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THE (ECONOMIC) IMPACTS OF CLIMATE CHANGE: SOME IMPLICATIONS FOR ASIAN ECONOMIES

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Abstract

This paper provides an overview of how economists think about climate change impacts with a focus on Asia. It is designed to discuss the steps along the causal chain from physical impacts to impacts on human and natural systems. It starts with a summary of the projected physical impacts of climate change on Asia based on the IPCC's 5th assessment report. It then discusses the concept of the social cost of carbon and how integrated assessment models are used to obtain estimates of this number. This includes a discussion of how a mapping from physical climate impacts to economic damages – called the damage function – is obtained. A recent literature using a mapping of weather/climate into GDP growth rates is discussed, including impact estimates from the literature. The second part of the paper contains an extensive discussion of the mitigation challenge, both physical and economic and concludes with a discussion of the policy challenges going forward.

Keywords: climate change, economic damages, carbon mitigation

JEL Classification: Q54

Contents

1. INTRODUCTION

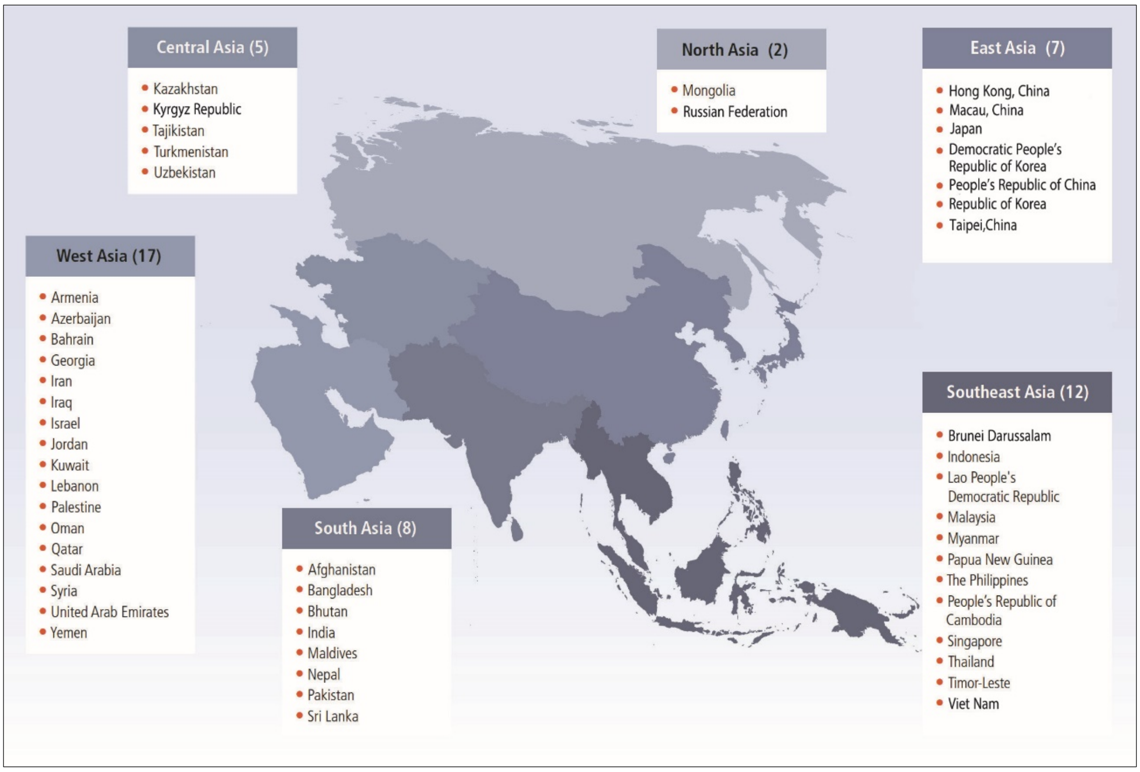
Climate change has been widely touted as the biggest environmental challenge humankind will encounter over the next centuries. The Intergovernmental Panel on Climate Change (IPCC) projects that in the absence of significant policy intervention, unmitigated climate change may lead to unprecedented changes in the climate system—including, but not limited to, changes in temperature, precipitation, and sea levels (IPCC 2013). These changes in the climate system will have significant impacts on human society. If we are serious about engaging in mitigation actions, costs will be incurred in the near future to achieve emissions reductions. These will bring about hard to measure benefits in terms of avoiding climate change further in the future. As climate change is a global phenomenon, it is not a single economy or group of economies that can solve this problem. It will take efforts by economies large and small to tackle this problem. Furthermore, impacts are not evenly distributed. The IPCC (2014) points out that poorer populations, especially in agrarian societies, are likely to suffer the most. In terms of sectors, agriculture and energy use are two that are highly exposed. Direct and indirect effects of climate change have also been shown to affect labor productivity, crime, violent conflicts, happiness, migration, mortality, and morbidity (Carleton and Hsiang 2016). However, our understanding of the impacts for most of these sectors is limited to specific locations and time periods. Also, solid methods to quantify impacts are still being developed.

This conference paper proceeds as follows. Section 2 provides a summary of climate change impacts on Asia based on the fifth assessment report by the IPCC. Section 3 discusses the methodologies used by economists to quantify damages from climate change and provides an overview of two recent papers which provide some empirical estimates of the impact of climate change on individual countries' GDP, as well country level estimates of the implied social cost of carbon. Section 4 discusses historical emissions and future emission scenarios more broadly and provides some insights into the contribution to emissions by different countries. Section 5 briefly discusses global efforts to arrive at a global climate policy regime. Section 6 discusses country level policy options going forward, and concludes.

