The impact of climate risk valuation on the regional mitigation strategies

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Highlights:

- **This paper discusses the impact of climate change attitudes on optimal mitigation in 15 regions.**
- **The results show that the optimal mitigation in developing countries is more sensitive to climate change attitudes than it is in developed countries.**
- **The average social carbon cost in developing countries is 20 times higher than that in developed countries.**

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Abstract:

Different assumptions and methodologies prompt divergent policy implications towards climate change. Although climate scientists would like to be as precise as possible, policymakers with different attitudes towards climate change will always choose the result that matches their own value judgment. This paper discusses the impact of climate change attitudes on optimal mitigation in 15 regions. The climate change attitude is reflected by a meta-analysis of 27 climate damage estimations and fit into five damage functions. The optimal mitigation is calculated using the non-cooperative scenario of the regional integrated model of climate economy (RICE). The results show that the optimal mitigation in developing countries is more sensitive to climate change attitudes than it is in developed countries. In 2100, the range of optimal emissions divides the average of optimal emissions by 20% in developing countries, which is twice the value of that in developed countries. The average social carbon cost in developing countries is 20 times higher than that in developed countries. This large uncertainty may be the combined result of high shadow prices of capital and large amounts of future emissions in these developing countries.

Key Word: Climate change; Climate damage; Impact assessment; Political attitudes; IAMs;

1. Introduction:

Cost-benefit integrated assessment models (IAMs) balance the marginal mitigation cost with the marginal mitigation benefits (i.e., the amount of climate damage that is avoided); therefore, IAMs inform us how the benefits of mitigation stack up against costs. The most important result is the estimation of the social cost of carbon (SCC), which denotes the dollar value of the reduced climate change damage associated with an additional ton of CO_2 emissions. The value has been set as the basis for an optimal carbon tax and plays a critical role in regulatory implementation and public debate

(Weyant, 2017). The United States has estimated the SCC as part of rulemaking cost-benefit analysis; since 2010, the policy benefit has been estimated at more than $1 trillion. In recent years, the value is increasingly adopted in state-level regulations (Larson, 2016; Schlatter, 2016; State of California, 2016).

However, the concept has been largely criticized for its uncertainty. The SCC estimation is sensitive to alternative socioeconomic paths (i.e., economic growth, demographic factors, mitigation and adaptation challenges such as marginal abatement costs) and the social discount rates (Yang et al., 2018). But among years of discussion, the SCC sensitivity to climate damage is always central (Pindyck, 2013). First, the impact of climate change is wide-ranging and hard to monetize (Hong et al., 2019; O'Neill et al., 2017). The fundamental productive elements are often found to be sensitive to climate change (Schlenker and Roberts, 2009), while the aggregate macroeconomic productivity may have little effect on temperature (Dell et al., 2012). The conflict between the macro- and micro-observations may make the research scope of climate impact estimation even more critical in relation to the estimated result (Yokohata et al., 2019). Similar inconsistency can also be found in estimation for marginal abatement cost, which is also critical for SCC estimates (An et al., 2021). Monetizing the climate change impact is also challenging. Several methodological approaches have been used to monetize climate change impact (Chegwidden et al., 2019; Tol, 2009). The various methods use natural science models and sum the physical effects of climate change (Tol, 2002). The result is scientifically reliable but cannot fully be extrapolated to the future. Statistical methods use the economic model and result in the welfare impacts of climate change across time and space (Burke et al., 2015; Camus et al., 2017; Dale et al., 2017). However, statistical methods cannot fully differentiate the impact of climate change from that of other factors, and the bias among studies will produce a larger range of uncertainty. Second, climate change is a complex issue with a temporal dynamic over a long-term time horizon. The heterogeneous nature of climate impacts across regions and generations has resulted in different projections of future climate change. The economist focusing on the policy implications of climate change emphasizes the trade-off between the climate and economic system and prefers to smooth the relationship between the economic and climate variables (Nordhaus, 2019; Nordhaus and Boyer, 2000). In contrast, the climate scientist often focuses on the nonlinear character of the earth system and suggests that several elements of the climate system could be tipped into a different state by global warming (Alley et al., 2003).

Given the wide range of estimations over climate damage, politician's attitudes towards climate change have become even more important (Kousser and Tranter, 2018). Many have been focused on the role of policy actors in determining the political capacity to respond to climate change (Dunlap, 2014; Parker et al., 2015). The literature is further enriched after Trump withdraws from Paris Agreement (Panno et al., 2019) and the Yellow Vests crisis (Douenne, T., & Fabre, 2020). Factors such as values, ideologies, and worldviews can shape people's climate beliefs, but the belief is not necessarily turning into actions (Hornsey et al., 2016). When making policy decisions, respondents' position in the policy process and the identified geographical scale of focus (tendency to think locally) dominant politician's attitudes towards climate change (Stedman, 2004). The difference in attitudes can be reflected in the climate damage projections. For example, a proactive climate policymaker might suggest an exponential damage function that indicates colossal damage in the long term, while a prudent policymaker might choose a linear function that indicates the steady growth of climate damage in the future.

