a linear interpolation to calculate temperature change in 2100. Using the 2100 value, we assume that temperatures increase linearly over time.

5.3.1.5 Climate change damages

Given that future climate change damages are very uncertain, we use 8 estimates from different sources for damages associated with different temperature changes, from Integrated Assessment Models, and from the econometrics literature.

Integrated assessment models are primarily used to analyze the interaction between climate and the economy (Nordhaus, 2008). In particular, they are used to derive optimal emissions pathways balancing the cost of mitigation with the benefits of avoided damages. However, they typically provide global damage estimates – and the damage estimates they rely on are global, too. RICE and FUND are notable exceptions: we therefore use estimates from RICE2010 (Nordhaus, 2014).[3] We also draw upon estimates relying on the GTAP model (Global Trade Analysis Project). Roson and Sartori (2016) (RS hereafter) assess the economic changes associated with higher temperature in different sectors (agriculture, health, tourism...) for 140 regions. We use their aggregate estimates of the percentage change of GDP in a 3°C scenario compared with the associated baseline, for the different regions. This percentage GDP change may be positive or negative depending on the region. We assume that this effect on GDP grows proportionally with global temperature.

Finally, we use estimates from the econometrics literature, which shows evidence that temperature changes have impacted economic growth in the past, and more heavily so in poorer countries. This difference is attributed either to

[2] `https://climexp.knmi.nl/plot_atlas_form.py`

[3] We are not aware of publicly available regional damage estimates from FUND.

national development levels (Dell et al., 2012), or to mean temperature (Burke et al., 2015). Burke et al. (2015) (BHM hereafter) derive a damage function from historical GDP and temperature data. The authors econometrically estimate the effect of higher than average annual temperature, controlling for other variables. They find a non-linear bell-shaped relationship between temperature and economic growth, showing a maximum for an annual average temperature of around 13°C.

Additionally, we consider econometric estimates from Dell et al. (2012) (DJO hereafter), who find a strong and significant effect of temperature on growth in poor countries, while the effect for rich countries is small. We account for the future divide between rich and poor countries in two ways: (1) a static version, where poor countries are defined as those currently below median income, a definition that is set over the whole horizon, (2) a dynamic version, with current median income defining the threshold between poor and rich countries, thus allowing countries to switch status over time. This second version accounts for some form of adaptation where income growth compensates (here almost fully) the negative impact of climate change.

For both damage functions, we use the regressions with 0 and 5-year lags. A distributed lag model with 5-lags adds up the effect of temperature in the current and 5 previous years. This allows capturing the cumulative effect of temperature on income rather than solely a short-run effect. We discuss the limitations of relying on econometric estimates to project future damages in section 5.5.1.

5.3.1.6 Computing economic growth

Using mitigation costs and climate damages for each country, GDP per capita Y at time t in a given RCP scenario is calculated as follows, for RICE and RS:

$$Y_{t,RCP} = X_{t,RCP}\Omega(GMT_t)Y_{t,baseline} \tag{5.1}$$

where $X_{t,RCP}$ is the mitigation cost factor, $\Omega(GMT_t)$ is the damage factor in the region for a global mean temperature change of GMT_t, and $Y_{t,baseline}$ is the GDP per capita in the corresponding baseline scenario.

For econometrics-based damage functions (BHM and DJO), the equation writes:

$$Y_{t,RCP} = X_{t,RCP}(1 + g_{t,baseline} + \Delta g(T_t))Y_{t-1,RCP} \tag{5.2}$$

Table 5.2 – Uncertain factors considered in the study

Dimension	Levels	Source
Socioeconomic	5 growth pathways	SSP database
Emissions	baseline and lower pathways among RCPs 2.6, 3.4, 4.5, 6.0	SSP database
Mitigation costs	regional costs from 2 to 4 models	SSP database
Distribution of mitigation costs	Equal distribution or proportional to income within regions	
Temperature	Low (10th percentile), Medium (mean), and High (90th percentile)	CMIP5
Damages	8 damage functions (IAM- and econometrics-based)	RICE2010, Roson and Sartori (2016), Dell et al. (2012), Burke et al. (2015)

where $g_{t,baseline}$ is the growth projected in a baseline without climate impacts and $\Delta g(T_t)$ is the loss of economic growth under national temperature T_t due to climate change.

In total, we are able to compute the projections for 161 countries, currently representing 96% of world population. We exclude countries for which we lack either initial GDP or future temperature projections.

The combination of different socioeconomic assumptions (5 SSPs), emissions pathways (baseline and between 2 and 4 RCPs, depending on the SSP), mitigation costs estimates (2 to 4 estimates depending on the SSP and RCP, with 2 variants of the distribution of costs within region for each estimate), temperature response to a given RCP (3 cases), and damage estimates (8 models) results in 3408 scenarios. Scenarios are consistent in the sense that for each combination, the mitigation costs are those estimated for the corresponding SSP/RCP, while climate damages are calculated according to the temperature change induced by the emission pathway against the temperature response. However, we ignore the fact that damages that damages for a given temperature change may also depend on the socioeconomic pathway. This limitation is discussed in section 5.5.1. Besides, some combinations of factors may be more plausible than others, but we nevertheless consider all of them without making *a priori* judgements about their likelihood.

5.3.2 Measuring income inequality

The literature distinguishes three types of income inequality (Milanovic, 2011): (1) unweighted international inequality compares countries' income regardless of their size, (2) population-weighted international inequality weighs countries' income according to their population (3) total inequality accounts for households' or individuals' revenue distributions within and across countries. We focus on the second type of inequality, which gives equal weight to all individuals across countries. This choice of international inequality is motivated as follows. First, between-nation inequality represents, as of today, the greatest source of inequality between individuals (Firebaugh, 2015; Bourguignon and Morrisson, 2002). Besides, future income distribution within a country is subject to policy choices that would be difficult to model.

Many indicators can be used to measure this type of inequality (Charles-Coll, 2011). The most routinely used index is the Gini index, which computes the dispersion of income, ranging from 0 (perfect equality) to 1 (one individual or entity owns all the income). The Gini index is the ratio of the mean absolute difference between two individuals or entities to twice the mean level of income. If countries indexed by i are ranked based on their per capita income I_i, with p_i their population, we can define the cumulated proportion of income and population as follows:

$$p_{c,i} = \frac{\sum_{k=1}^{i} p_k}{\sum_{k=1}^{N} p_k} \tag{5.3}$$

$$I_{c,i} = \frac{\sum_{k=1}^{i} I_k}{\sum_{k=1}^{N} I_k} \tag{5.4}$$

The Gini index then writes:

$$Gini = 1 - \sum_{k=i}^{N} (p_{c,i} - p_{c,i-1})(I_{c,i} - I_{c,i-1}) \tag{5.5}$$

with $I_{c,0} = 0$ and $p_{c,0} = 0$[4]. Appealing for its simplicity, the Gini index is also criticized, notably because it may be regarded as overly sensitive to

[4] The pairs ($p_{c,i}$,$I_{c,i}$) represent the Lorenz curve: a proportion $p_{c,i}$ of the population earns a proportion $I_{c,i}$ of global income. Graphically, the Gini coefficient is worth half the area between the Lorenz curve and the first bisector.

changes in the middle of the distribution, and because it measures relative inequality (Cowell, 2000). Indeed, a world with more inequality may still be better for the poorest in absolute terms. Thus, we also examine the absolute situation of the bottom 10%, as measured by the first income decile (see section 5.4.4).

5.4 Results

We compute the Gini index in all scenarios, and analyze the drivers of its evolution over the twenty-first century.

5.4.1 A trend reversal in inequalities

Both socioeconomic and climate-related uncertainties strongly influence the evolution of future inequalities (figure 5.1). In many scenarios, inequalities continue to decline for a few years or decades, but as climate change impacts gradually occur, they may outweigh the forecasted economic catch-up by low-income countries, and inequalities may rise again as a result.

We perform a PRIM analysis to identify the combinations of uncertainties that lead to this trend reversal, using the method described in Guivarch et al. (2016)[5]. The results of this analysis show that there are cases of trend reversal in all socioeconomic pathways, even in the most optimistic ones (see table 5.3). Inequalities rise again systematically in SSP 4, a socioeconomic world depicting a great divide between rich and poor countries. With the low prospect for catch-up assumed in SSP 3, a trend reversal in inequality can also occur, but only for high damage estimates (namely BHM (0 lag), and all DJO estimates). For other socioeconomic pathways, regressive damage specifications (i.e. econometrics-based) slow down the convergence, and make inequalities rise again under strong temperature change (either because of high emission or high temperature response).

In the cases where inequalities rise again, the timing of the trend reversal also varies depending on the uncertainties, in particular the combination of socioeconomic assumptions and damage function (see figure 5.2). The reversal occurs systematically as early as in the 2020s in SSP 4. In SSP 3, the occurring decade is determined by the damage estimates, but varies between lowest and highest damage estimates. For the more 'optimistic' socioeconomic

[5]Results from the PRIM analysis are provided in Appendix 5.A.

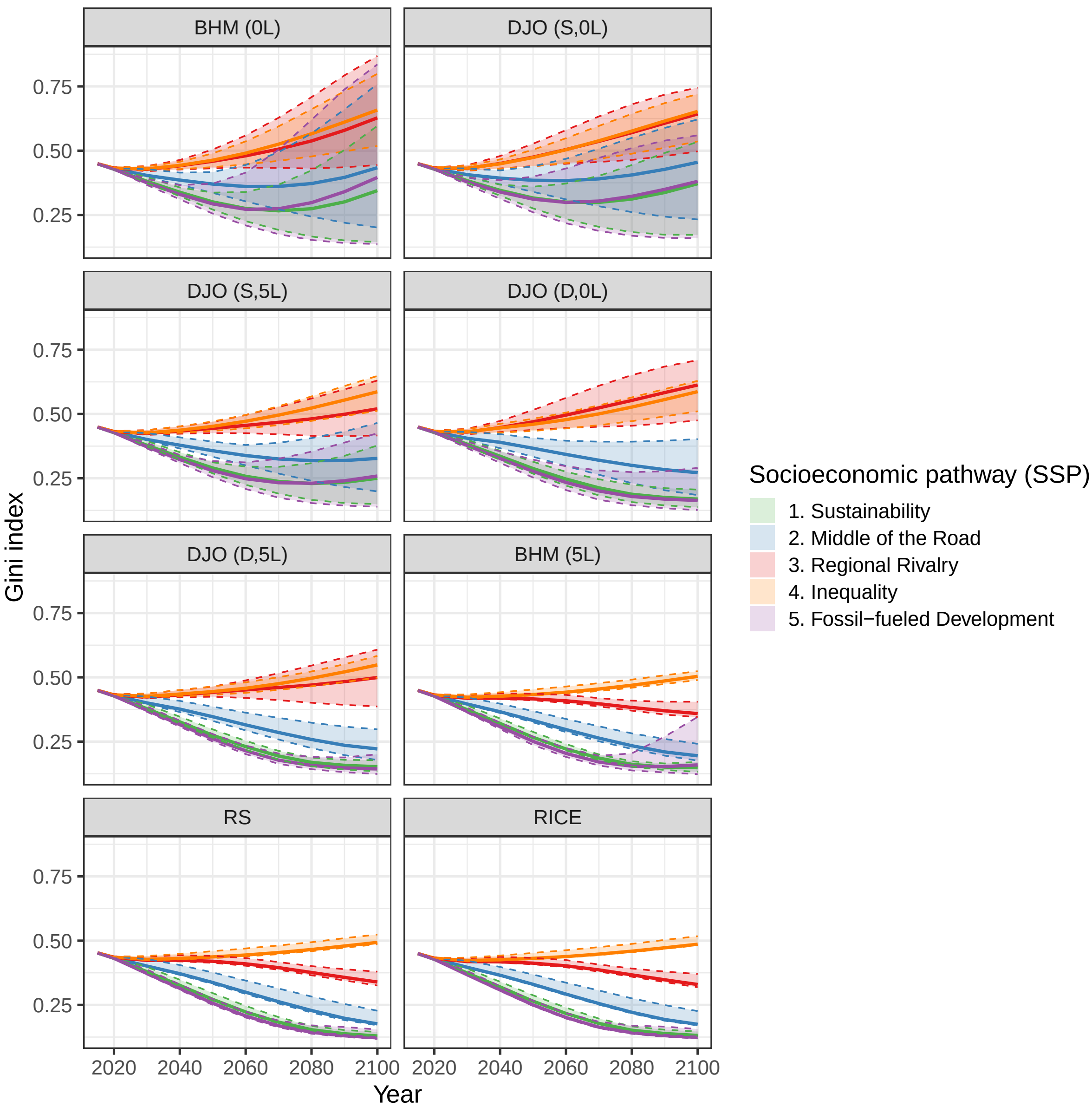

Figure 5.1 – Evolution of the Gini index over time. A panel corresponds to a damage function. For each socioeconomic pathway, the dotted lines represent the minimum and maximum values of the Gini index, while the plain line is the mean. 'DJO': Dell et al. (2012), 'BHM': Burke et al. (2015), 'RS': Roson and Sartori (2016). For DJO, 'S' and 'D' stand respectively for static and dynamic poor/rich distinction. For DJO and BHM, '0L' and '5L' refer to 0-year lag or 5-year lag regression.

Table 5.3 – Each line is a combination where a trend reversal in the Gini occurs, of factors leading to a trend reversal in inequality, as revealed by PRIM analysis. The trend reversal can occur in all SSPs, but in some SSPs only for high damages, a high RCP or a high temperature response.