2. PHYSICAL IMPACTS OF CLIMATE CHANGE

Joseph Fourier hypothesized the greenhouse effect in 1924. In 1896, Svante Arrhenius was the first scientist to make a quantitative prediction of global warming if one doubled the atmospheric concentration of carbon dioxide. Over the past ~125 years, scientists have studied the impact of higher greenhouse gas emissions on the global climate. The IPCC issues assessment reports roughly every seven years, which are meant to synthesize the current state of climate science. Working Group I (WG1) "aims at assessing the physical scientific basis of the climate system and climate change. Its main topics include: changes in greenhouse gases and aerosols in the atmosphere; observed changes in air, land and ocean temperatures, rainfall, glaciers and ice sheets, oceans and sea level; historical and paleoclimatic perspective on climate change; biogeochemistry, carbon cycle, gases and aerosols; satellite data and other data; climate models; climate projections, causes and attribution of climate change" (IPCC 2013). The report includes summary predictions for the entire globe, but also provides regional projections of the impacts of climate change. For a more comprehensive and recent review, I suggest consulting Hsiang and Kopp (2018) or the WG1 report (IPCC 2013). Working Group II (WG2) "assesses the vulnerability of socio-economic and natural systems to climate change, negative and positive consequences of climate change and options for adapting to it." In short, therefore, WG1 deals with the physical climate system and modeling, while WG2 summarizes the literature on impacts on human and natural systems (IPCC 2014). Figure 1 is taken from the fifth assessment report (AR5), which contains a chapter on impacts for Asia. Figure 1 displays a map for what the IPCC considers to be Asia.

Figure 1: IPCC AR5 WG2 Asia Map



Source: IPCC (2014).

The main conclusions drawn by the IPCC for their AR5 are paraphrased as follows (IPCC 2014).

- Warming trends and increasing temperature extremes are observed across most of the Asian region over the twentieth century. Observations show a rising number of warm days and a decreasing number of cold days. This trend is not slowing down. Precipitation trends have changing degrees of variability across Asia.
- Due to increasing water demand and suboptimal management practices, water scarcity is thought to be a major challenge going forward. Water availability is of massive importance due to the large population in the region. While future projections at the subregional level do not provide a clear forecast, rapid population growth and rising incomes can put additional pressures on water resources in the region. Management of water resources is paramount.
- Climate change will affect food production, yet the impacts will be variable depending on the location. However, it looks like many regions will experience a climate-driven decline in production, the clearest predictions being for reduced rice production due to the shortening of growing periods. It is noted that CO_2

fertilization may offset some of these drops in yield. Overall there may be some winners—Kazakhstan's cereal production, for example—and some losers (Western Turkmenistan and Uzbekistan). It is further noted that the area dedicated to high-yielding wheat could decrease significantly in the Indo-Gangetic Plain. Rising seas will cause problems for low-lying areas.

- There has been an observed shift in phenology, along with the growth and distribution of plant species and permafrost degradation. It is expected that climate change will amplify these impacts going forward.
- There is evidence that marine and coastal systems are experiencing increased stress from climate and other factors. Rising sea levels are expected to lead to increased coastal erosion and high water levels. There may be damage to mangroves, salt marshes, and coral reefs.
- It is expected that climate change will compound impacts caused by urbanization and industrial and broader economic development. "Climate change is expected to adversely affect the sustainable development capabilities of most Asian developing countries by aggravating pressures on natural resources and the environment. Development of sustainable cities in Asia with fewer fossil fuel-driven vehicles and with more trees and greenery would have a number of co-benefits, including improved public health" (IPCC 2014a).
- Human health, security, livelihoods, and poverty will be increasingly affected by extreme climate events. Mortality and morbidity, especially for vulnerable groups, is expected to increase due to heatwaves. The risk of diarrheal diseases, dengue fever, and malaria is expected via the increased risk of floods and droughts.
- AR5 concludes that "studies of observed climate changes and their impacts are still inadequate for many areas, particularly in North, Central, and West Asia" (IPCC 2014a). The call is for better projections of all significant precipitation, which affects water supplies. The assessment report further highlights a greatly limited understanding of the impacts of climate change on a large number of sectors, but singles out the urban environment.

Table 1 identifies the IPCC's summary of the state of scientific evidence in physical impact estimation. The crosses in the table suggest that for the Asian region there is insufficient evidence and that there are critical knowledge gaps. This table can serve as a map for a future research agenda, as understanding the historical and future impacts of climate change on these sectors is key for optimal policymaking.

The IPCC synthesizes physical and socio-economic impacts published in the literature. The literature attempting to estimate damage from climate change has exploded, even since publication of the AR5. In order to fill the gap for some of the sectors pointed out by the IPCC as lacking evidence, economists and statisticians have developed a number of methods to empirically estimate the projected costs of climate change. The next section discusses the evolution of these impact estimation techniques and how they are used in practice.

Table 1: State of Evidence Regarding Observed and Projected Impacts of Climate Change

Sector	Topics/Issues	North Asia		East Asia		Southeast Asia	
	O = Observed Impacts, P = Projected Impacts	O	P	O	P	O	P
Freshwater resources	Major river runoff	/	x	/	/	/	/
	Water supply	x	x	x	x	x	x
Terrestrial and inland water systems	Phenology and growth rates	/	/	/	/	x	x
	Distributions of species and biomes	/	/	/	/	x	x
	Permafrost	/	/	/	/	/	x
	Inland waters	x	x	/	x	x	x
Coastal systems and low-lying areas	Coral reefs	NR	NR	/	/	/	/
	Other coastal ecosystems	x	x	/	/	x	x
	Arctic coast erosion	/	/	NR	NR	NR	NR
Food production systems and food security	Rice yield	x	x	/	/	x	/
	Wheat yield	x	x	x	x	x	x
	Corn field	x	x	x	/	x	x
	Other crops (e.g., barley, potato)	x	x	/	/	x	x
	Vegetables	x	x	/	x	x	x
	Fruits	x	x	/	x	x	x
	Livestock	x	x	/	x	x	x
	Fisheries and aquaculture production	x	/	x	/	x	/
	Farming area	x	/	x	/	x	x
	Water demand for irrigation	x	/	x	/	x	x
	Pest and disease occurrence	x	x	x	x	x	x
Human settlements, industry, and infrastructure	Floodplains	x	x	/	/	/	/
	Coastal areas	x	x	/	/	/	/
	Population and assets	x	x	/	/	/	/
	Industry and infrastructure	x	x	/	/	/	/
Human health, security, livelihoods, and poverty	Health effects of floods	x	x	x	x	x	x
	Health effects of heat	x	x	/	x	x	x
	Health effects of drought	x	x	x	x	x	x
	Water-borne diseases	x	x	x	x	/	x
	Vector-borne diseases	x	x	x	x	/	x
	Livelihoods and poverty	x	x	/	x	x	x
	Economic valuation	x	x	x	x	/	/