Studies have discussed the optimal mitigation under damage risk valuation from various approaches, given the large inconsistencies in climate change assumptions and value judgments. Some studies discuss the uncertainty by changing the parameters (Anthoff et al., 2009) or the form of damage functions (Bretschger and Pattakou, 2019; Wouter Botzen and van den Bergh, 2012). Some studies introduce a more complex damage mechanism to discuss this uncertainty; for example, the original damage on net output can be extended to capital stock (Dietz et al., 2016), and the objective of maximizing the total welfare can be changed to maximizing the average utilitarianism (Scovronick et al., 2017). Probabilistic and stochastic versions of IAMs have also been developed and used to discuss the uncertainty related to damage (Lontzek et al., 2015; Tol, 2005). Most discussions are structurally based on the dynamic integrated climate-economy model (DICE), which is an archetypical cost-benefit IAM employed to assess the social cost of carbon for the US government. Keller et al. (2004) explored the combined effects of a climate threshold and parameter uncertainty; Crost and Traeger (2014) discussed the uncertainty by treating the damage parameters as stochastic; and Cai et al. (2016) incorporated tipping points into a stochastic dynamic IAM. However, the DICE model can only provide global optimization without national comparison. Ortiz et al. (2010) built a regional DICE model and used a Monte Carlo simulation of the key parameter to address the uncertainty in regions. Under the complex structure of IAM, they considered only the optimal policy scenario, which assumed the full participation of all regions in terms of combating climate change.

How much will climate risk valuation and attitudes affect future climate change? Will the effect be different among countries? This paper uses alternative damage functions to present different political attitudes while using the social carbon cost to reflect the impacts. Climate damage uncertainty is addressed by meta-analysis. We integrate the national damage estimations of 27 studies and fitting the results into five forms of damage functions. Different forms of damage functions are used to present the selection bias of the policymakers. To reflect the regional characteristics, we use the regional integrated model of climate economy (RICE) and divide the world into 15 regions (Table 1). Estimations were conducted under non-cooperative hypothesis, where each nation optimizes its national emissions by maximizing its national welfare. The optimal emission trajectory, SCC, and temperature increase are estimated under five types of damage functions, while comparisons are made between developed and developing countries.

Table 1 Abbreviation table

Abbreviation	Full name
ASIA	Asia countries
BASIC group	Brazil, South Africa, India, China
CGE	the Computable General Equilibrium model
DICE	The Dynamic Integrated Climate-Economy model
IAM	Integrated Assessment Model
LAM	Latin America and the Caribbean countries
MAF	the Middle East and African countries
NDC	National Determined Contribution
OAB	Other Annex B countries
OEU	Other European countries
REF	the Reforming Economies of the Former Soviet Union
RICE	Regional Integrated model of Climate and the Economy
SCC	Social cost of carbon
SSP	Shared socioeconomic pathway

2. Methods

The climate damage equation is constructed using the proper function form and parameters. The form of the function indicates the long-term expectation of climate change damage, while the parameters are fitted by creditable climate damage data. With limited knowledge on the nature of climate change, it is hard to predict the future physical process along with the economic impacts. Currently, there is no certain form of damage function being used in the literature. Moreover, while the impact of climate change is wide-ranging, from economic production to the things people value, the damage data cannot be observed directly. Most of the climate damage data are being estimated by experts, and the boundary of climate change damage and the methodology being used for estimation will both be affected by the results of these estimations. However, the boundary and methodology used to estimate climate change damage do not have a consensus. Therefore, we used the meta-analysis on national climate damage from 27 studies, and the data were aggregated into 15 regions in the RICE model and fit the data with five forms of damage functions to consider the different expectations of climate damage.

2.1 The regional integrated model of climate and the economy

RICE couples an economic model with a simple climate model to internalize the externality of climate change (Nordhaus and Yang, 1996). As an extension of DICE (Nordhaus, 2018), RICE provides optimal mitigation strategies at the national/regional levels. Considering the current bottom-up structure of the Paris Agreement, where nations committed to nationally determined contributions (NDCs) by maximizing national interests, the national optimal mitigation trajectory provided by the RICE model will be more suitable under the current situation (MacCracken, 2016).

The model we used was based on the latest version of the RICE model (Nordhaus, 2010), and changes were made in three parts, namely the climate module, regional definition, and damage function. First, we updated the climate module to incorporate the latest research on the carbon cycle (Archer et al., 2009; Nordhaus, 2017). Second, we extended the model to 15 regions by the international climate regime to provide a better understanding under the Paris Agreement. The European Union is featured as a pioneer in climate change with stringent mitigation policy. The United States, Russia, Japan, Canada, and other Annex-B (OAB) countries who participated in the Kyoto Protocol, also named the umbrella group, are laggards in terms of climate actions. These are mostly developed countries that want to keep their voice in international negotiation but who do not have much desire to invest in their future. The BASIC group (i.e., China, India, Brazil, and South Africa) represents countries with emerging power in climate negotiations. Economic development is booming in these countries, but the energy demand is also increasing. Other regions were categorized geographically following the IPCC Regional definition. The full list of countries included is shown in the Supplementary Information. By analyzing the climate risks of different parties and estimating the SCC in each region, the results may provide guidance for national climate action and the evaluation of national policies. Finally, the damage functions are discussed with alternative forms and parameters.

SCC and optimal emissions are calculated under the non-cooperation scenario, where nations optimize their emissions by maximizing their national welfare. The nation's mitigation policy reaches a Nash equilibrium, i.e., when given another nation's information, no country will gain benefits by changing its own strategy.