SSP	Damage	RCP	Temperature response
SSP 1	BHM (0L)	≥ RCP 3.4	All
	DJO (S,5L)	All	Medium, High
	DJO (S,0L)	≥ RCP 3.4	All
SSP2	BHM (0L)	≥ RCP 3.4	Medium, High
	DJO (S,5L)	≥ RCP 3.4	Medium, High
	DJO (S,0L)	≥ RCP 3.4	All
SSP3	BHM (0L)	All	All
	DJO (S,5L)		
	DJO (S,0L)		
	DJO (D,0L)		
	DJO (D,5L)		
SSP4	All	All	All
SSP5	BHM (0L)	≥ RCP 3.4	All
	DJO (S,5L)	≥ RCP 3.4	
	DJO (S,0L)	≥ RCP 3.4	

pathways (SSPs 1, 2 and 5), there is great variability in the date at which the trend reversal occurs for high damage estimates. In such cases, lower emission scenarios or low temperature response scenarios delay the reversal.

5.4.2 Analyzing the Gini index using regression trees

We analyze how the different uncertainties affect the Gini index, and we compute a regression tree to identify the main drivers of its value in 2100. We use recursive partitioning to select the factors in order to reduce the heterogeneity of the output value.[6] The regression tree identifies socioeconomic assumptions (SSPs) and the damage function as the first two nodes of the decision tree, suggesting that these dimensions are the most influential on inequalities in 2100 (figure 5.3). The first node splits the scenarios into two groups, the first one composed of scenarios with 'optimistic' socioeconomic assumptions (SSPs 1,2 and 5) in terms of convergence between poor and rich countries, and the second one composed of scenarios with pessimistic such assumptions (SSPs 3 and 4). Within each branch, the tree further splits scenarios according to the mag-

[6]We used rpart function of R (complexity parameter of rpart function is set at 0.02, meaning that a split is retained if it increases the fit by a factor 0.02)

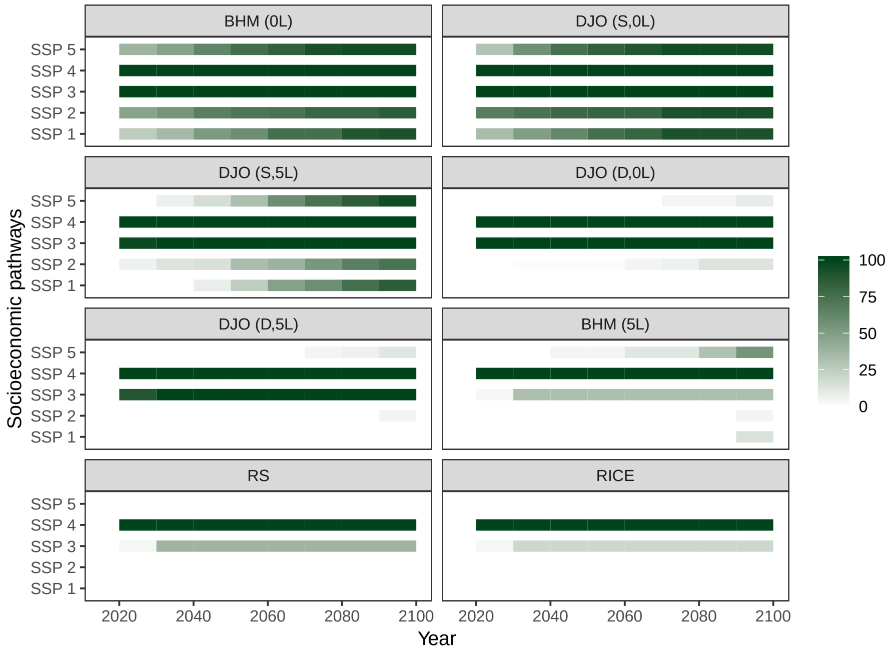

Figure 5.2 – Cumulated percentage of scenarios where a trend reversal has occurred, for a given combination of damage function and socioeconomic assumptions.

nitude of climate change damages. Interestingly, the grouping of the damage functions differs across the two branches of the tree. Indeed, when the vulnerability of countries depends on their income (in the 'dynamic' versions of DJO), climate damages strongly depend on the socioeconomic pathway: convergence assumptions limit the effect of climate change on inequalities, because poor countries can shield themselves from climate damages through development. The contrary holds if poor countries are assumed to slowly catch-up with rich countries. Finally, if optimistic SSPs are combined with high damages, the next node splits the remaining scenarios according to the level of emissions. All the other dimensions of uncertainties, that is mitigation costs, their distribution within regions, as well as temperature response uncertainty, contribute to a lesser extent to the Gini index in 2100.

For the highest damage estimates (i.e. mostly econometric estimates), the cascading effect of emission pathway and temperature response uncertainty translate into great variability in the benefits of avoided damages for the poorest, and thus a greater variability of the Gini index in 2100 (figure 5.4). With the most regressive specifications, damages are such that they may completely cancel out expected convergence in some scenarios, and lead to a higher Gini index in 2100 than today. In particular in SSP3, most scenarios with econo-

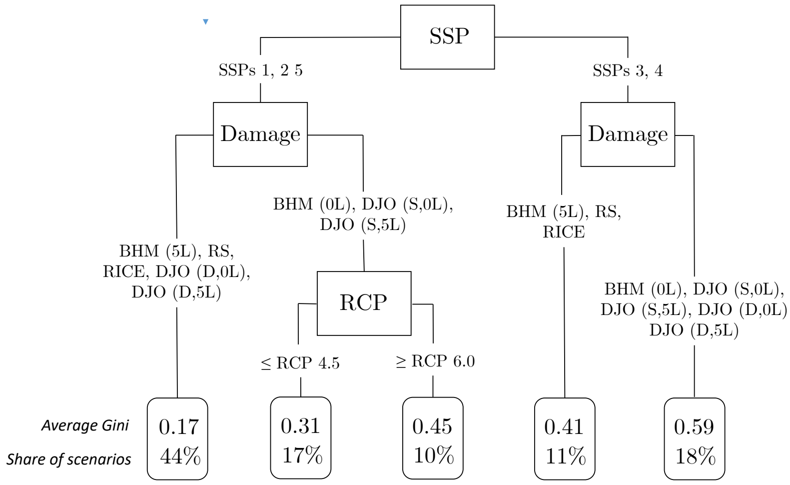

Figure 5.3 – Regression tree on the value of Gini in 2100. The algorithm splits scenarios to best predict the value of the output, thus generating groups with minimal heterogeneity. In each leaf of the tree, the upper number is the mean of Gini for the scenarios in the box, while the lower number is the percentage of scenarios it represents.

metric damage estimates show Gini levels higher than today, while it is not the case under low damage functions. Gini index can be higher than today in other socioeconomic pathways, but only when combining the most regressive damage functions (BHM (0L) and DJO (S,0L)) with the highest emission pathways. However, in the short run (the Gini index in 2050 is shown in figure 5.5), socioeconomic assumptions appear as the main drivers of inequalities, with limited variability across other dimensions.

5.4.3 Does mitigation reduce inequalities?

We compare inequality levels in 2100 across emissions pathways to analyze how the regressive impacts of climate damages compare to those of mitigation costs. We analyze which emission pathway, all else being equal, has the lowest inequality level (figure 5.6). Unsurprisingly, lower emission pathways are preferred when assuming regressive damages. We look specifically for the cases in which RCP 2.6 is the preferred emission pathway, because it is the only RCP likely to achieve the 2°C target.[7] Whether RCP 2.6 performs best in terms of inequality depends primarily on the damage function. With the most regres-

[7]Note that models have not produced this emission pathway under the most pessimistic socioeconomic pathway (SSP 3), where low growth is combined with high challenge to mitigation

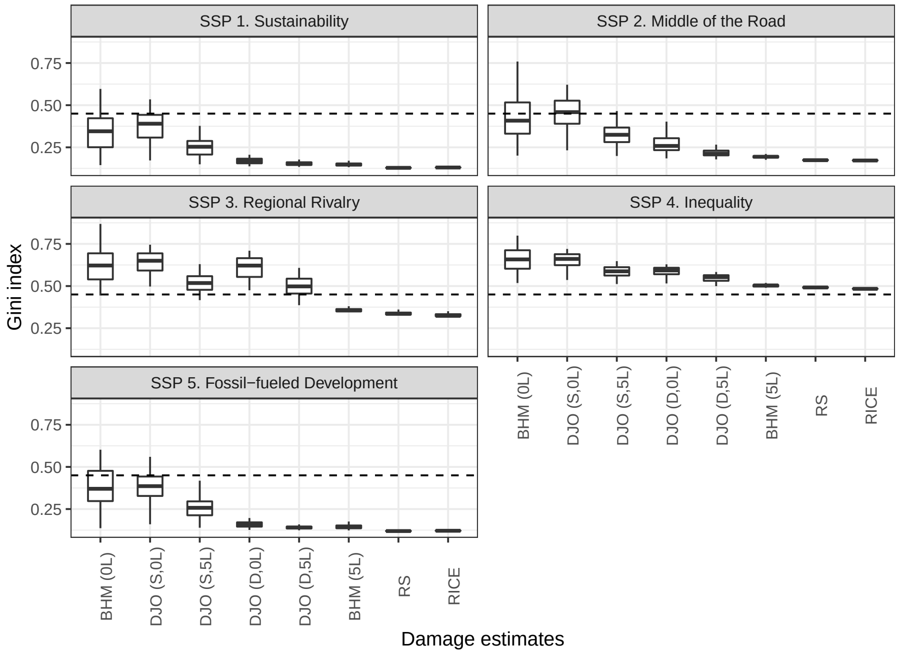

Figure 5.4 – Boxplot of the Gini index in 2100, for combinations of socioeconomic assumptions (panel) and damage functions (x-axis)

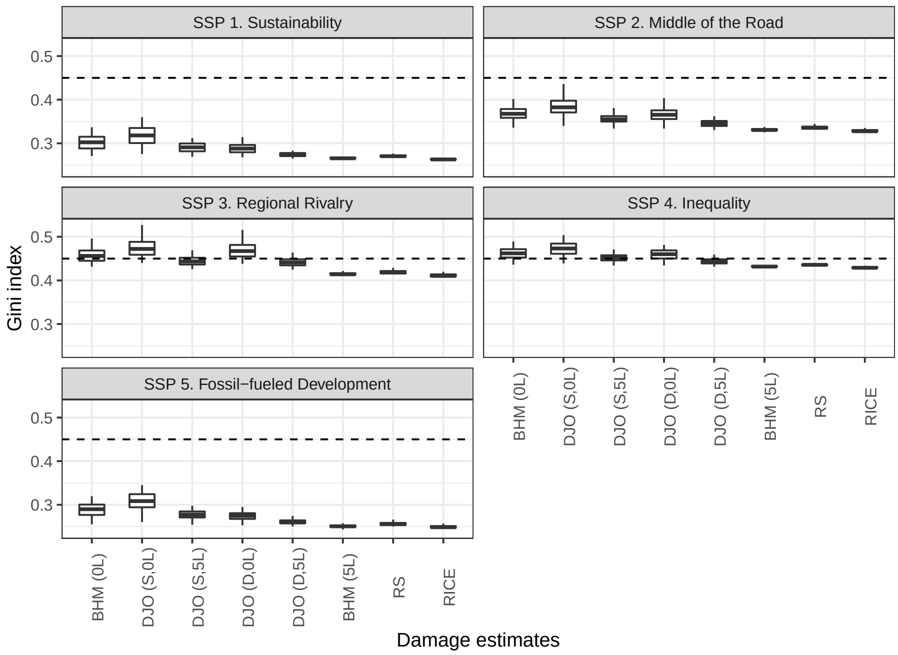

Figure 5.5 – Boxplot of the Gini index in 2050, for combinations of socioeconomic assumptions (panel) and damage functions (x-axis)

sive damage estimates (BHM, 0L), inequalities are always lowest under RCP 2.6 unless the high baseline emissions of SSP 5 is combined with the highest mitigation costs estimates (WITCH). Under the other econometric damage estimates, RCP 2.6 is the less unequal emission pathway either for optimistic SSPs with low challenges to mitigation (1, 2, 4), or when mitigation costs are low (all except WITCH). RCP 2.6 is less often the scenario with the lowest inequality levels IAM-based damage functions, i.e. RICE and RS. Netherless, even under low damage estimates, RCP 2.6 may still be the emission pathway with the lowest inequality level in some specific combinations, in particular for optimistic SSPs, provided that mitigation costs are not shared evenly within regions.

Likewise, looking at SSP 3, the damage estimate also primarily drives the comparison across emission pathways, and the same pattern can be observed. For high damages, avoided damages outweigh the cost to keep emissions compatible with RCP 3.4, while the contrary holds in the case of lower damages. Given that SSP 3 depicts a low-growth, low-technical progress world, mitigation is particularly costly, so that the lowest inequality levels do not always coincide with the lowest emission pathway.