continue on next page

Table 1 *continued*

Sector	Topics/Issues O = Observed Impacts, P = Projected Impacts	South Asia O	South Asia P	Central Asia O	Central Asia P	West Asia O	West Asia P
Freshwater resources	Major river runoff	/	x	x	x	x	x
	Water supply	x	x	x	x	x	x
Terrestrial and inland water systems	Phenology and growth rates	x	x	x	x	x	x
	Distributions of species and biomes	x	/	x	x	x	x
	Permafrost	/	/	/	/	/	x
	Inland waters	x	x	x	x	x	x
Coastal systems and low-lying areas	Coral reefs	/	/	NR	NR	/	/
	Other coastal ecosystems	x	x	NR	NR	x	x
	Arctic coast erosion	NR	NR	NR	NR	NR	NR
Food production systems and food security	Rice yield	x	/	x	x	x	/
	Wheat yield	x	/	x	x	/	/
	Corn field	x	x	x	x	x	x
	Other crops (e.g., barley, potato)	x	x	x	x	/	/
	Vegetables	x	x	x	x	x	x
	Fruits	x	x	x	x	x	x
	Livestock	x	x	x	x	x	x
	Fisheries and aquaculture production	x	x	x	x	x	x
	Farming area	x	/	x	/	x	x
	Water demand for irrigation	x	/	x	x	x	x
	Pest and disease occurrence	x	/	x	x	x	x
Human settlements, industry, and infrastructure	Floodplains	/	/	x	x	x	x
	Coastal areas	/	/	NR	NR	x	x
	Population and assets	/	/	x	x	x	x
	Industry and infrastructure	/	/	x	x	x	x
Human health, security, livelihoods, and poverty	Health effects of floods	/	x	x	x	x	x
	Health effects of heat	x	x	x	x	x	x
	Health effects of drought	x	x	x	x	x	x
	Water-borne diseases	/	x	x	x	x	x
	Vector-borne diseases	/	x	x	x	x	x
	Livelihoods and poverty	/	x	x	x	x	x
	Economic valuation	/	/	x	x	x	x

Key: / = Relatively abundant/sufficient information; knowledge gaps need to be addressed but conclusions can be drawn based on existing information. x = Limited information/no data; critical knowledge gaps, difficult to draw conclusions. NR = Not relevant.

Source: IPCC (2014a).

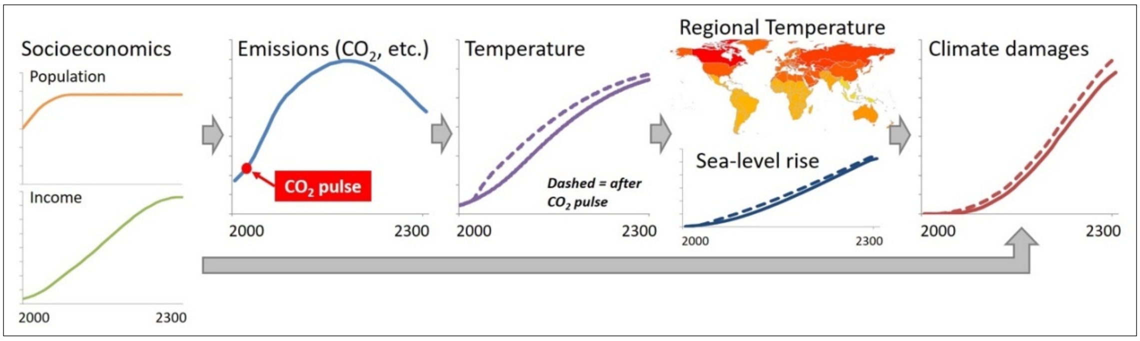
3. ECONOMIC IMPACTS OF CLIMATE CHANGE

Climate scientists have spent billions of dollars studying the physical impacts of climate change. Much of this work involves data collection on, below, and above ground, which is costly. Furthermore, global climate models (GCMs) take up significant amounts of supercomputer time, which is expensive. Governments and funding agencies across the globe have not hesitated to fund this work, and the body of literature and our understanding of the climate system reflect the magnitude of this investment. From a social scientist's perspective, one has to ask the question of how historical and future changes in the climate system will translate into impacts on human (e.g., urban) and human-natural (e.g., agricultural) systems. The literature on physical impacts is bigger than the literature on the economic impacts of climate change. There are two major interconnected ways in which economists and modelers have tried to estimate the economic impacts of climate change. The first modeling pathway is via so-called integrated assessment models, which are frequently used to estimate the social cost of carbon, which is the marginal damage of emitting one ton of CO_2 equivalent at a given point in time. The second approach uses econometric methods and variation in weather and climate to estimate damages from climate change. I discuss these modeling approaches and how they are interconnected in what follows below.

3.1 Integrated Assessment Models and Social Cost of Carbon

Integrated assessment models (IAMs) are, as the name would suggest, models that integrate projections of emissions pathways and a simple climate model with a damage function: this translates changes in, for example, surface temperature, precipitation, and sea level into economic damage. Figure 2 below helps us to conceptualize our thinking.

Figure 2: Causal Chain in Integrated Assessment Models



Source: Rose, Diaz, and Blanford (2017).

Due to the long lifetime of the major greenhouse gas (CO_2), IAMs usually go beyond this century and model damages over a few centuries. The most common models used go up to the year 2300. This poses a significant challenge, of course. The first step in an IAM is to project socio-economic scenarios—most importantly, future income and population levels over the next 300 years. Imagine being King George III in 1738 and having to project income and population levels for the year 2019. Even had he been armed with a computer, this would pose a stiff challenge. Most models adopt simplistic projections of these two variables, some suggesting continued increases in per capita incomes and a leveling of the population. One could, of course, adopt more advanced approaches, such as those proposed by Müller and Watson (2016). The socio-economic pathways are then translated into emissions of CO_2 equivalent over the time horizon. Some models also include other greenhouse gases with shorter (e.g., methane) and longer (e.g., SF_6) lifetimes. The constructed emissions pathways are then fed into a simplistic climate model which translates global emissions pathways into changes in temperature, precipitation, and sea level, depending on the model. Some models are global—hence the output from the climate model is a single time series for the entire planet; others have regional resolution for large aggregates (e.g., Europe, Asia). The regional models provide projections for the climate outcomes for each region.

At this point, we are in the same position in the causal chain that the much more complex GCMs from the previous section end, although at a much more simplistic level in terms of the climate outputs they provide and the detail of modeling.