2.2 Meta-analysis of damage risk valuation and expectation

2.2.1 Meta-analysis of risk evaluation

Several methodological approaches have been used in estimating the economic damage caused by climate change. The estimation of early climate damage can be done by interviewing experts (Nordhaus, 1994). Then, enumerative methods that monetize the "physical effects" of climate change based on natural science experiments can be used (Fankhauser, 2013; Griscom et al., 2017; Tol, 2002). The results of the latter methods were more physically realistic but had limited extrapolation capabilities. The statistical methods assume that the observed variation of economic activity with climate over space holds over time as well and provides an estimation of production loss for a range of temperatures (Burke et al., 2015; Mendelsohn et al., 2000). Other studies have used the computable general equilibrium (CGE) to estimate economic damage while considering the market reaction to climate change (Moore et al., 2017). As both methods have advantages and disadvantages, Tol (2018) conducted a meta-analysis of 27 published estimates contained in 22 studies. We aggregated the national data into 15 regions, and the results are shown below in Figure 1.

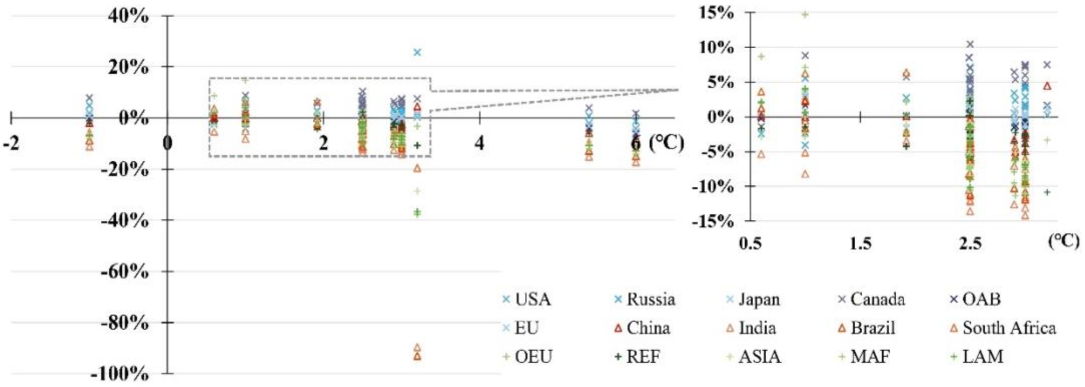

Figure 1 Meta-analysis of 27 climate damage estimations for 15 regions, damage valued by welfare equivalent income change (%) to temperature increase compared to the pre-industrial level. OAB: Other Annex B countries; MAF: Middle

East and Africa; LAM: Latin America and the Caribbean; OEU: Other European countries; REF: Reforming Economies of Eastern Europe and the Former Soviet Union

2.2.2 Meta-analysis of risk expectation

Experiments related to climate change also varied. Some extended the trend of current climate damage, assuming a quadratic or polynomial relationship between temperature and climate damage (Burke et al., 2015; Hope, 2013). Other studies assumed "tipping points" for harboring large-scale discontinuities, where a small change in a driver resulted in an irreversible change (Cai et al., 2016; Kriegler et al., 2009; Lontzek et al., 2015). We tried to include most of the functions in the model; however, the optimization structure of the RICE model has narrowed the possibility to only a few of the functions. Therefore, we excluded some of the forms that may result in an infeasible solution, only considering the following five forms of damage functions (Table 2).

Table 2 Forms of damage functions

No.	Damage function	Author	Characteristics
(1)	$(a*T)\ I_{T<TR} + (b*T)\ I_{T\geq TR}$ TR: temperature threshold	Meta-analysis (Tol, 2018)[5555]	Based on 27 published estimates
(2)	$a*T + b*T^2$	Tol [6]	Damage function from the framework for uncertainty, negotiation and distribution model (FUND). The model is one of the three models used to provide SCC for the US Government.
(3)	$a*T$	Hope [7]	Damage function from the policy analysis of the greenhouse effect model (PAGE). The model is one of the three models used to provide SCC for the US Government.
(4)	$a*T^2$	Nordhaus [8]	Damage function from the dynamic integrated climate-economy model (DICE). The model is one of the three models used to provide SCC for the US Government.

(5)	a*exp(T) +b	Karp [9]; van der Ploeg and de Zeeuw [10]	The climate damage is expected to increase exponentially. Like the tipping point assumption, the damage will increase dramatically after the threshold is reached.

3. Results

3.1 Meta damage function of 15 regions

Using the meta-analyzed damage data, we fit the climate damage parameters for the 15 regions. Five forms of damage functions for 15 regions are shown in Figure 2. With a small increment of temperature, the projected welfare change is largely reflecting the damage estimation. When the temperature rises up to 4°C, the projection will be determined by the form of damage functions.

Results show that the net impact of climate change at the earlier stage of global warming is estimated as a welfare loss for most countries, except for Russia, Canada, the USA, and the EU. According to the data included in our meta-analysis, the Arctic region will experience extremely cold weather, and climate change may introduce more favorable conditions to these countries. However, when the average surface temperature increases, the positive effect may become negative. It is unclear whether climate change will lead to a net welfare gain or loss for Canada and Russia. Based on the meta-analysis functions, Nordhaus and Hope predict the future climate impact by extending the current trend, and Russia and Canada will continue benefiting from the temperature increase.