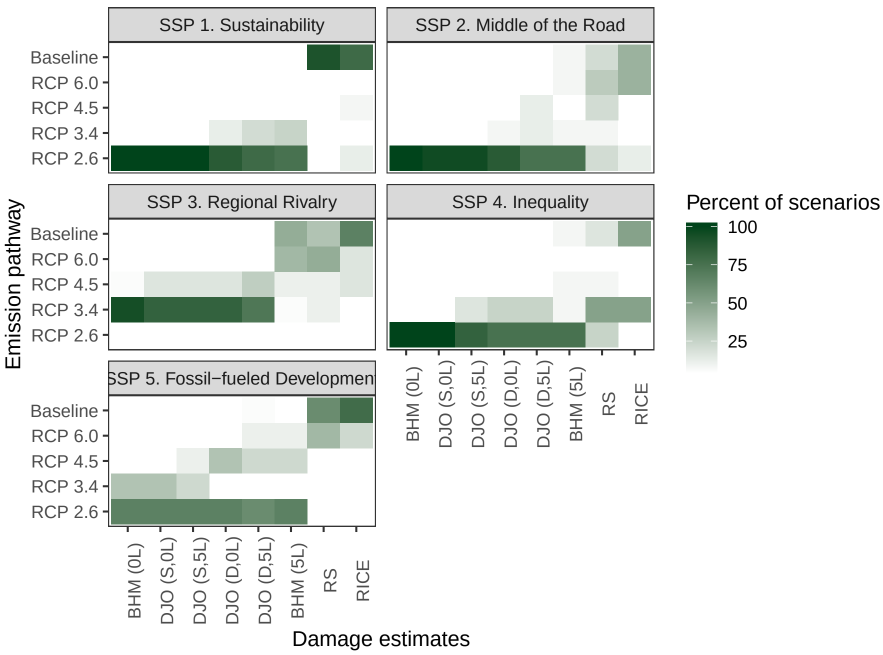

Figure 5.6 – Which emission pathway has the lowest inequality level? We compare inequality levels across emission pathways, all else being equal. The graph shows the percentage of scenarios in which each emission pathway has the lowest inequality level. We group scenarios based on SSP (panel) and damage estimates (x-axis). For instance, in SSP 1 and under BHM (0L) damages, RCP 2.6 always has the lowest Gini.

5.4.4 Does mitigation improve the situation of the poorest?

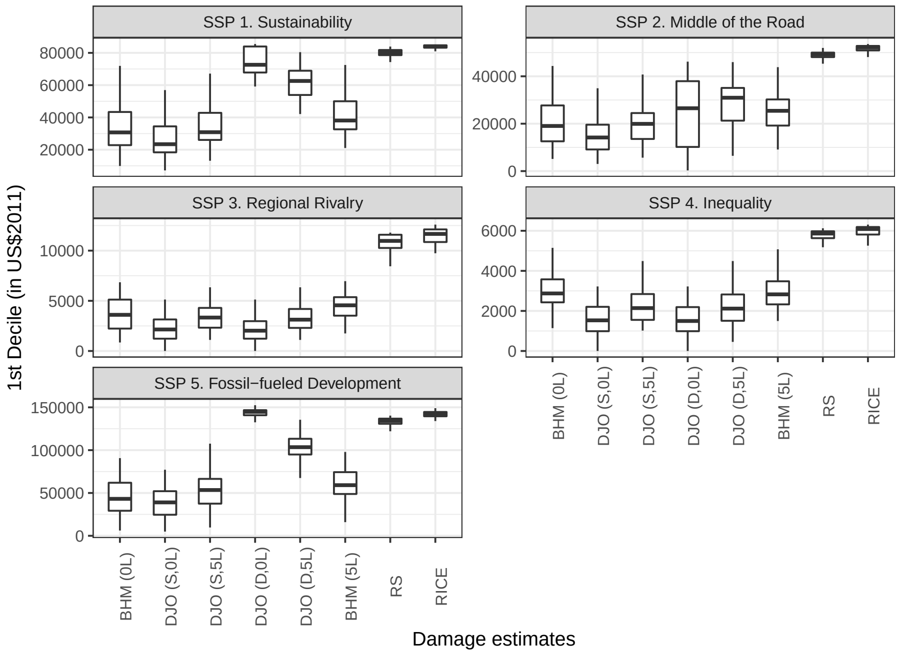

Figure 5.7 – Boxplot of the 1st income decile in 2100, for combinations of socioeconomic assumptions (panel) and damage functions (x-axis). Note that the scale of the y-axis differs across panels.

The Gini index only provides a relative measure of inequality, and thus does not give information about the absolute situation of the poorest. Here, we compute the first income decile in 2100, which reflects the situation of the poorest 10% (figure 5.7). Socioeconomic assumptions appear as the first driver of the situation of the poorest 10%, as it is the case with the Gini index, with differences larger than one order of magnitude across SSPs. There are also strong discrepancies between damage functions, and the most regressive results in terms of Gini are not necessarily the ones for which the situation of the poorest is the worst. However, the first income decile is almost systematically larger under RICE and RS damages than for econometrics-based damage functions.

We also compare the first income decile across emissions pathways (see figure 5.8). The distribution of the preferred emission pathway based on the value of the first income decile is generally close to that based on the Gini index. As it was the case for inequality, the situation of the poorest 10% tends to be better in lower emission pathways for econometrics-based damage functions.

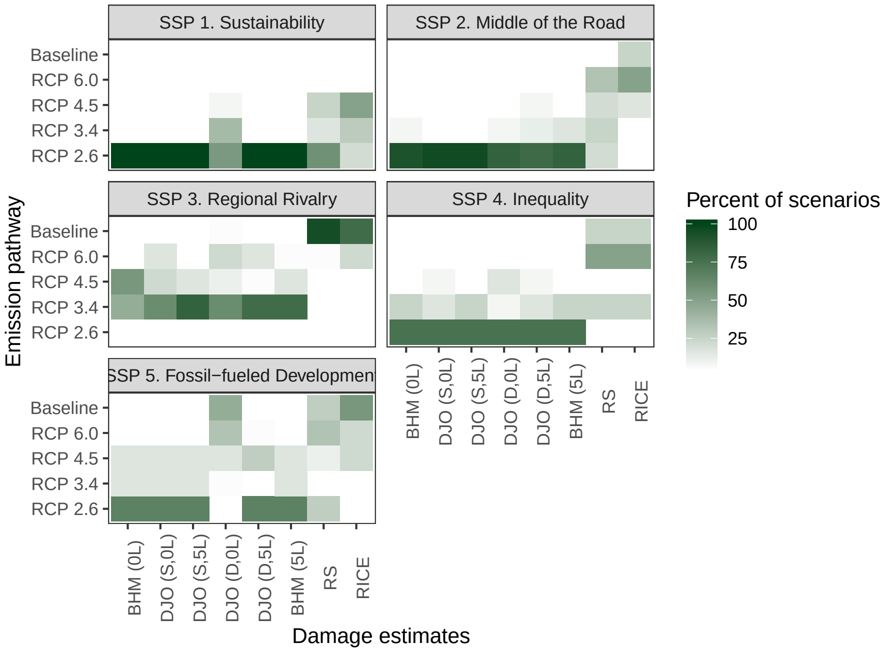

Figure 5.8 – What is the most favorable emission pathway in terms of the situation of the poorest 10%? We compare first income decile levels across emission pathways, all else being equal. The graph shows the percentage of scenarios in which each emission pathway has the greater first income decile. We group scenarios based on SSP (panel) and damage estimates (x-axis). For instance, in SSP 1 and with BHM (0L) damages, RCP 2.6 is always the emission pathway in which the situation of the poorest 10% is the best.

However, for the dynamic specification of DJO (0-lag) in high-growth SSP 5, rapid convergence allows the poorest 10% to become less vulnerable to climate change, so that mitigation does not improve their situation. Even under RICE damages, the first income decile can be higher for higher emission pathways. It is the case for SSPs where a significant number of countries stay behind (SSPs 3 and 4); and in SSPs 2 and 5, although only under low or moderate temperature response. Finally, with RS damages function, the poorest 10% are better off without mitigation if we assume low growth (SSP 3) or high mitigation costs (WITCH).

5.5 Discussion

5.5.1 Limitations of the study

Our results are conditional on the relative magnitude of the mitigation and damage cost estimates we use, as well as on their distribution across countries.

We highlight that many outcomes regarding future inequality will depend on the level of damages. Although we have tried to include as many estimates as possible in the analysis, IAM-based and econometrics damages all have limitations (Diaz and Moore, 2017). Econometrics-based damage functions represent a large share of the estimates used here. Although they allow for an empirically-grounded country-by-country treatment of damages, the validity of extrapolating into the future the short-term effects of weather on economic growth to assess the economic impact of climate change is subject to debate (Schlenker and Auffhammer, 2018). On the one hand, long-term adaptation may occur and reduce negative impacts. On the other hand, impacts could be exacerbated by non-linear effects outside of historical experience and by other potential sources of economic loss associated with climate change but not linked to temperature change, such as sea-level rise. Which of these two effects will prevail remains uncertain.

Another, related, limitation is the difficulty to account for the vulnerability of countries, as well as their ability to adapt to climate change in different socioeconomic pathways. Depending on the socioeconomic pathway, it may be more or less challenging – and thus costly – to adapt to a given temperature change. We account for some form of adaptation in the dynamic version of DJO damages, where damages depend on the level of income of the country. However, we do not proceed likewise for the other damage cases. Exploring in a more sophisticated manner the ability of future societies to cope with temperature changes would greatly improve the study, and strengthen the role of the socioeconomic pathway, as it does in the dynamic setting of DJO damages, but it would also increase its complexity.

The magnitude of the actual macroeconomic mitigation costs may also exceed the evaluations given by IAMs that quantified the SSPs, in particular considering real-world frictions and second-best mechanisms which were not accounted for by those models (Guivarch et al., 2011). In addition, the distribution of mitigation costs among countries will ultimately result from the relative ambition for emissions reduction as defined by their nationally determined contribution to the Paris Agreement, the stringency of policies implemented to reach those, and international climate finance and technology transfer mechanisms (Aldy et al., 2016). The distribution of costs may therefore be more or less regressive than the distribution implied by the mitigation policies represented by the IAMs in the SSP database. Many effort-sharing approaches, for instance accounting for historical responsibility, lead to more stringent targets for developed countries, suggesting that international negotiations may lead to distributions that are less regressive than cost-optimal approaches (van den Berg et al., 2019). Considering such cases would reduce the burden of mitigation on poor countries, and thus reinforce the result that mitigation can reduce inequalities.

Considering inequalities among individuals (Dennig et al., 2015; Alvaredo et al., 2018) and not only between countries, and accounting for dimensions of inequality beyond income, such as health inequalities, would complement our analysis of the inequality implications of climate change damages and mitigation. Such extensions would bring further complexity, but have the potential to amplify the results because poor households are particularly vulnerable to climate change impacts (Hallegatte and Rozenberg, 2017). Health inequalities would probably worsen under severe climate change, since health impacts due to climate change disproportionally affect the poor (Patz et al., 2005; Haines et al., 2006), and mitigation generally results in health co-benefits (Smith et al., 2014).

5.5.2 Conclusion

We study how greenhouse gas reduction may affect inequality through mitigation costs and avoided climate damages, with effects going in opposing directions. We build scenarios to account for their influence on future inequalities, and explore uncertainties along different dimensions: socioeconomic assumptions, emission pathways, mitigation costs, the regressivity of mitigation costs, temperature response, and climate change damages. We show that socioeconomic assumptions and climate change damages are the main drivers of the outcomes in the long term. The emission pathway also influences future inequalities, while the temperature response, the mitigation costs and their distribution play a lesser role. In most scenarios, inequalities among countries decline in the short to medium run, but can start rising again as climate change impacts gradually outweigh the expected economic convergence between low- and high-income countries. We show this occurs systematically in scenarios assuming low socioeconomic convergence between rich and poor countries (SSP 4). It can occur in all other socioeconomic pathways when considering high (i.e. econometrics-based) damage, but only under the most pessimistic temperature responses or the highest emission pathways. Whether mitigation reduces inequalities depends primarily on damage estimates. Under the highest damage estimates, it is very likely that inequalities may rise again, in particular in socioeconomic pathways with rather low challenge to mitigation, and when mitigation costs estimates are low. Mitigation can also reduce inequalities under less regressive damage functions, though under more specific assumptions regarding socioeconomic evolution and mitigation costs. In such scenarios, the benefits of avoided damages dominate the regressive effect of climate policies. The same drivers play a crucial role when looking at the situation of the poorest 10%, and the benefits of avoided damages on the first income decile outweigh those of mitigation costs in the same scenarios.

Our results are subject to several caveats and should be interpreted with caution. Nonetheless, they indicate that the cascading uncertainties in emission pathways, temperature and damage estimates can lead the distributional impacts of future climate change to counterbalance the projected convergence of countries' incomes. We further stress the divide between IAM- and econometrics-based damage functions, showing that they do not only differ in terms of the aggregate level of damage, but also in terms of their effect on inequality. If climate change is as regressive as econometrics-based damage functions suggest, climate mitigation policies are key to limit the rise of future inequalities between countries.

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5.A PRIM analysis

Results from the PRIM analysis are reported in the next pages.