The IAMs' point of departure is that they take the output from their climate module and feed it into a damage function. A damage function maps levels of the relevant climate variables (e.g., temperature) into outcomes of economic interest. These include, but are not limited to, productivity, agricultural production, human mortality, infrastructure impacts, energy consumption, and disease vector spread.

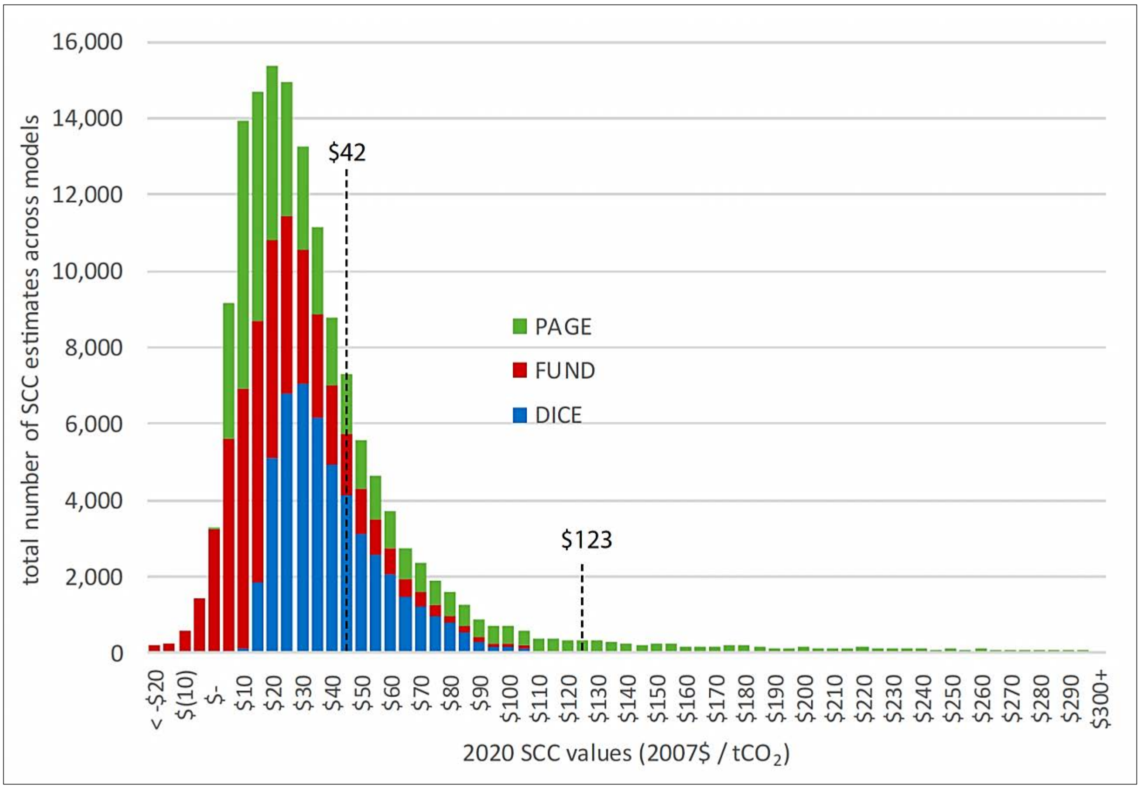
Furthermore, human society is extremely multidimensional and many products and services we consume directly or indirectly rely on factors that are not valued in markets. For example, the benefits of watershed protection provided by forests is extremely difficult to monetize. Another example is the existence of animal species whose existence humans value (e.g., tigers, bald eagles) yet which are not traded in markets. One way to think about this is that certain animals are traded for human consumption (e.g., chickens), and hence there are ways to monetize their market value. Since we do not consume tigers or eagles, it is extremely difficult to monetize damage to these species, so what is needed are damage functions for the most important 'sectors' of the economy that map climate into welfare outcomes. I will describe in more detail below what the cutting-edge methods are that are currently being developed, but it is fair to say that the current IAMs use damage functions developed in the 1990s and early 2000s, which are terribly out of date. To summarize, in theory, IAMs go end to end from a time series of emissions scenarios to a time series of values for outcomes of interest.

How is this related to climate change? Conceptually, this is pretty straightforward. What one could do is feed a time series of emissions scenarios that are consistent with a no or low climate change scenario and calculate a stream of damages and compare this to the damages generated by feeding the model an emissions path consistent with increased emissions of greenhouse gases. We could then simply calculate the difference between the two paths, and if the costs from climate change (e.g., higher mortality) are bigger than the benefits (e.g., higher yields of crops in high latitude regions), we refer to this as damage. If changes in emissions are small, assuming that there are no feedback effects on, for example, production is reasonable. However, if changes in emissions are large, causing significant increases in, say, temperature, then there could be feedback effects through the direct effects of a change in climate on productivity. Some IAMs are able to represent this feedback loop and some do not have it built in. There are a few IAMs which can be run as optimization problems and are well suited to these types of large impact simulations.

The most policy-relevant use of IAMs is arguably their use in the estimation of the social cost of carbon (SCC). The SCC is the present value of the damage caused by a ton of CO_2 emitted at a given point in time. To relate this to what is discussed above, what is done in practice is that modelers run an IAM with a baseline path of socio-economics and the resulting emissions and then add a 'pulse' of CO_2 emissions at a given point in time. That pulse is supposed to mimic a one ton increase in emissions. One then calculates the stream of damages until 2300 by taking the difference between the two-time series of damages. This results in a stream of damages to the year 2300. As any economist will note, future consumption is valued differently from present consumption; hence this time path of damages has to be discounted in order to make damages three hundred years in the future comparable to damages today. When discounting, the most important choice a modeler has to make is what discount rate to use. Policy applications have used 2.5%, 5%, and 7%. The higher the discount rate, the less weight is placed on future damages.

Calculation of the SCC in the past was a mostly academic exercise. There were a variety of teams working on different models to calculate this global number. This is an important point: since greenhouse gases are global pollutants, the origin of emissions does not matter. Furthermore, the right number from a social welfare point of view is the global SCC: much like in *The Lord of the Rings*, it is the "number to rule them all." There have been some efforts, which I will discuss below, to calculate domestic numbers, even though from a global policy perspective the right number is the global one. From an academic perspective, it does not really matter who or which country calculates this number.