In contrast, according to the function used by Tol and Karp, the negative climate impact in Russia and Canada will exceed the positive impact, and the net impact will reverse in these two countries near the threshold of 5°C. With increasing research into the Arctic region, many studies have found negative effects of climate change on the Arctic countries (Stephen, 2018). The melting permafrost, the release of diseases trapped in the permafrost, and the loss of ecosystem service will also cause irreversible damage to humans, yet have not been included in our studies (O'Garra, 2017; Ranjan, 2014).

The damage estimation for developing countries is generally higher than for developed countries. With less capability to implement serious adaptation measures, developing countries may suffer more from climate change, while the climate impact further hinders the development of the economics. Geographically, many developing countries are situated in low latitude areas where concentrates 80% of the climate damage (Mendelsohn et al., 2006). The climate damage of developed countries is less than 15% of the total income, even when the average temperature increases to 7℃ above the pre-industrial level. Whereas for the developing countries, the income loss will account for 10-40% of the income. Under the damage function proposed by Nordhaus, India will suffer 51.2% of welfare equivalent income loss at a change of 7℃.

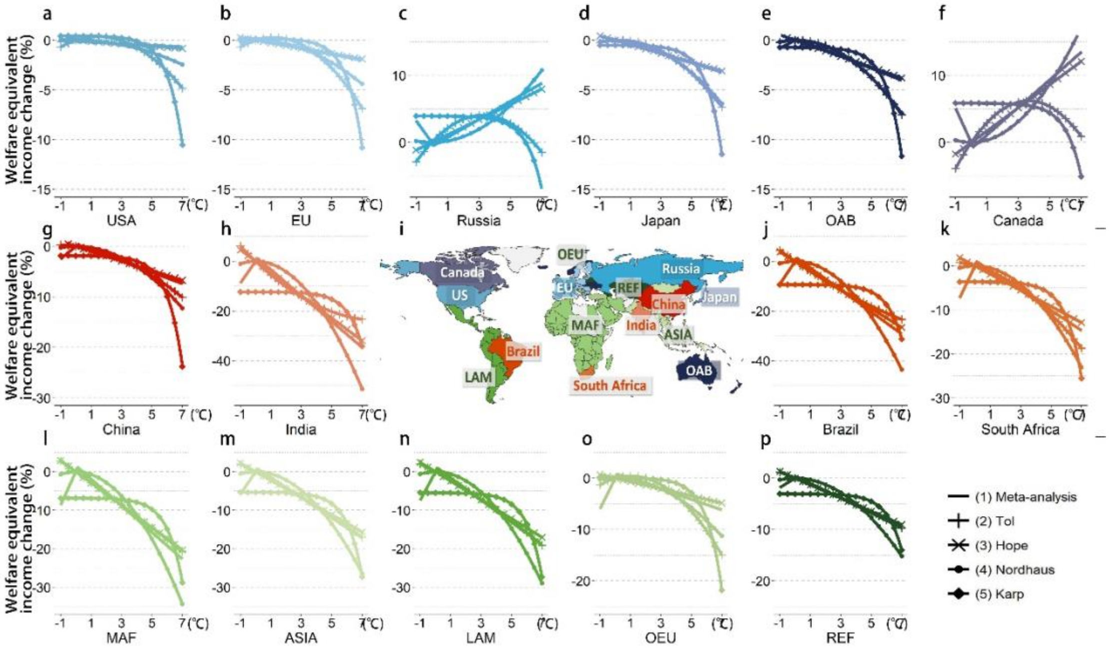

Figure 2 Welfare equivalent income change (%) under five damage functions. OAB: Other Annex B countries; MAF: Middle East and Africa; LAM: Latin America and the Caribbean; OEU: Other European countries; REF: Reforming Economies of Eastern Europe and the Former Soviet Union.

3.2 Optimal mitigation under damage risk and evaluation

The different expectations of climate change will not significantly alter the optimal emissions under the non-cooperation scenario; however, they will significantly change the SCC of each nation (Table 3). Under the non-cooperation scenario, the optimal emission in developing countries will be doubled or even tripled from 2020 to 2050, while emission in developed countries decreases gradually from 2020 to 2050. India's emission increases from 2.7 GtCO$_2$ to 6.2 GtCO$_2$ during this period, while China's emission increases to 21.1 GtCO$_2$ in 2050. The result provided considers the current trend of carbon intensity change, balancing the marginal mitigation cost with the future climate damage, but the result does not consider the political benefits or risk preferences in combating climate change. China is seeking its new identity as a responsible middle-income country and has made ambitious climate commitments. The reputation gain and intention to lower future climate change risks will significantly reduce the likelihood that China's emissions will reach 21.1 GtCO$_2$ in 2050. Countries that may not worsen off by climate change (e.g., Russia and Canada) will not spend additional budget in mitigation. However, with substantial improvement in energy efficiency and technological change, all countries may have a natural carbon intensity decline without policy. The intensity decline will still reduce the overall emission for the two countries.