Characterizing cases where there is a trend reversal

1. Iteration 1

Using 0.5 as a threshold, you will have:
 1762 out of 3408 above the threshold (51.7 percent)
 1646 out of 3408 below the threshold (48.3 percent)

```
    box index density coverage support dims
[1,]         1       1   0.2452  0.1268    1
```

```
         Box 1                      Remove Variable Stats
  dimension name rel bound   density coverage support      qpval rmv
1           SSP4  >    0.5     0.517        1       1 1.717e-124   1
```

2. Iteration 2

Using 0.5 as a threshold, you will have:
 1330 out of 3408 above the threshold (39.03 percent)
 2078 out of 3408 below the threshold (60.97 percent)

```
     box index density coverage support dims
[1,]         1  0.8263  0.26466 0.12500    1
[2,]         2  1.0000  0.05414 0.02113    2
```

```
         Box 1                      Remove Variable Stats
  dimension name rel bound   density coverage support    qpval rmv
1     DJO..S.0L.  >    0.5    0.3903        1       1 2.81e-76   1
```

```
         Box 2                      Remove Variable Stats
  dimension name rel bound   density coverage support    qpval rmv
1     DJO..S.0L.  >    0.5    0.3903   1.0000   1.000 2.63e-10   2
2           SSP3  >    0.5    0.8263   0.2647   0.125 1.08e-06   1
```

Choosing Box 2

3. Iteration 3

Using 0.5 as a threshold, you will have:
 1258 out of 3408 above the threshold (36.91 percent)
 2150 out of 3408 below the threshold (63.09 percent)

```
     box index density coverage support dims
[1,]         1  0.8028  0.27186 0.12500    1
[2,]         2  1.0000  0.05723 0.02113    2
```

```
         Box 1                      Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.3691        1       1 5.969e-75   1
```

```
         Box 2                      Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.3691   1.0000   1.000 3.987e-16   2
2           SSP3  >    0.5    0.8028   0.2719   0.125 1.356e-07   1
```

Choosing Box 2

4. Iteration 4

```
Using 0.5 as a threshold, you will have:
 1186 out of 3408 above the threshold ( 34.8 percent)
 2222 out of 3408 below the threshold ( 65.2 percent)

     box index density coverage support dims
[1,]         1  0.7559  0.27150 0.12500    1
[2,]         2  1.0000  0.06071 0.02113    2

         Box 1                   Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5     0.348        1       1 4.302e-66   1

         Box 2                   Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.3480   1.0000   1.000 2.786e-23   2
2           SSP3  >    0.5    0.7559   0.2715   0.125 1.771e-09   1

Choosing Box 2

5. Iteration 5

Using 0.5 as a threshold, you will have:
 1114 out of 3408 above the threshold ( 32.69 percent)
 2294 out of 3408 below the threshold ( 67.31 percent)

    box index density coverage support dims
[1,]         1  0.6573  0.25135 0.12500    1
[2,]         2  0.9524  0.07181 0.02465    2
[3,]         3  1.0000  0.06463 0.02113    3

         Box 1                   Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.0L.  >    0.5    0.3269        1       1 3.924e-44   1

         Box 2                   Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.0L.  >    0.5    0.3269   1.0000   1.000 4.984e-23   2
2           SSP5  >    0.5    0.6573   0.2513   0.125 7.712e-11   1

         Box 3                   Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.0L.  >    0.5    0.3269  1.00000 1.00000 9.886e-24   3
2           SSP5  >    0.5    0.6573  0.25135 0.12500 7.030e-13   2
3            RCP  >    2.5    0.9524  0.07181 0.02465 2.981e-02   1

Choosing Box 3

6. Iteration 6

Using 0.5 as a threshold, you will have:
 1042 out of 3408 above the threshold ( 30.58 percent)
 2366 out of 3408 below the threshold ( 69.42 percent)

    box index density coverage support dims
[1,]         1  0.6338  0.25912 0.12500    1
[2,]         2  0.9524  0.07678 0.02465    2
[3,]         3  1.0000  0.06910 0.02113    3
```

```
         Box 1                        Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.3058        1       1 3.874e-44   1

         Box 2                        Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.3058   1.0000   1.000 4.080e-32   2
2           SSP5  >    0.5    0.6338   0.2591   0.125 5.426e-12   1

         Box 3                        Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.3058  1.00000 1.00000 3.491e-33   3
2           SSP5  >    0.5    0.6338  0.25912 0.12500 6.122e-14   2
3            RCP  >    2.5    0.9524  0.07678 0.02465 2.981e-02   1

Choosing Box 3

7. Iteration 7

Using 0.5 as a threshold, you will have:
 970 out of 3408 above the threshold ( 28.46 percent)
 2438 out of 3408 below the threshold ( 71.54 percent)

    box index density coverage support dims
[1,]         1  0.5869  0.25773 0.12500    1
[2,]         2  0.9524  0.08247 0.02465    2
[3,]         3  1.0000  0.07423 0.02113    3

         Box 1                        Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.2846        1       1 1.363e-38   1

         Box 2                        Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.2846   1.0000   1.000 9.117e-45   2
2           SSP5  >    0.5    0.5869   0.2577   0.125 1.833e-14   1

         Box 3                        Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.2846  1.00000 1.00000 8.529e-47   3
2           SSP5  >    0.5    0.5869  0.25773 0.12500 6.928e-16   2
3            RCP  >    2.5    0.9524  0.08247 0.02465 2.981e-02   1

Choosing Box 3

8. Iteration 8

Using 0.5 as a threshold, you will have:
 898 out of 3408 above the threshold ( 26.35 percent)
 2510 out of 3408 below the threshold ( 73.65 percent)

    box index density coverage support dims
[1,]         1  0.4883   0.2316 0.12500    1
[2,]         2  0.9333   0.1247 0.03521    2
[3,]         3  1.0000   0.1069 0.02817    3

         Box 1                        Remove Variable Stats
```

```
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.0L.  >    0.5    0.2635        1       1 3.482e-23   1

         Box 2                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.0L.  >    0.5    0.2635   1.0000   1.000 3.439e-42   2
2           SSP2  >    0.5    0.4883   0.2316   0.125 5.703e-26   1

         Box 3                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.0L.  >    0.5    0.2635   1.0000 1.00000 4.809e-41   3
2           SSP2  >    0.5    0.4883   0.2316 0.12500 8.421e-32   2
3            RCP  >    2.5    0.9333   0.1247 0.03521 1.329e-03   1

Choosing Box 3

9. Iteration 9

Using 0.5 as a threshold, you will have:
 802 out of 3408 above the threshold ( 23.53 percent)
 2606 out of 3408 below the threshold ( 76.47 percent)

     box index density coverage support dims
[1,]         1  0.4648  0.24688 0.12500    1
[2,]         2  0.9167  0.10973 0.02817    2
[3,]         3  1.0000  0.08978 0.02113    3

         Box 1                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.2353        1       1 3.795e-25   1

         Box 2                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.2353   1.0000   1.000 9.028e-31   2
2           SSP1  >    0.5    0.4648   0.2469   0.125 5.060e-21   1

         Box 3                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.2353   1.0000 1.00000 2.934e-30   3
2           SSP1  >    0.5    0.4648   0.2469 0.12500 1.474e-25   2
3            RCP  >    2.5    0.9167   0.1097 0.02817 1.902e-03   1

Choosing Box 3

10. Iteration 10

Using 0.5 as a threshold, you will have:
 730 out of 3408 above the threshold ( 21.42 percent)
 2678 out of 3408 below the threshold ( 78.58 percent)

    box index density coverage support dims
[1,]         1  0.4178  0.24384 0.12500    1
[2,]         2  0.8542  0.11233 0.02817    2
[3,]         3  1.0000  0.08767 0.01878    3

         Box 1                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.2142        1       1 2.823e-21   1
```

```
         Box 2                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.2142   1.0000   1.000 4.529e-34   2
2           SSP1  >    0.5    0.4178   0.2438   0.125 1.169e-18   1

         Box 3                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.2142   1.0000 1.00000 2.093e-33   3
2           SSP1  >    0.5    0.4178   0.2438 0.12500 1.327e-19   2
3        Climate  >    1.5    0.8542   0.1123 0.02817 4.156e-05   1

Choosing Box 3

11. Iteration 11

Using 0.5 as a threshold, you will have:
 666 out of 3408 above the threshold ( 19.54 percent)
 2742 out of 3408 below the threshold ( 80.46 percent)

    box index density coverage support dims
[1,]         1  0.3611   0.3123 0.16901    1
[2,]         2  1.0000   0.1081 0.02113    2

         Box 1                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1           SSP3  >    0.5    0.1954        1       1 1.464e-20   1

         Box 2                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1           SSP3  >    0.5    0.1954   1.0000   1.000 2.547e-47   2
2     DJO..D.0L.  >    0.5    0.3611   0.3123   0.169 1.413e-32   1

Choosing Box 2

12. Iteration 12

Using 0.5 as a threshold, you will have:
 594 out of 3408 above the threshold ( 17.43 percent)
 2814 out of 3408 below the threshold ( 82.57 percent)

    box index density coverage support dims
[1,]         2   0.850   0.1717 0.03521    2
[2,]         3   0.975   0.1313 0.02347    3
[3,]         4   1.000   0.1077 0.01878    4

         Box 2                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.1743   1.0000   1.000 2.216e-44   2
2           SSP2  >    0.5    0.2958   0.2121   0.125 2.322e-36   1

         Box 3                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.1743   1.0000 1.00000 5.718e-38   3
2           SSP2  >    0.5    0.2958   0.2121 0.12500 2.700e-32   2
3        Climate  >    1.5    0.8500   0.1717 0.03521 2.562e-04   1

         Box 4                    Remove Variable Stats
```

```
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5    0.1743   1.0000 1.00000 9.262e-34   4
2           SSP2  >    0.5    0.2958   0.2121 0.12500 5.360e-37   3
3        Climate  >    1.5    0.8500   0.1717 0.03521 3.815e-03   2
4            RCP  >    2.5    0.9750   0.1313 0.02347 1.978e-01   1

Choosing Box 4

13. Iteration 13

Using 0.5 as a threshold, you will have:
 530 out of 3408 above the threshold ( 15.55 percent)
 2878 out of 3408 below the threshold ( 84.45 percent)

   box index density coverage support dims
[1,]         2  0.7333   0.1660 0.03521    2
[2,]         3  0.9000   0.1358 0.02347    3
[3,]         4  1.0000   0.1208 0.01878    4

        Box 2                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.1555   1.0000   1.000 2.008e-40   2
2           SSP2  >    0.5    0.2676   0.2151   0.125 3.084e-26   1

        Box 3                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.1555   1.0000 1.00000 6.991e-41   3
2           SSP2  >    0.5    0.2676   0.2151 0.12500 5.191e-31   2
3        Climate  >    1.5    0.7333   0.1660 0.03521 2.080e-04   1

        Box 4                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.1555   1.0000 1.00000 1.946e-48   4
2           SSP2  >    0.5    0.2676   0.2151 0.12500 5.360e-37   3
3        Climate  >    1.5    0.7333   0.1660 0.03521 8.559e-06   2
4            RCP  >    2.5    0.9000   0.1358 0.02347 1.179e-03   1

Choosing Box 4

14. Iteration 14

Using 0.5 as a threshold, you will have:
 466 out of 3408 above the threshold ( 13.67 percent)
 2942 out of 3408 below the threshold ( 86.33 percent)

    box index density coverage support dims
[1,]         2  0.9167   0.1888 0.02817    2
[2,]         3  1.0000   0.1545 0.02113    3

        Box 2                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.0L.  >    0.5    0.1367   1.0000   1.000 1.966e-56   2
2           SSP1  >    0.5    0.2629   0.2403   0.125 1.047e-41   1

        Box 3                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.0L.  >    0.5    0.1367   1.0000 1.00000 2.992e-54   3
2           SSP1  >    0.5    0.2629   0.2403 0.12500 1.584e-50   2
```

```
3            RCP  >    2.5    0.9167   0.1888 0.02817 1.902e-03   1

Choosing Box 3

15. Iteration 15

Using 0.5 as a threshold, you will have:
 394 out of 3408 above the threshold ( 11.56 percent)
 3014 out of 3408 below the threshold ( 88.44 percent)

    box index density coverage support dims
[1,]         1  0.2361   0.3452 0.16901    1
[2,]         2  1.0000   0.1827 0.02113    2

         Box 1                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1           SSP3  >    0.5    0.1156        1       1 4.369e-16   1

         Box 2                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1           SSP3  >    0.5    0.1156   1.0000   1.000 4.845e-50   2
2     DJO..D.5L.  >    0.5    0.2361   0.3452   0.169 7.318e-46   1

Choosing Box 2

16. Iteration 16

Using 0.5 as a threshold, you will have:
 322 out of 3408 above the threshold ( 9.448 percent)
 3086 out of 3408 below the threshold ( 90.55 percent)

     box index density coverage  support dims
[1,]         3  0.7143  0.12422 0.016432    3
[2,]         4  0.9643  0.08385 0.008216    3
[3,]         5  1.0000  0.04348 0.004108    4

         Box 3                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..5L.  >    0.5   0.09448   1.0000 1.00000 1.312e-19   3
2           SSP5  >    0.5   0.20892   0.2764 0.12500 4.180e-12   2
3        Climate  >    1.5   0.54762   0.1429 0.02465 7.976e-03   1

         Box 4                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..5L.  >    0.5   0.09448   1.0000 1.00000 3.333e-17   3
2           SSP5  >    0.5   0.20892   0.2764 0.12500 6.237e-12   2
3        Climate  >    2.5   0.54762   0.1429 0.02465 1.148e-06   1

         Box 5                    Remove Variable Stats
  dimension name rel bound   density coverage  support     qpval rmv
1       BHM..5L.  >    0.5   0.09448  1.00000 1.000000 7.623e-10   4
2           SSP5  >    0.5   0.20892  0.27640 0.125000 1.323e-06   3
3        Climate  >    2.5   0.54762  0.14286 0.024648 3.958e-04   2
4     Elasticity  <    1.5   0.96429  0.08385 0.008216 6.010e-01   1

Choosing Box 5

17. Iteration 17
```

```
Using 0.5 as a threshold, you will have:
 301 out of 3408 above the threshold ( 8.832 percent)
 3107 out of 3408 below the threshold ( 91.17 percent)

     box index density coverage  support dims
[1,]         3    0.50   0.0598 0.010563    3
[2,]         4    0.75   0.0299 0.003521    4

         Box 3                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..5L.  >    0.5   0.08832  1.00000 1.00000 9.949e-06   3
2           SSP3  >    0.5   0.15962  0.22591 0.12500 5.456e-07   2
3     Elasticity  <    1.5   0.31944  0.07641 0.02113 1.830e-02   1

         Box 4                    Remove Variable Stats
  dimension name rel bound   density coverage  support     qpval rmv
1       BHM..5L.  >    0.5   0.08832  1.00000 1.000000 5.454e-04   4
2           SSP3  >    0.5   0.15962  0.22591 0.125000 5.475e-05   3
3        AIM.CGE  >    0.5   0.31944  0.07641 0.021127 7.300e-02   2
4     Elasticity  <    1.5   0.50000  0.03987 0.007042 7.300e-02   1

Choosing Box 4

18. Iteration 18

Using 0.5 as a threshold, you will have:
 292 out of 3408 above the threshold ( 8.568 percent)
 3116 out of 3408 below the threshold ( 91.43 percent)

    box index density coverage  support dims
[1,]         4    0.60  0.08219 0.011737    3
[2,]         5    0.75  0.08219 0.009390    4
[3,]         6    1.00  0.08219 0.007042    4

         Box 4                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5   0.08568   1.0000 1.00000 1.728e-12   3
2           SSP2  >    0.5   0.14554   0.2123 0.12500 1.101e-09   2
3        Climate  <    1.5   0.31667   0.1301 0.03521 2.056e-04   1

         Box 5                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5   0.08568  1.00000 1.00000 1.287e-13   4
2           SSP2  >    0.5   0.14554  0.21233 0.12500 4.659e-11   3
3        Climate  <    1.5   0.31667  0.13014 0.03521 4.179e-09   2
4            RCP  >    2.5   0.60000  0.08219 0.01174 5.748e-02   1

         Box 6                    Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..0L.  >    0.5   0.08568  1.00000 1.00000 4.469e-17   4
2           SSP2  >    0.5   0.14554  0.21233 0.12500 4.979e-14   3
3        Climate  <    1.5   0.31667  0.13014 0.03521 3.541e-12   2
4            RCP  >    3.5   0.60000  0.08219 0.01174 4.738e-06   1

Choosing Box 6

19. Iteration 19
```

```
Using 0.5 as a threshold, you will have:
 268 out of 3408 above the threshold ( 7.864 percent)
 3140 out of 3408 below the threshold ( 92.14 percent)

     box index density coverage  support dims
[1,]         4  0.6786  0.07090 0.008216    4
[2,]         5  0.9286  0.04851 0.004108    4
[3,]         6  1.0000  0.03731 0.002934    5

         Box 4                         Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..5L.  >    0.5   0.07864  1.00000 1.00000 1.283e-09   4
2           SSP5  >    0.5   0.13850  0.22015 0.12500 6.697e-07   3
3     Elasticity  >    1.5   0.29762  0.09328 0.02465 2.564e-04   2
4        Climate  >    1.5   0.52381  0.08209 0.01232 7.232e-02   1

         Box 5                         Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1       BHM..5L.  >    0.5   0.07864  1.00000 1.00000 2.253e-08   4
2           SSP5  >    0.5   0.13850  0.22015 0.12500 2.421e-06   3
3     Elasticity  >    1.5   0.29762  0.09328 0.02465 3.710e-04   2
4        Climate  >    2.5   0.52381  0.08209 0.01232 1.607e-03   1

         Box 6                         Remove Variable Stats
  dimension name rel bound   density coverage  support     qpval rmv
1       BHM..5L.  >    0.5   0.07864  1.00000 1.000000 9.537e-07   5
2           SSP5  >    0.5   0.13850  0.22015 0.125000 1.378e-05   4
3     Elasticity  >    1.5   0.29762  0.09328 0.024648 9.766e-04   3
4        Climate  >    2.5   0.52381  0.08209 0.012324 1.862e-03   2
5  WITCH.GLOBIOM  <    0.5   0.92857  0.04851 0.004108 4.766e-01   1

Choosing Box 6

20. Iteration 20

Using 0.5 as a threshold, you will have:
 258 out of 3408 above the threshold ( 7.57 percent)
 3150 out of 3408 below the threshold ( 92.43 percent)

    box index density coverage  support dims
[1,]         6  0.6667  0.06202 0.007042    4
[2,]         7  1.0000  0.06202 0.004695    4

         Box 6                         Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.0757  1.00000 1.00000 2.071e-12   4
2        Climate  <    1.5    0.1174  0.19380 0.12500 4.009e-06   3
3           SSP2  >    0.5    0.2394  0.13178 0.04167 3.257e-03   2
4            RCP  >    3.5    0.4000  0.06202 0.01174 7.510e-03   1

         Box 7                         Remove Variable Stats
  dimension name rel bound   density coverage support     qpval rmv
1     DJO..S.5L.  >    0.5    0.0757  1.00000 1.00000 3.553e-15   4
2        Climate  <    1.5    0.1174  0.19380 0.12500 2.323e-08   3
3            RCP  >    4.5    0.2394  0.13178 0.04167 4.295e-07   2
4           SSP2  >    0.5    0.4444  0.09302 0.01585 2.318e-06   1
```