Figure 3: Interagency Working Group Estimates of the SCC



Notes: The figure combines the 50,000 2020 3% discount rate estimates from each of the three USG models to illustrate their influence on the aggregate histogram that determines the official USG SCCs for 2020 at 3% — the average ($42) and 95th percentile ($123).

Source: Rose, Diaz, and Blanford (2017).

The Obama administration commissioned a set of federal agencies to put together a working group charged with calculating an official SCC to be used in federal rulemaking in the United States. This was the biggest effort put together by any government in history. This Interagency Working Group (IWG) involved representatives from the Council of Economic Advisers, the Council on Environmental Quality, the Department of Agriculture, the Department of Commerce, the Department of Energy, the Department of Transportation, the Environmental Protection Agency, the National Economic Council, the Office of Energy and Climate Change, the Office of Management and Budget, the Office of Science and Technology Policy, and the Department of the Treasury. In short, all agencies with any relation to environment, climate change, energy, and cost benefit analysis in the federal government were at the table. The IWG chose three IAMs to produce a SCC estimate: DICE,[1] FUND,[2] and PAGE.[3] DICE is a global IAM, while FUND and PAGE both have regional resolution. The IWG had the goal of feeding the three models an identical set of inputs (e.g., socio-economics), using an identical set of discount rates, while at the same time characterizing uncertainty over the SCC. Figure 3 plots the SCC estimates for the year 2020 across the three models using a discount rate of 3%.

The figure displays the distribution of the 50,000 model runs for each IAM using quasi identical assumptions about socio-economic pathways and an identical discount rate of 3% for a ton of CO_2 emitted in the year 2020. The average value across all models and runs is $42/ton, which is the most frequently cited number. In an effort to be transparent, the United States Environmental Protection Agency published the full set of estimates for different assumptions about the discount rate and year of emissions. Table 2 below is a reproduction of the estimates.

Table 2: Interagency Working Group Estimates of the SCC by Discount Rate and Year of Emissions

	Discount Rate and Statistic			
Year	**5% Average**	**3% Average**	**2.5% Average**	**High Impact (95th pct at 3%)**
2015	$11	**$36**	$56	$105
2020	$12	**$42**	$62	$123
2025	$14	**$46**	$68	$138
2030	$16	**$50**	$73	$152
2035	$18	**$55**	$78	$168
2040	$21	**$60**	$84	$183
2045	$23	**$64**	$89	$197
2050	$26	**$69**	$95	$212

A few things stand out from this table. Firstly, as mentioned above, the higher the discount rate, the lower the SCC estimate. For a ton of CO_2 emitted in the year 2020, if one applies a discount rate of 2.5%, the SCC is $68, while for a 3% discount rate this number falls to $42; if one goes to 5%, the number drops to $12. The last column only looks at the 95th percentile of the distribution of estimates and discounts it at 3%, which of course results in a much higher SCC, since only the highest estimates are considered by design. For 2020, this number is $123 per ton.

The second aspect to notice in this table is the fact that the SCC is increasing over time—in other words, the later a ton is emitted, the higher the social cost of carbon. For example, using the 3% discount rate, a ton emitted in 2020 causes $42 in discounted damages, while a ton emitted in 2050 causes $69 in discounted damages. There are two reasons for this. The first is that as time goes on, the stock of CO_2 in the atmosphere increases, resulting in incrementally higher damage due to nonlinearities. The second reason that the SCC is increasing over time is that damages in some models are proportional to income, which is a reasonable assumption given that, for example,

[1] DICE can be found at https://sites.google.com/site/williamdnordhaus/dice-rice.

[2] FUND can be found at http://www.fund-model.org.

[3] PAGE is not open source. Some references can be found at https://www.climatecolab.org/wiki/PAGE.

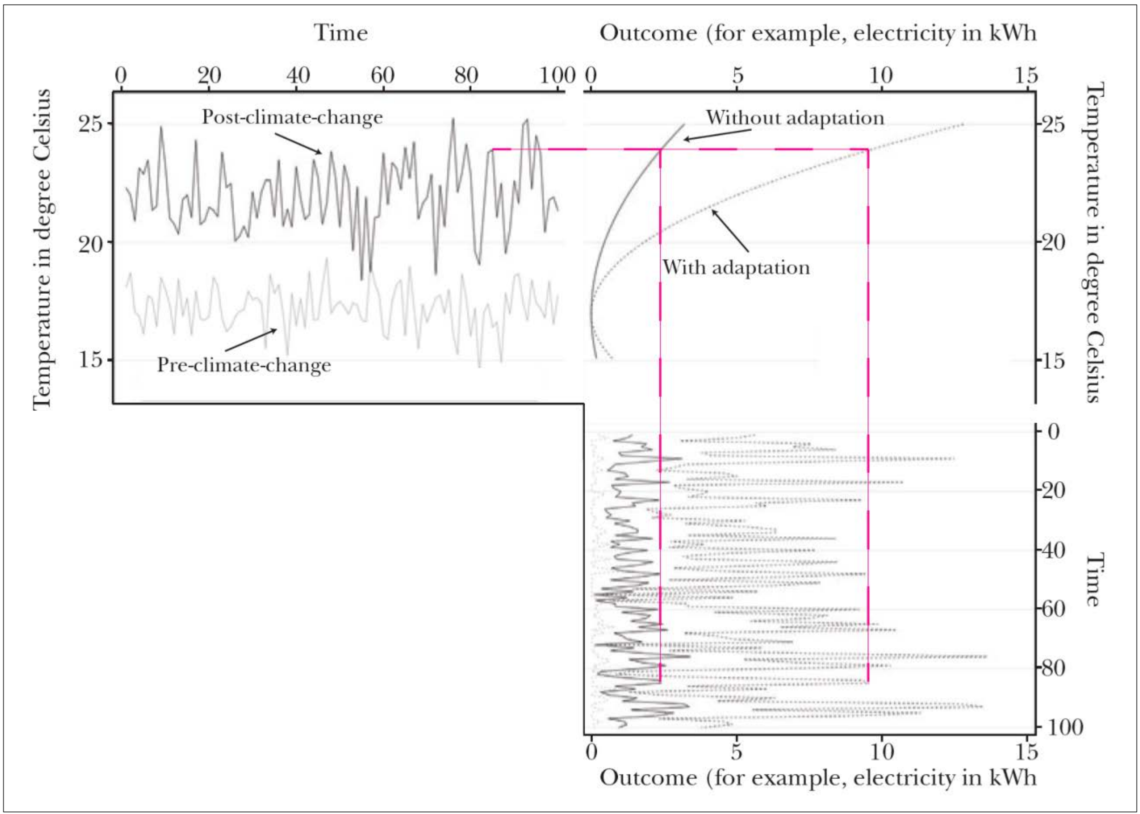
the value of assets affected by climate change is thought to be increasing in line with income, which in turn is expected to grow over time.