The SCC, also known as the optimal carbon tax (Crost and Traeger, 2014), is greatly affected by the climate change attitude (i.e., assumptions and value judgment). The range of SCC values under different climate functions is even larger in developing countries. As the prediction goes beyond 2050, the variance is even higher. Comparatively, India and China have a higher SCC than the other countries, indicating more serious monetized climate damage for each additional ton of carbon emissions.

Table 3 Carbon tax and optimal emissions in major economics in 2020 and 2050.

	2020 Optimal Emission (GtCO$_2$)			**2050 Optimal Emission (GtCO$_2$)**			**2020 SCC ($/GtCO$_2$)**			**2050 SCC ($/GtCO$_2$)**		
	Average	Max	Min	Average	Max	Min	Average	Max	Min	Average	Max	Min
USA	5.3	5.4	5.1	4.2	4.4	3.9	3.8	10.3	0.5	6.6	19.5	0.6
EU	3.2	3.2	3.1	2.1	2.1	2.0	3.9	8.2	1.4	6.7	17.2	1.6
Russia	1.9	1.9	1.9	1.6	1.7	1.6	-0.4	1.3	-1.4	-0.1	3.2	-2.3
Japan	1.2	1.2	1.2	1.0	1.0	1.0	0.7	1.2	0.4	1.0	2.2	0.4
Canada	0.5	0.5	0.5	0.4	0.4	0.4	-0.5	0.8	-1.4	-0.4	1.6	-2.3

China	11.5	11.7	11.4	21.1	22.1	19.8	6.8	8.4	4.9	20.5	34.5	10.7
India	2.7	2.7	2.6	6.2	6.5	5.6	15.5	27.9	6.0	44.9	96.0	20.1
Brazil	0.6	0.6	0.6	1.0	1.0	1.0	3.8	6.1	1.8	5.8	10.4	3.4
South Africa	0.5	0.5	0.5	0.7	0.7	0.6	5.2	22.9	0.6	10.8	48.5	0.8

Different damage projections may change the optimal mitigation rate but will not significantly change the average surface temperature in 2100. The average surface temperature above the pre-industrial level at the end of this century will be approximately 4.3°C. Temperature increases the least under the exponential damage function proposed by Karp, with a value of 4.27 °C at the end of this century. The function including the quadratic term is relatively higher, and the temperatures under Nordhaus's and Tol's functions are 4.29°C and 4.33°C, respectively. The two linear functions both end with a 4.35°C temperature increase relative to the pre-industrial level, and this value was the highest compared with the other function forms. The main reason behind this result is climate lag, but the result might also be caused by the mechanism of optimization, as each nation considers only their national interest and minimizes the mitigation only to balance their national damage. Compared with the cooperative scenario, the original mitigation level under the non-cooperative scenario is relatively low; thus, the impact of damage functions will not significantly change the temperature in 2100.

3.2.1 Optimal mitigation in the Annex B countries

The differences in climate risk valuation and expectation have limited impacts on the optimal emission growth of the Annex-B countries, mainly because their climate impacts are relatively small, and the emission levels are comparatively low (Figure 3).

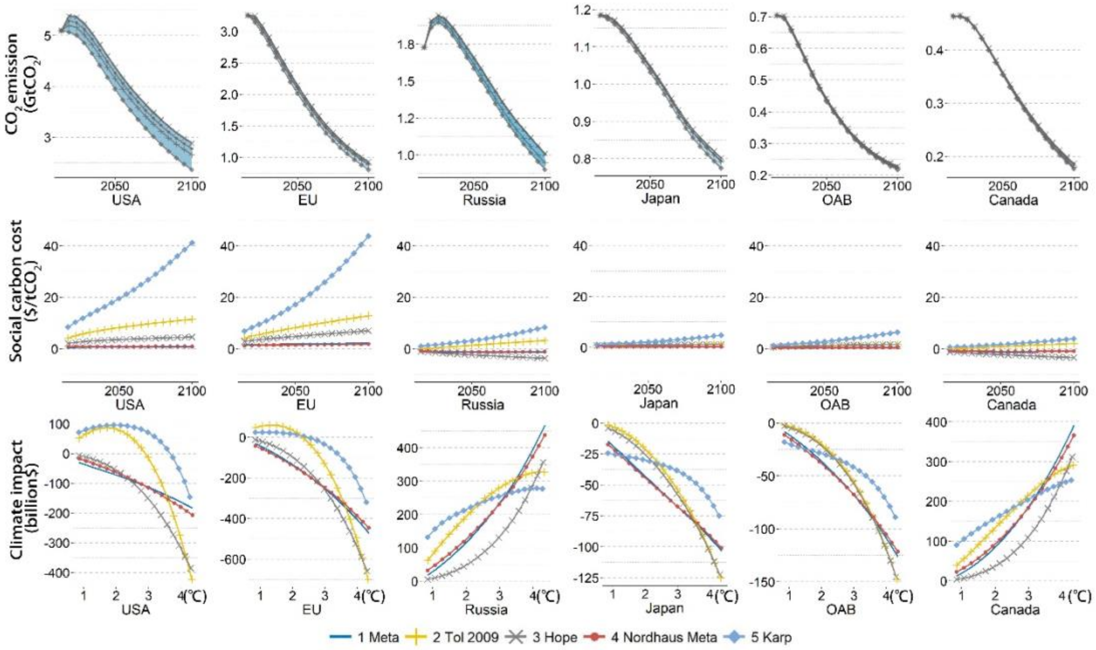

Figure 3 Optimal emission, social carbon cost, and climate impact in the Annex-B countries. OAB: Other Annex B countries.