Chapter 6

From direct to final economic impacts of climate change: the case of heat stress on labour productivity

Abstract

The biophysical impacts of climate change are heterogeneous and hit poorest regions hardest. However, it is unclear how this heterogeneity in exposure to direct impacts translates into heterogeneity in economic losses, because spillovers can transmit vulnerabilities across regions and sectors. In this article, we describe the indirect effects of heat stress on future labour productivity and the mechanisms at play using an Integrated Assessment Model. We simulate sector and region-specific reductions in labour productivity owing to climate change in different emission scenarios. We quantify the resulting losses from heat stress in different regions. The preliminary results suggest that indirect effects tend to exacerbate both the direct impacts and their unequal distribution. Thus, interactions between sectors and regions are key to understand the impact from climate change.

Introduction

The biophysical impacts of climate change are strongly heterogeneous between regions. For instance, water stress, droughts, heat waves and loss of agricultural yields will be unevenly distributed, and will hit poorest countries hardest (Byers et al., 2018; Arnell et al., 2019).

However, it is unclear how differences in sectoral or regional biophysical exposure translate into heterogeneity in terms of economic impacts. Indeed, impacts at a given place or to a particular sector can be amplified or dampened because of the teleconnectedness of socioeconomic systems. Sectors are vulnerable to the impacts occurring in other parts of the economy, either because they rely on intermediate goods produced by other sectors, or because they compete for the same inputs. For instance, water availability needs in agriculture can constrain hydro-power resources or the cooling of thermal units (Neumann and Strzepek, 2014). In such cases, the combination of impacts exceeds the sum of single impacts (Harrison et al., 2016). Beside inter-sectoral linkages, climate change impacts can also cross borders, notably via international trade. A region relying on inputs produced in an exposed region can face higher importing prices, or suffer from lower demand if revenues abroad contract. The consequences of such inter-linkages is revealed notably in the case of natural disasters, when a weather shock at a given place propagates along the supply chain, thereby increasing the total cost (Otto et al., 2017; Henriet et al., 2012).

The final economic losses and their distribution depend on how the direct physical impacts propagate in the economic system, notably via changes in trade patterns. However, both the magnitude and direction of the regional spillover effects are ambiguous. Less affected regions can find themselves in a better position to export on international markets and thereby take advantage by capturing a greater market share. Conversely, they may also suffer from raised importing prices from goods produced in more affected regions. This leads to ambiguous term of trade effects. For instance, Schenker (2013) shows that 20% of the costs from climate change in the US is attributable to impacts occurring outside the US. Similarly, Knittel et al. (2020) suggest that labour productivity reductions outside Germany, despite improving the country's relative position on the global market, lead to a net loss of GDP. This is in line with Constant and Davin (2019), which show that the transmission of impacts between heterogeneous regions can occur even if terms of trade improves in the North.

A widely discussed example of how trade affects the costs from climate change impacts is the study of crop yield on agriculture. The literature shows that production and trade adjustments are key to alleviate the impacts of climate change in different countries, by fostering efficient production reallocation (Costinot et al., 2016; Gouel and Laborde, 2018; Baldos et al., 2019). However, in the context of multi-sector economies, impacts can also induce macroeconomic structural change, either exacerbating or dampening direct damages (Kalkuhl and Edenhofer, 2016).

In this article, we study reductions in labour productivity due to heat stress, which has regionally heterogeneous impacts. Though reduced labour productivity only represents a specific impact channel from climate change, its effects will hit many sectors, and have been shown to contribute to a large share of total estimated damages (Dellink et al., 2019; Roson and Van der Mensbrugghe, 2012). We quantify the final economic impact of reductions in labour productivity and their distribution in two contrasted socioeconomic and emissions scenarios. We implement labour productivity losses due to climate change in a multi-regional, multi-sectoral integrated assessment model. This approach has the advantage of capturing a wide range of indirect economic effects, and interactions between regions and sectors.

We discuss how indirect effects can amplify or dampen climate change impacts across sectors and regions. Our preliminary results show that direct impacts, estimated disregarding general-equilibrium effects, strongly underestimate impacts at the global level. Direct impacts are also biased at the regional level: they underestimate impacts in the most exposed regions while the contrary occurs for the least affected economies. Unaffected regions are found to gain from other regions being exposed to climate change. This suggests that adjustments in production, prices and trade are likely to exacerbate inequalities due to the direct impacts of climate change. Our results are robust to assumptions about the substitutability and price elasticity between domestic and international goods, which is in line with previous studies Bosello and Parrado (2014); Orlov et al. (2020). While they do not affect the direction of the effects, we also find that labour market imperfections increase the costs from climate change impacts.

Our results thus suggest that total economic damages based on a mere enumeration and addition of sectoral or regional damages severely underestimate the potential losses at the global level, and their unequal distribution.

The paper is structured as follows. Section 6.1 presents the literature on the effect of heat on labour. Section 6.2 describes the integrated assessment model used, explains how heat stress impacts on labour productivity owing to climate change were introduced in the model and presents the two emissions scenarios. Section 6.3 presents the results, and section 6.4 concludes.

6.1 Effect of heat on labour

Climate change is expected to increase average and daily maximum temperatures as well as the number of hot days in most regions, making extreme heat events more frequent and intense (IPCC, 2014). Excessive heat and humidity reduce work capacity - the physiological equivalent of labour productivity - as individuals need to slow down and rest longer to prevent adverse health effects while also becoming more prone to work accidents. In extreme cases, heat stress may result in injuries and illnesses such as heat strokes, as the body is no longer able to transfer internal heat to the external environment to maintain a healthy temperature.

Many workers are exposed to rising temperatures worldwide. In 2020, more than 1 in 3 workers were employed in agriculture or construction worldwide, almost 2 in 3 in low income countries (ILO, 2020). Agriculture and construction are sectors where labour productivity is sensitive to extreme weather as work is physically intense and mainly outdoors. Despite large productivity gains and increasing mechanisation, many sectors and regions remain highly labour intensive. Labour is still a critical factor of production globally - 51% of global income was allocated to labour in 2017 (ILO, 2019) - and more specifically in less developed regions, where output and income are closely tied to labour productivity. In Sub Saharan Africa, labour represented around 58% of agricultural costs (Hertel and de Lima, 2020), while agriculture employed 53% of the labour force in 2019 for example (ILO, 2020). Thus reductions in labour productivity owing to additional heat exposure in the context of global warming is likely to have a significant impact on livelihoods and economic development.

A recent body of research has estimated reductions in labour productivity owing to climate change-induced heat stress at the global and regional levels (Kjellstrom et al., 2009; Dunne et al., 2013; Chavaillaz et al., 2019). However, efforts to quantify the resulting economic impacts are still limited and mainly do not account for interactions between regions (DARA, 2012; Steininger et al., 2016; Roson and Sartori, 2016). In this article, we follow the tracks of Takakura et al. (2017), Orlov et al. (2020) and Knittel et al. (2020) by implementing climate-related labour productivity losses in the framework of computable general equilibrium (CGE) models. We explicitly compare the benefits of such approach compared to estimates based on direct impacts, absent general-equilibrium effects. We do so with an integrated assessment model which account for the second-best nature of labour markets (Guivarch et al., 2011).

6.2 Methods

6.2.1 Overview of the IMACLIM-R economic model

To capture a range of macroeconomic impacts associated with labour productivity losses owing to climate change, heat-induced reductions in worker productivity are implemented in IMACLIM-R, a global recursive-dynamic, 12 sector, 12 region model (see Bibas et al. (2015) for model documentation). This energy-economy model is routinely used to quantify climate mitigation costs and analyse transition pathways towards a low-carbon economy (Waisman et al., 2012). The dual accounting in energy and financial flows follows the Arrow-Debreu axiomatic (Arrow and Debreu, 1954), and allows to combine realistic engineering representations of the evolution of technical systems with a consistent set of prices.

This general equilibrium model also allows for short-term departures away from a balance growth trajectory as it accounts for a range of market imperfections and inertias, such as rigidities on labour markets (i.e., unemployment) and on capital markets (inertia on capital stocks), imperfect competition - represented by a price markup -, and imperfect foresight to model 'routine' behaviours. The equilibrium is second best and allows for capacity shortages, overcapacity and unemployment.

Three features of the model are of particular interest for our study. First, international trade of goods is modelled following the Armington assumption of imperfect product competition. Agents consume composite goods that are a blend of imperfectly substitutable domestic and imported varieties. On the international market, exports are aggregated into a pool and redistributed as imports based on region-specific terms of trade. Second, labour markets are not perfectly flexible in the model, which limits their ability to adjust in response to climate change impacts. Rigidities arise notably because wage variations are constrained by a regional wage curve, which links real wages to unemployment rate (Blanchflower and Oswald, 1995). Finally, labour is not substitutable with other inputs, owing to the Leontief specification of the production function.