Following publication of the IWG SCC estimates, the Obama administration asked the National Academies of Sciences, Engineering, and Medicine (NAS) to author an independent report assessing the IWG effort and providing a path forward. The NAS (2017) report was published and has given rise to an effort at Resources for the Future, a Washington DC based think tank, to implement the recommendations. This effort is being conducted outside the federal government as the current administration has disbanded the IWG and halted all work on the social cost of carbon. The White House has instructed all agencies to use a domestic SCC using discount rates as high as 7%, which led to SCCs ranging from $1 to $7 per ton. One of the main recommendations of the NAS was to drastically improve the quality and coverage of damage functions in the IAMs used for the calculation of the SCC. The next section discusses what has been done historically to estimate damage functions and what the current best practice is.

3.2 Damage Function Estimation

It helps to conceptualize what a damage function is attempting to do. It sounds simple. A damage function maps climate into an outcome. This has often been described as how a long run average of weather (climate) maps into an outcome of interest (e.g., electricity consumption, agricultural yields). Figure 4 helps fix these ideas.

Figure 4: Mapping Weather into Impacts—Accounting for Adaptation



Note: The top left panel shows the weather pattern of temperature generated in two climate regimes. The light gray time series depicts a pre-climate-change world and the dark series shows a post-climate-change world, with a temperature series displaying higher mean and variance. The top right panel displays two damage functions (the parabolas) which map weather into an outcome, in this case temperature into household electricity consumption (measured in kilowatt-hours). The effect can be seen in the bottom panel.

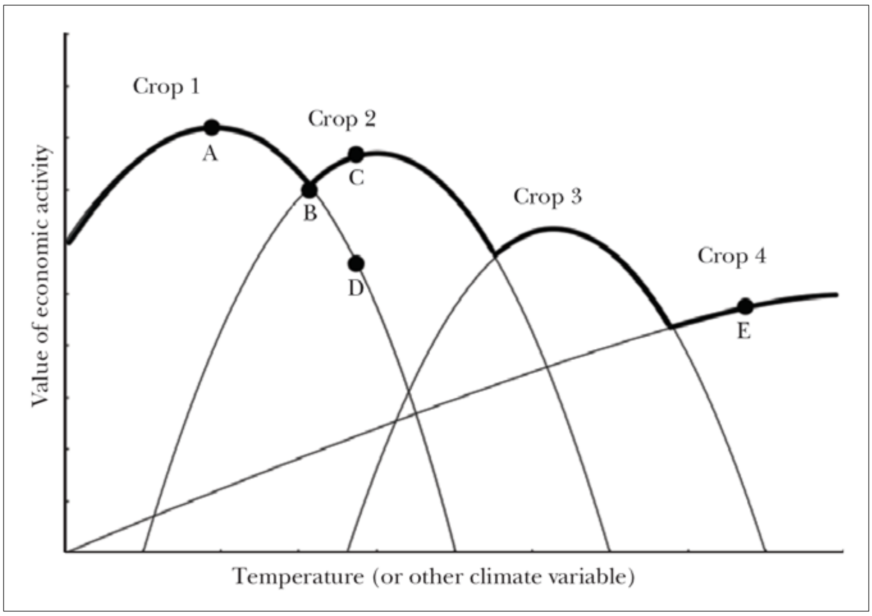
Source: Auffhammer (2018).

When you leave your house in the morning, you have to decide what to wear. If you look outside your window and it is cold and rainy, you will wear warmer clothes and bring an umbrella, if you have one. The next day it may be sunny and warm, and you will leave your home in a short-sleeved shirt. What you encounter on a day to day basis is weather. In most places, weather is highly variable across and even within seasons. Summer months are usually warmer and drier, while winter months are usually colder and wetter. Climate can coarsely be characterized as the full statistical distribution of weather. If that distribution is stationary—meaning the moments of the distribution are constant over time—one would still expect day to day variation in weather, but on average expect a similar number of hotter and cooler days during the summer, etc. Let’s use a sector which is highly sensitive to weather: electricity consumption. Assume a location with a cool pleasant climate, like San Francisco. Fashionable San Francisco old and young alike live in houses and apartments that usually do not have air conditioning equipment. What this means is that on the occasional very hot day, San Franciscans will complain loudly and head to the park to eat ice cream, hoping for cooler days. Since these hot days are a rare occurrence in a world without climate change, the cost of installing and operating air conditioning may be greater for most residents compared to the benefits they would derive from the few days they would use it. However, if San Francisco inherits the climate of Beijing, which is much warmer and more humid, especially in the summer, most San Franciscans would probably find it optimal to install air conditioning. Hence electricity use would go up. We call this adaptation. The top left panel of Figure 4 displays the weather from a pre-climate change world in light gray. The temperature series is mapped via the damage function into electricity consumption. This pre-climate change damage function is shown in the top right panel by the solid line. This translates into the pre-climate change electricity consumption shown by the dark solid line in the bottom right panel. Now, if climate changes and the weather is drawn from a distribution with a higher mean and variance, as indicated by the dark solid time series in the top left panel, the question arises as to what the right damage function is. If individuals understand that climate has changed, they will adapt (in our case, install more air conditioning) and the damage function changes. The new damage function is steeper, especially at higher temperatures. This means that the new normal weather is mapped into electricity consumption through the “with adaptation” damage function in the top right panel. The correct post-climate change consumption time series is the light gray dotted time series in the bottom right panel. The difference between the dotted line and solid line in the bottom panel is the damage from climate change.

Why is this so important? A damage function one would want to use in an IAM should account for adaptation, carry a causal interpretation, and have global coverage. This sounds straightforward, but turns out to be quite difficult in practice. The literature on damage function estimation goes back about five decades and can be split into roughly five strands.

The first and most widely adopted approach for estimating climate change damage stems from a seminal paper by Mendelsohn, Nordhaus, and Shaw (1994). They study the agricultural sector for the United States, but the method has been applied in a number of other sectors (e.g., energy consumption). The insight behind this method can best be demonstrated by Figure 5 below.