The optimal carbon emissions in all Annex-B countries peaked around 2025 and then declined. Under different climate risk perceptions, countries should optimize their optimal emission reduction rates accordingly. As larger emitters will be more sensitive to emission reduction rates, the optimal emission of the USA has a wider range of uncertainty, with a range of 0.52 GtCO$_2$. The average range of the optimal emissions of Annex-B countries is 0.13 GtCO$_2$ in 2100. By dividing the uncertainty range by the average national emission, the USA ranked the highest, at 19.5%, while the average fluctuation rate of the Annex-B countries was equal to 9.9%.

The highest SCC of the Annex-B countries ranged from 4.0 $/tCO$_2$ (Canada) to 43.8 $/tCO$_2$ (EU) in 2100. Three function forms indicate an increasingly positive impact of climate change in Russia and Canada. As the temperature increase is within 5°C for all scenarios, the net climate impacts in these two countries remained positive, estimated at approximately $400 billion in 2100. However, the positive impacts do not indicate emissions should be increased in these countries. The emission reduction rate is decreased to zero in the two countries, indicating that the countries will not exert extra effort to reduce emissions. However, with technological innovation, the carbon intensity is assumed to decline naturally with economic growth. Therefore, the emissions in these countries will still decrease gradually over time. The climate impact in the USA is projected to be mostly positive within this century under the function proposed by Tol and Karp. However, as the impact quickly reverses after this period, the SCC in the USA is positive throughout the period. Although emissions might have some positive impacts in the near term, the USA is still considered to have reduced social welfare given the considerable damage that might be caused in the long term.

3.2.2 Optimal mitigation in the BASIC countries

The optimal mitigation in BASIC countries is more sensitive to climate change perception (Figure 4). Emissions in these countries were projected to have rapid growth with economic development. Given the geographical locations and economic situations, these countries all experience negative impacts of climate change, while the damage is even more serious than in developed countries. A large amount of emissions and a high level of climate damage make their optimal mitigation strategies more sensitive to climate change perception. Optimal emissions of China have the widest range of uncertainty of 4.90 $GtCO_2$. The average range of the optimal emissions of BASIC countries is 2.27 $GtCO_2$ in 2100. By dividing the uncertainty range by the average national emissions, India ranked the highest, at 53.2%, followed by China (34.7%). The average fluctuation rate of BASIC countries was 24.3%, which was twice the value of the Annex-B countries. Assumptions and value judgment towards climate change may have a higher impact on climate policies, which means the optimal national emissions determined by an idealistic policymaker may be much lower than those determined by a cynical policymaker. For a cynical policymaker to perceive low climate damage and expect linear growth of climate damage, the optimal emissions would be much higher than those determined by an idealistic policymaker, who perceives serious climate damage and expects exponential growth. If the actual climate damage is higher than the cynical policymaker has expected, the economic damage might be higher than the economic income produced by the emissions.

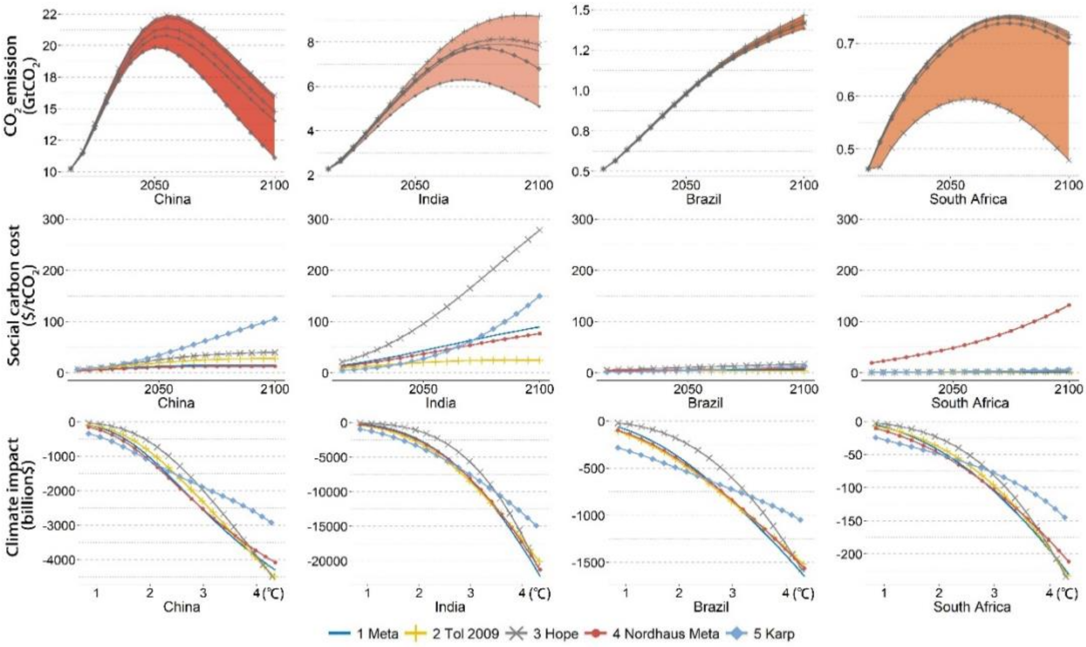

Figure 4 Optimal emission, social carbon cost, and climate impact in the BASIC countries.