6.2.2 Introducing heat stress impacts on labour productivity

We add a heat stress impact module to IMACLIM-R to relate anthropogenic CO2 emissions to future regional temperature changes. Local warming projections are then converted into region and sector-specific labour productivity reductions. While other approaches consider damages from exogenous physical change along different emission pathways (Takakura et al., 2017; Orlov et al., 2020), in our case emissions are generated endogenously by the model. This full-coupling allows to provide a representation of the economy and energy system that is consistent with the emissions (see figure 6.1).

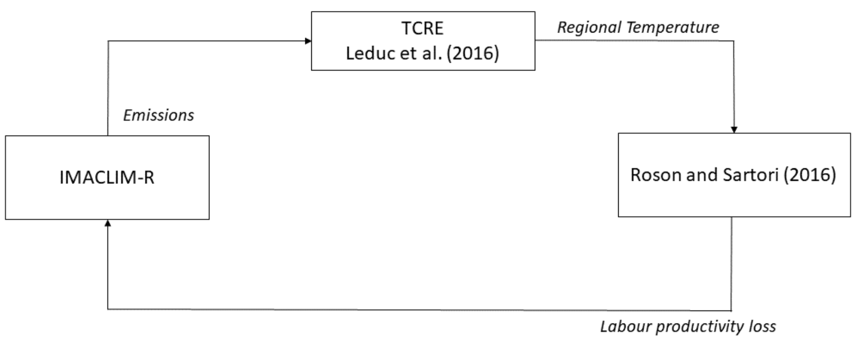

Figure 6.1 – Schematic representation of the methodology used to introduce reductions in labour productivity in IMACLIM-R

6.2.2.1 Temperature change projections

CO2 emissions stemming from economic activity between 2001 and 2100 - namely industrial processes and fossil fuels - are endogenously calculated by the IMACLIM-R model. They are determined by scale factors (population, exogenous labour productivity), energy intensity of economic activity, and energy efficiency. [1] Global emissions stock is then converted into regional temperature changes assuming a linear response of climate change (Leduc et al., 2016) – the proportionality coefficient is the Transient Climate Response to cumulative carbon Emissions (TCRE).

6.2.2.2 Heat-induced labour productivity losses

We use estimates from Roson and Sartori (2016) to convert regional temperature changes into labour productivity reductions in the different sectors. They estimate annual working hours lost owing to increases in temperature relative to baseline climate (1985-2005) in 140 countries. Their approach combines monthly temperature and humidity distributions with a simplified version of the Hothaps function provided in Kjellstrom et al. (2009) between WBGT and 'work ability' for three different levels of work intensity to compute reductions in worker productivity. Work ability is assumed to decrease only once a temperature threshold is exceeded: 26°C for high intensity sectors such as agriculture, 28°C for medium intensity sectors like manufacturing, and 30°C for office work as in services. Beyond this lower threshold, work ability declines linearly until the sector-specific upper thresholds (36°C, 43°C and 50°C respectively) are reached, at which point productivity losses are assumed to remain at 75%.

The country-level productivity loss by work intensity estimates are aggregated into 12 IMACLIM-R regions (see table 6.1) using GDP weights to obtain regional reductions in labour productivity for each work intensity for any change in temperatures between 0 and 5°C. Each of the 12 IMACLIM-R sectors is assigned to one of the three sensitivity categories based on working conditions: construction and agriculture are high work intensity sectors, manufacturing, energy sectors and all transportation sectors (except air transport) correspond to medium intensity, and services and air transport are low intensity sectors.

6.2.2.3 Scenarios

In IMACLIM-R, emissions and hence regional warming patterns are driven by the interaction between natural growth (i.e., exogenous demographic and labour productivity trends) and a host of market, technological, energy effi-

[1] Land use change emissions are not represented in the model, AFOLU emission trajectories are added exogenously (Riahi et al., 2017)

Abbreviation	Region
CAN	Canada
CIS	Former Soviet Union
EUR	Europe
USA	United States
JAN	OECD Pacific
CHN	China
RAL	Rest of Latin America
AFR	Africa
MDE	Middle East
BRA	Brazil
IND	India
RAS	Rest of Asia

Table 6.1 – Regions in IMACLIM-R

ciency and resource availability factors that can be set exogenously to depict alternative visions of the future. We build two baselines (i.e., without explicit emissions reductions policies) describing contrasted emissions trajectories and socioeconomic pathways to depict alternative trajectories of global warming and heat stress. The low emissions scenario is consistent with SSP 1 (Riahi et al., 2017) storyline, both in term of population and economic growth, but also in terms of other socioeconomic assumptions, such as high energy efficiency, availability of low carbon technologies and fossil energy. The high emissions scenario describes a world with similar natural growth, but consistent with SSP3 population trends, low energy efficiency, difficult access to low carbon technologies and high fossil energy availability. Thus, the high emissions scenario describes a world that reflects the SSP3 storyline, but with an SSP1 global growth trajectory. This allows us to build two scenarios with similar global growth trajectories but contrasting emissions. See appendix 6.E for a comparison of the GDP and CO2 emission trajectories with the ones from SSPs.

To isolate the impact of heat stress on economies in the context of climate change, we compare scenarios where climate change impacts reduce labour productivity to corresponding scenarios where climate change impacts are not accounted for.

6.3 Preliminary results

6.3.1 Direct labour productivity loss

First, to get a sense of the impacts of climate change, we compute the labour productivity losses in the different sector categories (low, medium and high-intensity) in the 12 regions (see figure 6.2). These productivity losses are widely heterogenous, both between sectors and regions. 'Rest of Asia' and 'India' are the most exposed regions: labour productivity in high intensity sectors is reduced by more than 10% even in the low emissions scenario. Medium work intensity sectors experience declines in labour productivity larger than 5% in half of the regions in the high emissions scenario. Latin America, Africa, East Asia and the Middle East are mildly exposed to heat stress. In contrast, Canada, Europe and Former Soviet Union do not incur any losses in labour productivity, while the US only does so at the end of the century in high work intensity sectors under the high emissions scenario. The service and air transport sectors are only affected in the most exposed regions.

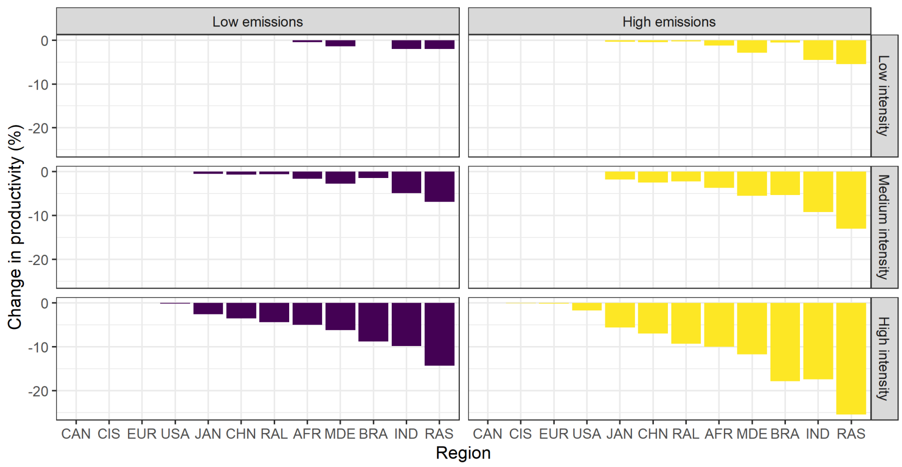

Figure 6.2 – Loss of labour productivity in 2100 due to climate change, for high, medium, and low intensity work.

6.3.2 Global and regional loss

Losses in labour productivity induce significant damages after 2050 in both scenarios: global GDP is more than 1% lower than in the case where we do not account for climate change impacts. Economic damages are similar in both scenarios until 2045 as a result of comparable global temperature changes.

After that year however, temperatures in the high emission scenario rise at a faster rate than in the low emission scenario, thus creating a widening gap in world GDP losses. In 2100, global surface temperatures have increased by 2.1°C compared to 2000 in the low emission scenario, producing losses equal to 2% of global GDP compared to a the case where there is no impact from climate change. In the high emission scenario, economic damages total 4% of world GDP, for a global temperature rise of 3.6°C. These losses are on the higher end of those found in Orlov et al. (2020); Takakura et al. (2017). Both studies find global losses around 0.5-1% for RCP 2.6 in 2100, while losses range from 1.5% to 4% in RCP 8.5. Greater losses are found in Takakura et al. (2017), probably attributed to larger estimated reductions in productivity based on ISO safety standards (Orlov et al., 2020). In our case, higher losses are probably related to the fact that labour is not substitutable, and to the second-best nature of labour markets.[2]

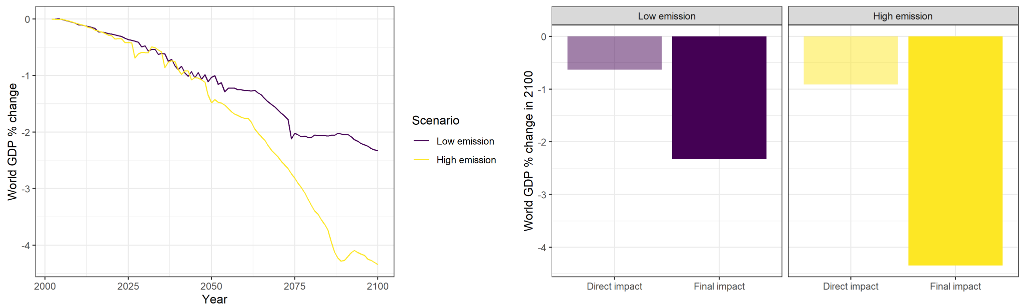

Figure 6.3 – World GDP loss, compared to the corresponding scenario without climate change impacts. Left figure depicts the evolution of World GDP loss. Right figure compares direct to final losses in 2100.

The economic cost of heat stress is significant and vary widely among regions (see figure 6.4). The 'Rest of Asia' (RAS) region loses 12.4% (6.2%) of its GDP in the high (low) emissions scenario as a result of heat impacts, while India's GDP losses are 7.9% (6.2%). Conversely, the cold regions which are not exposed to heat stress experience gains in terms of GDP. Canada's GDP rises by 2.9% in 2100 in the high emissions scenario.

We can compare the final losses of GDP to the 'direct impacts' estimated using a naive first-order approach (Roson and Sartori, 2016). The approach consists in monetizing the labour productivity loss at the corresponding wage level in the no-impact scenario. This direct loss gives an indication of the vul-

[2] A greater rigidity of labour market is explored in Appendix 6.C, and is found to increase the impacts.

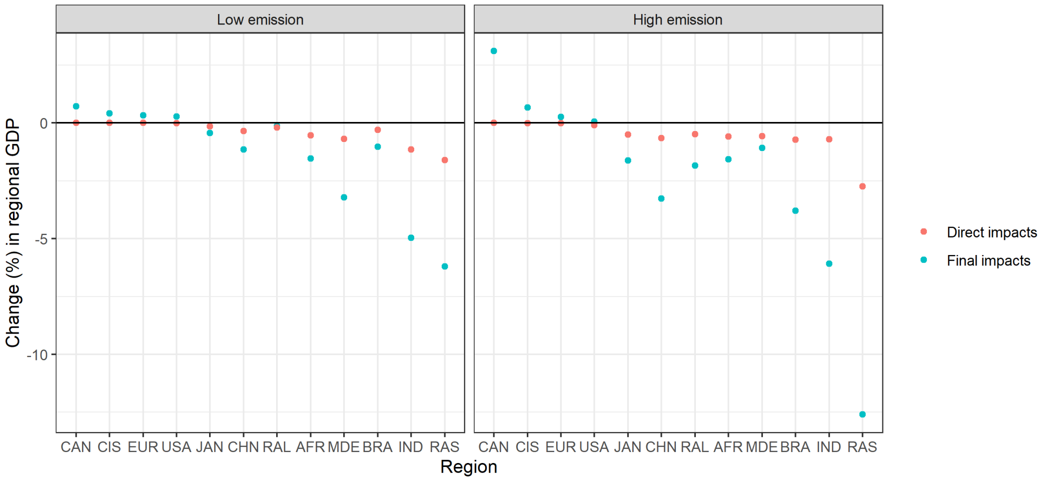

Figure 6.4 – This figures compares final impacts (i.e. change in regional GDP compared to a scenario with no climate change impacts) to direct impacts (i.e. estimated impact when valuing losses in productivity at the wage level in the no-impact scenario). A decomposition of final impacts by sector can be found in Appendix

nerability of the economies and their structure to the local impacts of climate change, before any sectoral and regional readjustment by production prices and quantities. For instance, regions where highly sensitive sectors (agriculture, construction) represent a larger share of the economy are inherently more vulnerable than others. Likewise, this index captures the importance of labour and wages in a given sector, by giving an indication of how much the sector would have to pay in extra wages to maintain production levels under decreased productivity, if prices were not allowed to change.

We find that direct impacts are poor predictors of final impacts, both at the global (see figure 6.3) and regional levels (see figure 6.4). At the regional level, indirect effects can either amplify or dampen direct impacts. In the impacted regions, direct impacts underestimate actual economic costs from climate change. The contrary occurs for regions which are not affected by heat stress. This shows the ambiguous role of trade and structural change in either dampening or amplifying the direct impacts of climate change. As a result, at the global level, losses are severely underestimated if we do not account for economic feedbacks.