Figure 5: Crop Choice and Profits in the Long Run



Note: Imagine a single farmer, who is currently growing crop 1 and earning profits corresponding to the *y* value at point *A*. If faced with a significantly hotter climate, the farmer becomes indifferent between growing crop 1 and crop 2 at point *B.* If climate warms further still, the farmer would be much better off at point C (switching to crop 2) rather than at point *D* (continuing to grow crop 1).

Source: Auffhammer (2018).

Assume that a farmer is currently planting crop 1 as (s)he is operating in an area with a cool climate. If the climate gets warmer, (s)he could continue to grow the same crop and make profits as given by point D. However, the farmer could make profits as indicated by point C, simply by switching crops. If one assumes rational, profit-maximizing farmers, the impact of climate change on profits is given by the thick black line in the figure, the envelope of the individual crop/use profit functions, which are functions of, for example, temperature. Econometrically, this is relatively straightforward to implement. If one has data on profits and climate for farmers across different climate zones, one could assume that, conditional on other confounders, the cross-section would give one the envelope of the profit functions exactly. How does one implement this in practice? One runs a cross-sectional regression of outcomes of interest (e.g., agricultural profits) on complex functional forms of long run averages of weather (=climate) and other observable confounders such as soil quality and proximity to roads, to name some examples. The advantage of this method is that it actually identifies the effect of climate on the outcome of interest. The disadvantage of this method is that if one omits confounders that explain variation in the outcome of interest and that are correlated with climate, the estimation suffers from omitted variables bias. The consequences of this can be grave.

Another method, which is less frequently used, is simply using time series regressions of outcomes of interest on functions of weather. One example is Franco and Sanstad (2008), who regress electricity load for the state of California on population weighted averages of weather. Other more recent examples of this work are Auffhammer, Baylis, and Hausman (2017) and Wenz, Auffhammer, and Levermann (2017), who estimate the impacts of weather on electricity for the entire US and European countries individually. The advantage of this approach is that it allows researchers to estimate dose response/damage functions for variables that are only available at very coarse levels of aggregation. However, these regressions only identify the effect of weather on the outcomes of interest and do not incorporate the impacts of adaptation, which is of course a significant, if not detrimental drawback.

A third method, which has been more frequently applied in the recent damages literature, has employed the use of longitudinal data sets, often referred to as panel data sets. Early examples of these papers are Auffhammer, Ramanathan, and Vincent (2006) and Deschênes and Greenstone (2007). These papers build on the time series regression approach discussed above, but have the advantage that one has observations on an outcome of interest for multiple units (e.g., states or counties) over a number of years. The existing literature has used variation across time and cross-sectional units to estimate the dose response/damage function. The advantage of this approach is that one can control for confounders through a fixed effects strategy that controls for unobservable differences that are time invariant across units and shocks common to all or a subset of units for a given year. Hence the risk of omitted variables bias that the Ricardian approach suffers from is much lower here. The drawback is the same issue that time series regressions suffer from. The response functions estimate a relationship between an outcome of interest and weather—not climate, which lacks an adaptation response.

A recent paper by Burke and Emerick (2016) provides a fourth and very clever way to address the confoundables and the adaptation issue at the same time. The authors demonstrate a new method using data on US agricultural output across counties, benefiting greatly from the availability of highly disaggregated annual data over a long period. They calculate a long difference in agricultural output, where they determine the difference between a five-year moving average at the end and the beginning of their sample period. This long difference is the outcome of interest, telling us how much agricultural yields or profits have changed over, say, 40 years. On the right-hand side they use trends in temperature over the same time period. The differencing is equivalent to including unit fixed effects, and using trends gives the estimated coefficients a long run interpretation, which contains adaptation. Burke and Emerick (2016) show for their data that there is little evidence of an adaptation response. This approach has not been used widely outside agriculture.

The fifth and most recent approach has incorporated panel data estimation techniques, but augmented the specifications by interacting the weather response coefficients with cross-sectional variables measuring both climate (long run averages of weather) and income. A recent example of this work is Auffhammer (2018). The idea is a simple one. The weather response of, for example, energy consumption is different in areas with a hot versus a cool climate. Interacting the weather variables with a cross-sectional climate variable allows for empirical estimation of this response heterogeneity. An interaction of the weather variables with cross-sectional income allows for heterogeneity in the weather response as a function of income. Richer economies are thought to be able to adapt more easily, and this interaction captures this difference in response. The beauty of this approach is that if one has projections of income and climate, one can simulate how the damage function changes as climate and incomes change going forward. Carleton et al. (2019) make some strong assumptions, but using a dataset on mortality for the majority of humankind, provide extrapolations of climate change-induced mortality for all countries in the world to the end of the twenty-first century. This approach is possible with shorter time series than the long differences approach. It also has the benefit of shifting the response function, which the long differences approach cannot do, in a forward looking way. If one is interested in the detection and attribution of historical climate change, I would argue that the long differences approach is the best tool available, data permitting.

The papers discussed above mostly focus on single economies for individual sectors. In order to construct a damage function for all sectors across the world, one would need to write a few thousand empirical papers to get good coverage. I would encourage young scholars to start writing these papers. Another approach is to estimate a single damage function using GDP data, measuring the value of all goods and services produced for a country in a given year. Burke, Hsiang, and Miguel (2015) have written a paper providing a correlation between the growth rate of GDP and a nonlinear measure of changes in temperature to estimate how damaging climate change will be to the major world economies. While there is discussion about the empirical model adopted in the paper, they show a highly nonlinear relationship between GDP growth rate and temperature which resembles an environmental Kuznets curve—an inverse U. Growth rates peak at about 13° Celsius and are increasing at lower temperatures and decreasing at higher temperatures. The issue with approaches like this is that GDP does not measure everything that has value. It excludes the value of non-market resources, which is likely to be significant. Furthermore, this paper again uses short run variation. For technical reasons discussed in McIntosh and Schlenker (2006), the approach here includes some adaptation response but not complete adaptation. In the next section, I will discuss some of these results and provide some context for the Asian economies.