The SCC values of the BASIC countries are much higher than those of the Annex-B countries, with the highest levels ranging from 17.4 \$/tCO$_2$ (Brazil) to 278.6 \$/tCO$_2$ (India) in 2100. The high level of monetized damage per additional emission can be explained from two aspects. First, according to the proposed damage functions, climate change has a greater effect on the percentage of economic outcomes (GDP) in these countries than in developed countries. Under Hope's damage function, the total damage is as high as 20% of the total GDP in India (\$22273 billion) and 17% of the GDP in Brazil (\$1651.44 billion) at the end of this century. On the other hand, the shadow prices of capital in these countries are also higher comparatively, which potentially make the cost of mitigation even higher. Therefore, even under such an extreme level of climate damage, emissions in these countries do not decline to zero.

3.2.3 Optimal mitigation for regions

The optimal emissions in the five regions are also sensitive to climate change perceptions (Figure 5). With high-speed economic development, emissions in MAF sharply increase throughout the century. The total emissions reach 13.8 GtCO$_2$ in 2100, which is nearly five times higher than in 2015. Climate change damage is estimated to be approximately 10% of the total GDP in MAF, ASIA, and LAM. The damage will also be incredibly serious, e.g., up to 20,237 billion$ in MAF at the end of this century, given the rapid economic development in these regions. Damage is considerably lower in the OEU and REF, estimated at approximately 5% of the total economic outcome. In 2100, the optimal emissions of MAF have the widest range of uncertainty, at 2.19 $GtCO_2$, and the average range of the optimal emissions of the five regions is 0.92 $GtCO_2$. By dividing the uncertainty range by the average national emissions, LAM ranked the highest, at 30%. The average fluctuation rate of the five regions is 16.6%, which is slightly lower than that of the BASIC countries but still higher than that of the Annex-B countries.

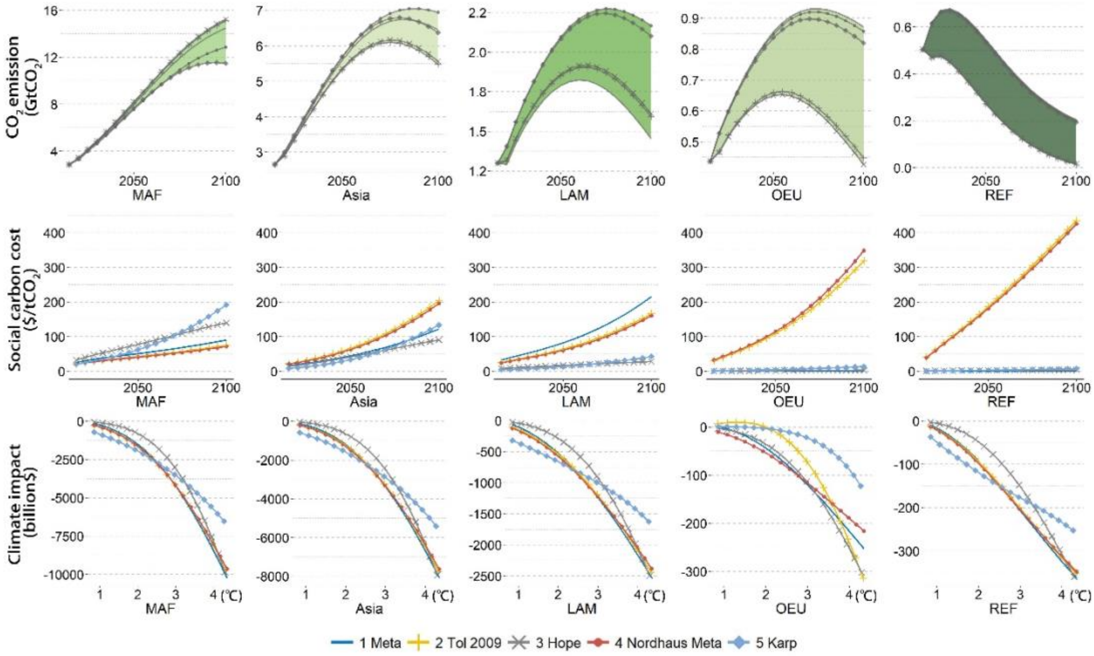

Figure 5 Optimal emission, social carbon cost, and climate impact in the five regions. MAF: Middle East and Africa; LAM: Latin America and the Caribbean; OEU: Other European countries; REF: Reforming Economies of Eastern Europe and the Former Soviet Union.

The highest SCC of the five regions ranged from 191.7 $/$tCO_2$ (MAF) to 435.4 $/$tCO_2$ (REF) in 2100. Although the climate damage in the OEU and the REF is low, their SCC values are the highest among all regions under the function with the quadratic term (Tol and Nordhaus). This high value may result from the increasing climate damage projected in the long term or from the high shadow price of consumption in the two countries.