Two factors play a role in the amplification of the damages: inter-regional and inter-sectoral effects. First, the decrease in productivity makes exposed regions less competitive in international markets. As a result, the volume of their exports decrease, and production is used for domestic consumption. Second, losses in different sectors induce price increases and wage reductions, which propagate and contribute to depress demand, notably in the most elastic sectors, such as service. The need to meet demand in inelastic sectors such as agriculture leads to reallocation of labour toward these sectors. Meanwhile, the contrary occurs in the least exposed regions. The increase in prices abroad allow them to capture a greater share of international demand, so they expand notably in agriculture and industry, and reduce the volume of imports.

Our results are qualitatively unaffected by several sensitivity analysis (graphs are shown in Appendix). We find that the magnitude of the results are affected by temperature response uncertainty, but the qualitative results are unchanged. Assuming a greater regionalization of trade has a surprisingly small effect on regional and global costs of climate change. Finally, increases in labour market rigidity tend to moderately increase the cost of impacts.

6.3.3 Comparison to the literature

Our results suggest that important indirect effects via demand and trade contribute to explain the heterogeneity in the final impacts. We find global losses on the high end of those reported in similar studies which account for reductions in labour productivity in a general equilibrium model, but most importantly the distribution of final impacts differs significantly (Orlov et al., 2020; Takakura et al., 2017; Knittel et al., 2020). More specifically, in our case, unaffected regions benefit from losses that occur in the most impacted regions. Though the least impacted regions face higher importing price, this cost is outweighed by the benefits of their improved competitiveness on international markets. This result also contrasts with other studies, which suggest that the least affected regions are vulnerable to the impacts occurring abroad (Schenker, 2013; Constant and Davin, 2019), though they do not account for heterogeneity in impacts across sectors, which can complexify the change in comparative advantage as a result of climate change impacts. This calls for more research to identify the conditions under which trade and spillovers allow to smooth heterogeneous impacts, as in the cited studies, or exacerbate inequalities in impacts as in our case.

The computational cost of our model prevents us to apply a decomposition method to better track the spillovers across regions, as in Schenker (2013). Indeed, this requires generating all the combinations in which only some regions are affected. However, as a next step, we could test for scenarios in which only specific regions or sectors are affected by climate change, as in Snyder et al.

(2020), to better understand when impacts abroad result in gains or losses for the unaffected region.

6.3.4 Limitations

There are several limitations to this study. The first strand of limitations comes from the way we estimate labour productivity reductions. The estimates from Roson and Sartori (2016) that we use have several weaknesses. For instance, they only consider monthly average temperatures, which do not capture losses in labour productivity coming from temperature variations at a smaller temporal scale. Besides, we do not look at planned adaptation mechanisms such as the use of air conditioning or increased mechanisation in exposed sectors, although they would most likely reduce the impacts. Though these constitute valid concerns about the productivity loss estimates, our primary interest was to highlight the propagation of impacts in a globalized economy.

Second, in our economic model, it must be noted that labour and intermediate consumption goods are not substitutable: they are used in fixed proportions as inputs to produce a given amount of output in each sector. This contrasts with other CGE models where inputs can be substituted for one another in the production process according to their relative prices, and thus limit the possibility to adjust inputs in response to decrease in labour productivity. Labour is also assumed to be non-mobile across regions, although it is expected that climate change will induce some migration towards less exposed regions (McLeman, 2019). Heat stress could have dramatic effects on migration flows between hot, populated regions such as South and Southeast Asia and colder, richer regions, with serious implications for labour markets. We leave this question for future research.

6.4 Conclusion and future perspective

In this article, we explore how the unequal distribution of direct impacts from climate change leads to differences in final economic impacts in the case of heat stress on labour productivity. This study is primarily motivated by the lack of clear answers in the literature about the contribution of indirect inter-sectoral and inter-regional effects to the cost of climate change impacts.

We explore the economic impacts of heat stress through its effect on labour productivity using an Integrated Assessment Model, which allows depicting different possible evolutions for socio-technical systems when market imperfections are accounted for. We find that global economic losses amounting to 2% under the low emissions and 4% under high emissions, for global temperature increases of respectively 2°C and 4°C since pre-industrial times. Regional-level losses display strong heterogeneity. India and the 'Rest of Asia' region incur GDP losses exceeding 5% in 2100 under low emissions, and greater than 12% for a high emissions trajectory, while some cold regions experience net GDP gains through international trade effects. The distribution of climate damages thus increases regional inequalities.

In particular, we compare these losses to the direct economic losses, based on exposure to heat stress and structural vulnerability, absent inter-sectoral and inter-temporal effects. Final economic impacts can be far off from such first order approximations, highlighting the key role of adjustment in prices and structural change. We show that direct impacts underestimate the losses in the most exposed regions. Conversely, regions that are unaffected by direct impacts exhibit gains.

This suggests that sector or region-specific studies on the impacts of climate change are likely to misrepresent the magnitude of the impacts. Thus, a deeper understanding of the conditions under which inter-regional and inter-sectoral spillovers propagate and amplify direct physical impacts in globalized economies is an important area for future research.

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6.A Central case: additional graphs

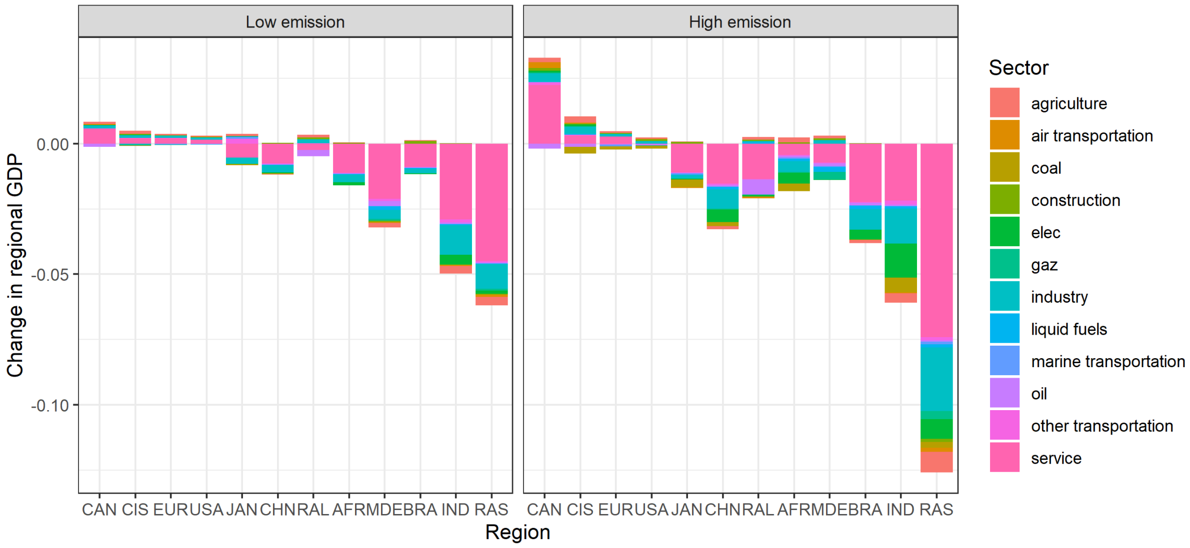


Figure 6.5 – Sectoral decomposition of final regional impacts, in 2100, in the central case.

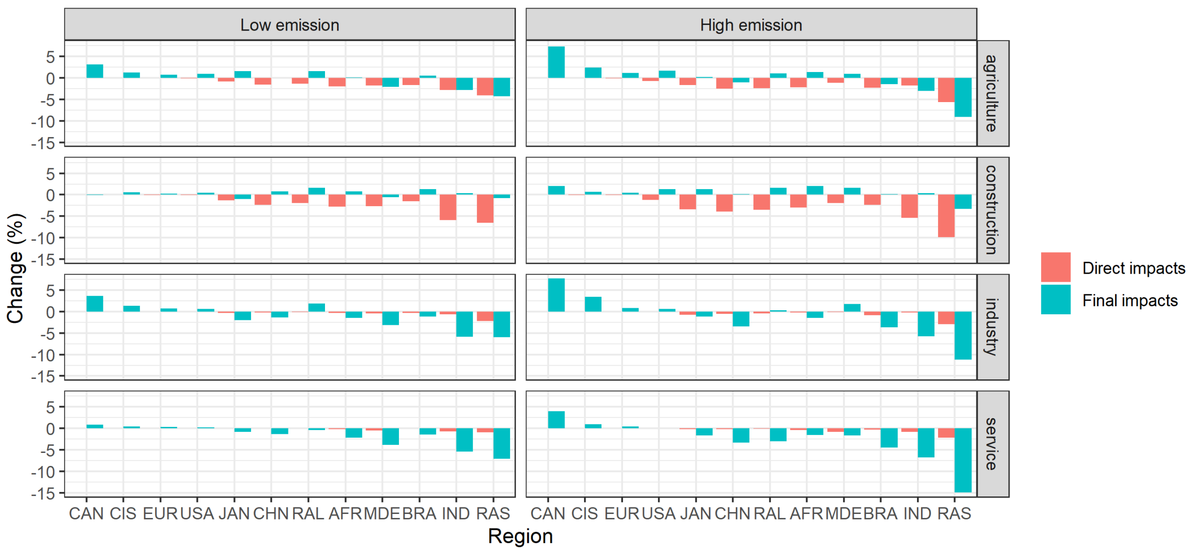


Figure 6.6 – Direct and final economic impacts, estimated as the change of sectoral GDP compared to a no-impact scenario, for construction, agriculture, industry and service, in the central case.

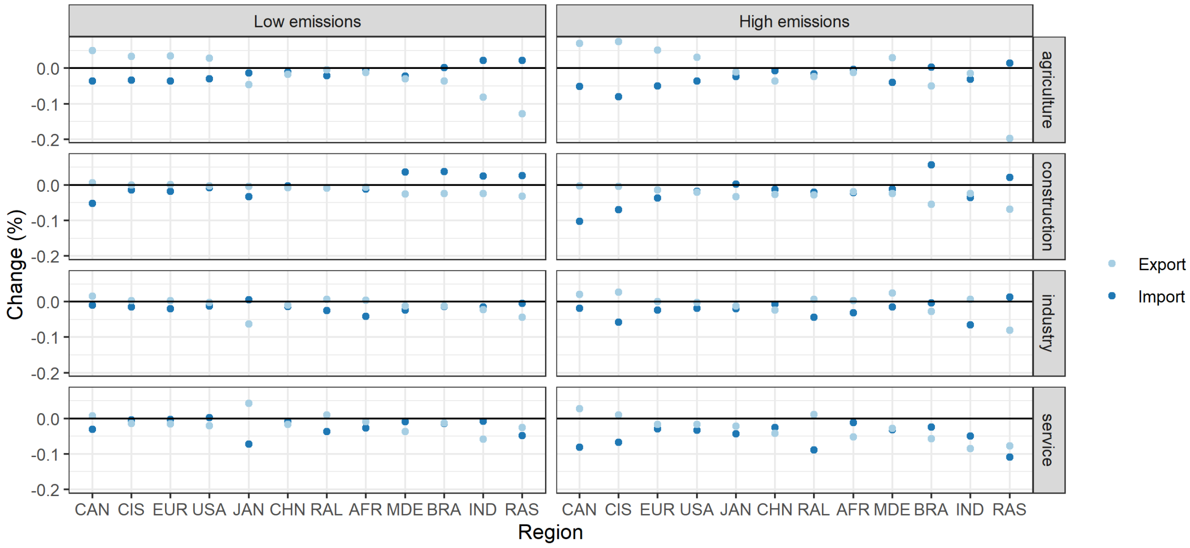


Figure 6.7 – Change in import and export volumes compared to a no-impact scenario.

6.B Climate uncertainty

Given that estimates found from (Leduc et al., 2016) are based on an ensemble of twelve Earth system models, uncertainty can be accounted for in our analysis by using the range of likely values (1 standard deviation from the mean) for climate sensitivity parameters. This reflects inter-model uncertainty regarding the sensitivity of carbon and climate processes to a given amount of cumulated emissions. Uncertainty in climate response does not alter the qualitative results.

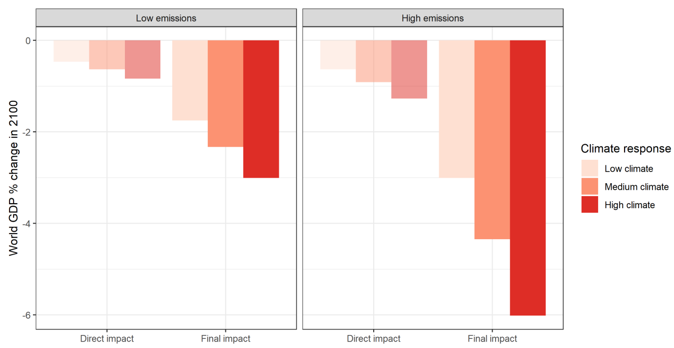


Figure 6.8 – Climate uncertainty. Global final economic loss (change compared to a no-impact scenario) in 2100.