4. Conclusion

How much will climate risk valuation and attitudes affect climate change policy? Will the effect be different among countries? This study answers these questions by analyzing the impact of climate change attitudes on a nation's optimal mitigation strategy through meta-analysis. We use 27 studies of climate damage estimation to present value judgments of climate damage, while five forms of damage functions are used to present the assumptions and future expectations of climate change. Under the non-cooperation scenario of the RICE model, each nation maximizes its national welfare and balances the marginal mitigation cost with the marginal mitigation benefit (the climate damage avoided).

The climate risk valuation and attitudes will affect both the optimal emission trajectory and the social carbon cost, while the impact is more significant in developing countries. For India, alternative climate change perspectives bring a 4 $GtCO_2$ range of optimal emissions, while the average emission estimation is 7.6 $GtCO_2$ in 2100. The range equals 53% of the average, which shows considerable uncertainty. The number is 35% for China, 19% for the USA, and 15% for the EU. On average, the uncertainty range for the nine developing countries/regions are accounts for 20% of the optimal emission, which is twice the value of that for the six developed countries/regions.

The range of the SCC is also much higher in developing countries than that in the developed countries, indicating it is much more difficult for developing countries to follow the optimal mitigation strategies. In 2100, the estimated SCC range from \$1/tCO_2 to \$435/tCO_2 for the REF countries under different climate change perspectives. The gap between the highest and lowest estimation is \$254/tCO_2 (\$24/tCO_2 - \$279/tCO_2) for India and \$93/tCO_2 (\$15/tCO_2 - \$105/tCO_2) for China, which is a much wider range compared to the range for the US (\$1/tCO_2 - \$41/tCO_2) and the EU (\$2/tCO_2 - \$44/tCO_2). The reason behind this is the high degree of uncertainty around the damage estimation and the high shadow prices of capital. With such a wide range of uncertainties, the optimal strategy might be easily biased under different climate change assumptions and value judgments. For example, the linear damage function proposed by Hope usually results in higher optimal emissions and a lower SCC. If a policymaker in a developing country is promulgating optimal mitigation policy using a linear function, but the actual climate damage is more like an exponential form, the optimal emissions posited under the linear function will no longer be optimal. The climate damage will be greater than expected, and the marginal mitigation cost will be much lower than the marginal mitigation benefits, making it economically efficient to achieve larger emissions reductions for the nation.

According to the meta-analysis, the total climate damage in developing countries is projected to be higher than that in developed countries. The total damage in India could be 50 times that in the USA in 2100. The climate damage estimates the economic impact in each term, while the SCC measures the discounted monetized climate damage for an incremental increase in carbon emissions. According to our results under the non-cooperative scenario, the average SCC is also higher in developing countries. In 2100, the average SCC in the Annex-B countries is estimated to be from 0.1 \$/tCO_2 (Canada) to 13.5 \$/tCO_2 (EU) in 2100. In the BASIC countries, the number is higher, ranging from 10.0 \$/tCO_2 (Brazil) to 123.8 \$/tCO_2 (India). The five developing regions have the highest levels of average SCC, ranging from 113.6 \$/tCO_2 (MAF) to 174.7 \$/tCO_2 (REF) in 2100. This indicates that, in a global non-cooperative optimal situation, one incremental unit of carbon emission in a developing country usually causes more monetized climate damage than that in a developed country.

The EU Carbon Border Adjustment Mechanism is announced to come into force by the end of 2022 to prevent carbon leakage (European Commission, 2020). By imposing a fee on carbon-insensitive imports from countries with less stringent climate policy, the mechanism is aimed to incentivize the development of carbon pricing schemes in third parties. Although there is no doubt such a mechanism may boost climate actions and awareness, our results illustrate the challenge of establishing a carbon pricing scheme in developing countries. According to the meta-damage estimates, developing countries are more vulnerable, while this vulnerability will further hinder their economic development. A sharply rising social carbon cost indicates the benefit from emission reduction and illustrates a range of uncertainty if these developing countries price the carbon by its social cost. The price mechanism could focus more on the production side to incentivize technological innovation.

There are many limitations that can be addressed in future studies. First, regional aggregate results cannot inform policy-making, as countries are in different economic and environmental development stages. Although our results underscore the basic problems of political economy at the heart of the current bottom-up voluntary regime, questions remain as to what emerging economies should do to balance emission reduction with economic growth. The social carbon cost is much higher in these developing countries, yet these countries need carbon emissions to develop their economies and pay for the social costs. Sustainable development is always suggested as a way to solve the dilemma, but much more effort should be made to elaborate how to develop sustainably and profitably. Second, there is still a limitation in applying all the damage functions in the RICE model; as the RICE model is an optimization model, some functions may produce an infeasible solution. Third, the outcome of a meta-analysis invariably depends on the studies included. As with all meta-analyses, publication bias, search bias, and selection bias are, to some degree, unavoidable. Even so, the importance of these studies has been widely recognized outside medical sciences where they originated, such that they are now standard in social sciences as well. Future work may be improved from these three aspects and provide a more detailed analysis for discussion.

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Technical reports:

National GDP and the capital stock are adopted from International Monetary Fund Investment and Capital Stock Dataset, available online at https://www.imf.org/external/np/fad/publicinvestment/. Population data is derived from the United Nations World Population Prospects, which is available online at https://population.un.org/wpp/. All the data and code used in this paper are uploaded to Github at https://github.com/Eleanor1994/RICE-with-meta-damage-functions.

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