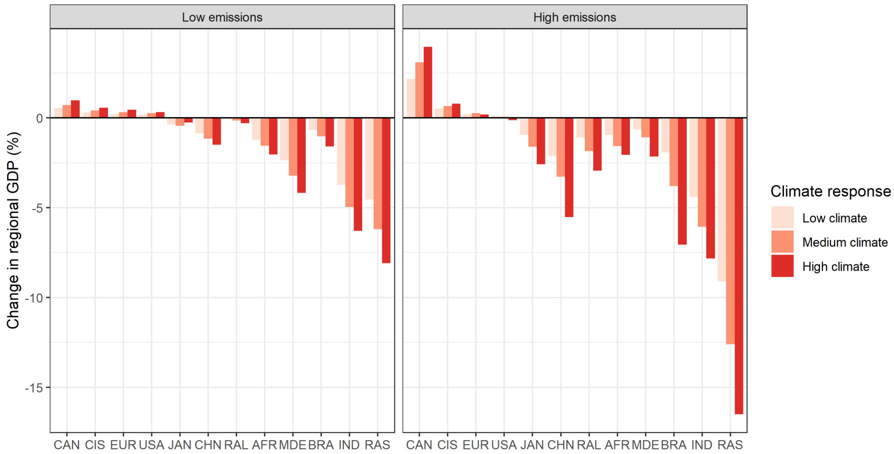


Figure 6.9 – Climate uncertainty. Final economic loss in 2100 by region

6.C Sensitivity to trade

We perform a sensitivity analysis to trade. We assume a lower substituability between domestic and foreign goods, together with a lower sensitivity to world prices (Armington elasticity) to reflect a world with greater regionalization of trade. Surprisingly, results show very little variation to such change.

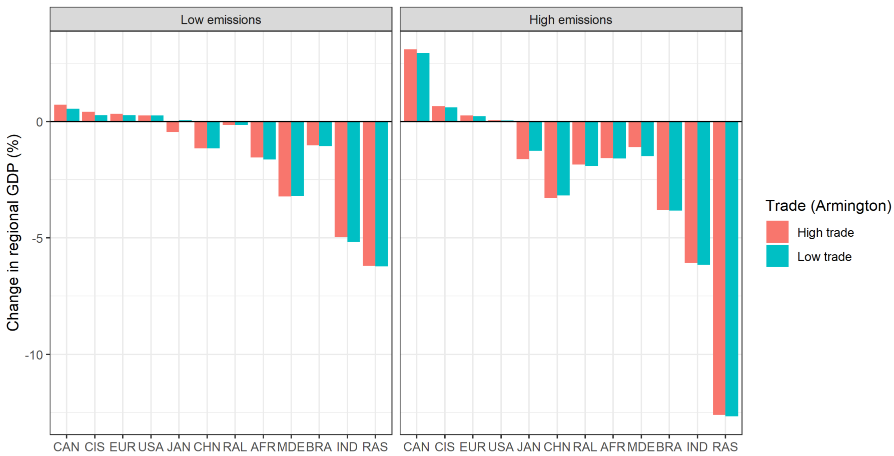


Figure 6.10 – Sensitivity to trade assumptions.

6.D Sensitivity to labour market rigidity

We perform a sensitivity analysis to the strength of labour market rigidity. Figures 6.11 and 6.12 show global and regional loss in the case of a reduced wage curve elasticity, which further prevents wages to adjust in response to decreased productivity. Going from an absolute value of the wage curve elasticity of 1, in our central case, to 0.55, to reflect higher labour market rigidity, increases the cost of climate change-induced reduction in labour productivity.

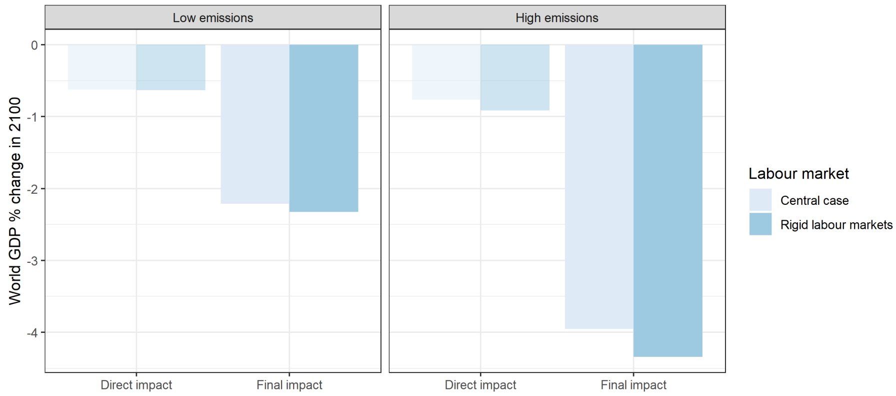


Figure 6.11 – Sensitivity to labour market rigidities. Final global economic loss (change compared to a no-impact scenario) in 2100.

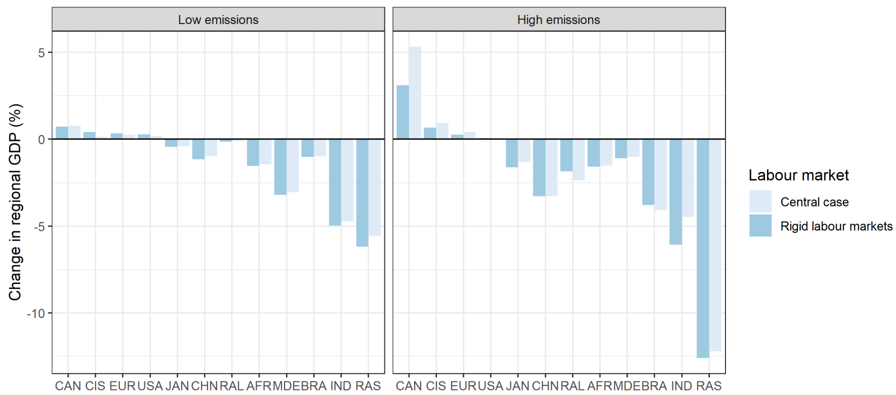
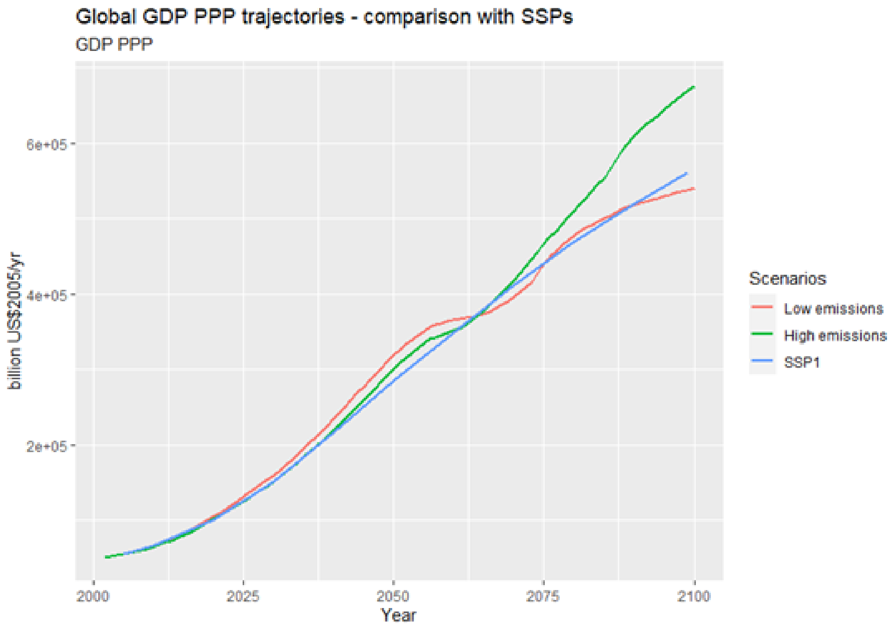


Figure 6.12 – Sensitivity to labour market rigidities. Final regional economic loss (compared to a no-impact scenario) in 2100.

6.E Comparison of our scenarios with the SSPs



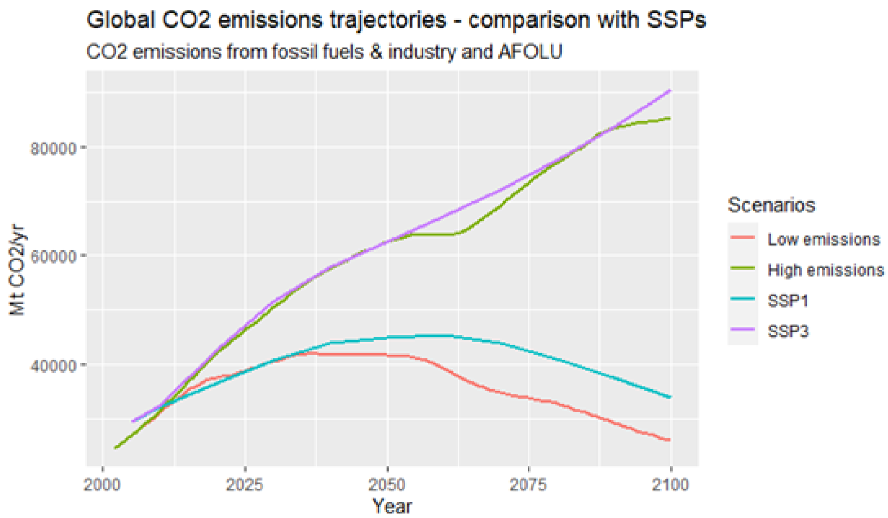


Figure 6.13 – Our two scenarios follow natural growth trajectory from SSP 1, but the other socioeconomic assumptions are based on SSP 1 for the low emissions scenario and on SSP 3 for the high emissions scenario.

Chapter 7

General conclusion

Being able to evaluate the overall economic impacts from climate change is key to assess the benefits of mitigation. Whether it is for assessing the benefits of avoided emissions of policies or projects at a local level, the benefits of containing global climate change below a certain level, or the benefits of alternative mitigation pathways.

However, the diversity of climate change impacts and the many ways in which they affect the economy makes it difficult to propose high-level indicators for the economic impacts of climate change. This has led economists to rely on simplified representation of damages when comparing the costs and benefits of different mitigation pathways. The most widely used representation depicts the damage from climate change as losses of output, increasing with global temperature warming. This representation is however insufficient to capture the risk, temporal dynamics and distributional effects that are key to assess the benefits of mitigation. Aggregating these dimensions can lead to biased evaluation of the present value of mitigation, and misleading assessments of avoided impacts in different mitigation pathways.

In particular, in the first two chapters of this thesis, I explore how better accounting for the dynamics of damages can shed light on the welfare-maximizing mitigation strategies. First, thinking of damages as gradually increasing with temperature is at odds with the fact that the climate system and our ability to manage the impacts can exhibit non-linear dynamics. Explicitly modelling damage risk, and disentangling it from expected damages, reveals that in some circumstances judging climate damage purely based on their expected damage leads to drastically underestimate the Social Cost of Carbon, and thus the value of lower emission pathways as a hedge against abrupt thresholds.

While the temporal dynamics of damages plays a key role in assessing the damages along a given emission pathway, the effect of the speed of warming as a source of ecological and economic cost is still missing from simplified representation of damages. The dynamics of change is important to evaluate the ability of socio-ecological systems to cope with never-seen changes. Conceptually, it departs from the view that climate change is simply a stock externality, whose damage accumulate, and places greater emphasis on how fast the stock increases. This bears critical implications for the way we formulate climate targets, because it means that both the ultimate temperature target and the rate at which we reach it matter.

In the second part of the thesis, I show that too high-level representation of damages as a global cost obscures the intricate links between climate change and intragenerational inequality. Both mitigation and climate change damages have potential inequality-inducing effects, which need to be accounted for to assess the fairness of different emission pathways and mitigation strategies. However, this aspect is insufficiently explored in cost-benefit Models whose focus has been on the intergenerational dimension of climate change. When we factor in the economic impacts of climate change on future growth projections at the country level, the prospect for the catch-up of poor countries is affected. However, such exercise also reveals a wide gap across existing estimates of damages at the regional and country-level: this stresses the need to further refine existing methods to capture climate change damages at a finer level, either at the country or even at the household level. The distribution of future damages is however difficult to assess in globalized and deeply interconnected economies, in which direct impacts can spillover through trade. The preliminary results on the impacts of heat stress suggest that economic spillovers may exacerbate the unequal distribution of losses.

In an attempt to provide insights on specific aspects of the evaluation of climate change impacts, the thesis also has also opened a lot of research avenues. Both the influence of warming rates and that of catastrophic tipping point raise important questions for the assessment of mitigation pathways with an overshoot, which would involve negative emissions. Such pathways have recently received a lot of attention, and have been questioned notably for their cost-effectiveness and feasibility (Minx et al., 2018; Fuss et al., 2014). My work leads me to think that it is unlikely that they pass the cost-benefit test. Indeed, these types of emissions pathways are associated with rapid increases of temperatures, and a temporary overshoot of the target. If we think of damage as a stock issue, it makes sense to try to limit the final temperature. But this strategy can be associated with high costs if the speed of change matters, or some irreversibilities are locked in while overshooting the target.

Climate change damages will always be contested, and the way we can quantify or represent them will always appear crude compared to the complexity of the issue. This has led some to suggest that we should give up on cost-benefit analysis of different emission pathways, and instead focus on cost-effective strategies to reduce emissions (Kaufman et al., 2020). However, even under a cost-efficiency approach, where the objective is to find the way reach neutrality at a given point in time, climate change will affect the economy, and this can also alter the least-cost path. Climate change impacts can affect mitigation options, for instance by reducing yields for bioenergy, constraining hydropower resources, or because of the timing of public spending on mitigation and adaptation. While throughout my thesis I try to analyse the joint effect of mitigation and impacts on the economy, I do not look at the interaction between the two. I plan to study the vulnerabilities of low carbon strategies to climate change impacts. As a first step, I will explore such vulnerabilities at the national level.

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