3.3 Overview of Estimates at the Country Level for Asian Economies

While the previous section discussed the different approaches to damage estimation, there is far from complete coverage for the different sectors of each economy. There are a number of studies using the hedonic approach for agriculture; a few panel data studies for agriculture, mortality, and energy consumption (Carleton and Hsiang 2016); and one study that uses the panel data approach accounting for adaptation (Carleton et al. 2019). There is, of course, a larger literature in field journals and white papers which use a variety of methods for single sectors. In this section, I provide an overview of the types of result targeted at providing estimates of the impact of climate change. The first set of estimates stems from the paper by Burke, Hsiang, and Miguel (2015) discussed in the previous section, using a simple regression framework accounting for partial adaptation. The projected climate change impacts shown in Table 3 for selected Asian Development Bank (ADB) member countries are presented for the worst-case emissions scenario and are calculated relative to per capita GDP in the year 2010. The estimates from this paper are the only country-level impacts of climate change currently available for most countries.

The average impact on per capita GDP across countries by the mid-century is –13.6%, and the average impact by the end of the century is –12.35%. These numbers do not sound unreasonable, and are slightly higher than the number predicted by some integrated assessment models. Yet what stands out here is the massive spread in impacts. For mid-century, the range of impacts just from climate change on per capita GDP is from –40 (Pakistan) to +88% (Mongolia). If we go to the end of the century, the spread of projections becomes even larger. Projected impacts range from –87% (Pakistan) to +881% (Mongolia). These projections have received a significant amount of media attention, and it has been widely reported that global per capita GDP is projected to decrease by roughly 23% by the end of the century. Before using these numbers in decision-making, it is important to remember that this paper has been criticized for making some strong functional form assumptions, where temperature affects the growth rate instead of the level of per capita GDP, which means that the shocks propagate through time. A recent working paper by Newell, Prest, and Sexton (2018) has pointed out that functional form assumptions have significant consequences for the point estimates. Furthermore, GDP only measures market impacts and ignores non-market impacts, and is hence incomplete.

Table 3: Climate Change Impacts on Selected ADB Member Countries

Country	Change in GDP p.c. (2040–2059) in %	Change in GDP p.c. (2080–2099) in %
Afghanistan	–4.78	–28.43
Armenia	19.28	73.50
Australia	–12.60	–44.77
Azerbaijan	–2.53	–18.17
Bangladesh	–36.49	–83.65
Brunei Darussalam	–34.16	–81.47
Bhutan	–1.17	–11.76
People's Republic of China	–7.51	–34.07
Fiji	–23.63	–65.40
Georgia	5.52	8.94
Indonesia	–31.44	–77.93
India	–38.78	–86.16
Japan	–5.97	–28.23
Kyrgyz Republic	29.53	132.64
Cambodia	–38.94	–81.57
Korea, Republic Of	3.09	1.89
Kazakhstan	32.17	158.87
Lao People's Democratic Republic	–32.21	–79.17
Sri Lanka	–32.14	–78.71
Mongolia	87.81	881.11
Malaysia	–33.53	–80.70
Nepal	–31.08	–78.09
New Zealand	–0.41	–6.41
Papua New Guinea	–24.30	–66.96
Philippines	–30.61	–76.38
Pakistan	–39.54	–87.07
Solomon Islands	–31.35	–77.07
Thailand	–37.81	–84.70
Tajikistan	1.36	–9.47
Turkmenistan	–14.10	–51.11
Uzbekistan	–8.45	–37.20
Viet Nam	–33.60	–80.82
Vanuatu	–26.14	–69.40
Samoa	–27.87	–72.30

Source: Burke, Hsiang, and Miguel (2015).

Another recent paper (Ricke et al. 2018) has used the GDP damage function used in Burke, Hsiang, and Miguel (2015) and another paper by Dell, Jones, and Olken (2012) to calculate a country-specific SCC. As discussed above, in terms of global policymaking, the number that matters from a global perspective is the global SCC. There is, of course, the issue that mitigation happens at the country level. There is an argument for a domestic SCC, which suggests that countries will only find it optimal from a domestic perspective to take action if the benefits of action outweigh the costs. Hence one would want to calculate a country-specific SCC, which ignores damage caused elsewhere. The only framework currently which has country-level resolution is the Burke, Hsiang, and Miguel (2015) framework. Ricke et al. (2018) used this framework to calculate a social cost of carbon at the country level and characterize the uncertainty around it. To give us an idea of the magnitude, I have used their publicly available estimates and generated the median, 16.7th and 83.3rd percentiles at the country level for ADB member countries with available estimates. I only included runs for SSP3 and 5, using the emissions scenario RCP 8.5 and a constant discount rate of 3%, yet using all available damage functions in the paper. Hence these estimates differ slightly from the main estimates in the paper. The aggregate SCC across all countries for this study is estimated to be $1,060, which is, of course, significantly higher than the IWG estimate of $42 per ton. This is largely due to the damage function estimated by Burke, Hsiang, and Miguel (2015). If one takes that approach at face value, Table 4 reports the estimated SCC at the country level.

What emerges from this table is that the SCC for the smaller countries is, well, smaller. Population and economy size matter in this calculation. Hence bigger economies are more likely to have larger estimates. The People’s Republic of China (PRC) and India have CSCCs north of $100. Very few countries have CSCCs that are negative. The most noteworthy of these is Mongolia which, according to Burke, Hsiang, and Miguel (2015), is projected to experience significant increases in per capita GDP from climate change.

While, for the purposes of this paper, the country-level estimates are interesting, I would like to caution the reader from taking these point estimates at face value, since they depend on two papers (Burke, Hsiang, and Miguel 2015; Dell, Jones, and Olken 2012) which adopt a very specific functional form to arrive at a damage function. The overall damages predicted by these models are much larger than those predicted by more recent incarnations of the classic IAMs. The DICE model by Nobel Laureate Bill Nordhaus in a recent publication (Nordhaus 2017) estimates a SCC of $31 dollars. This is, of course, significantly lower than what Ricke et al. (2018) report. An important route forward, in my view, is to build empirically validated sectoral damage functions that cover as much of the globe as possible and aggregate across space. The Climate Impact Lab is currently working on developing a credible method to do so, which should be applied to more sectors than mortality, agriculture, and energy consumption. The Climate Impact Lab comprising experts from the University of Chicago, UC Berkeley, Rutgers University, and the Rhodium Group, is aggressively pursuing this approach. I would encourage readers to follow their advances and start expanding this literature.[4]

[4] The Climate Impact Lab can be found at https://www.impactlab.org.

Table 4: Country Level Social Cost of Carbon (CSCC)

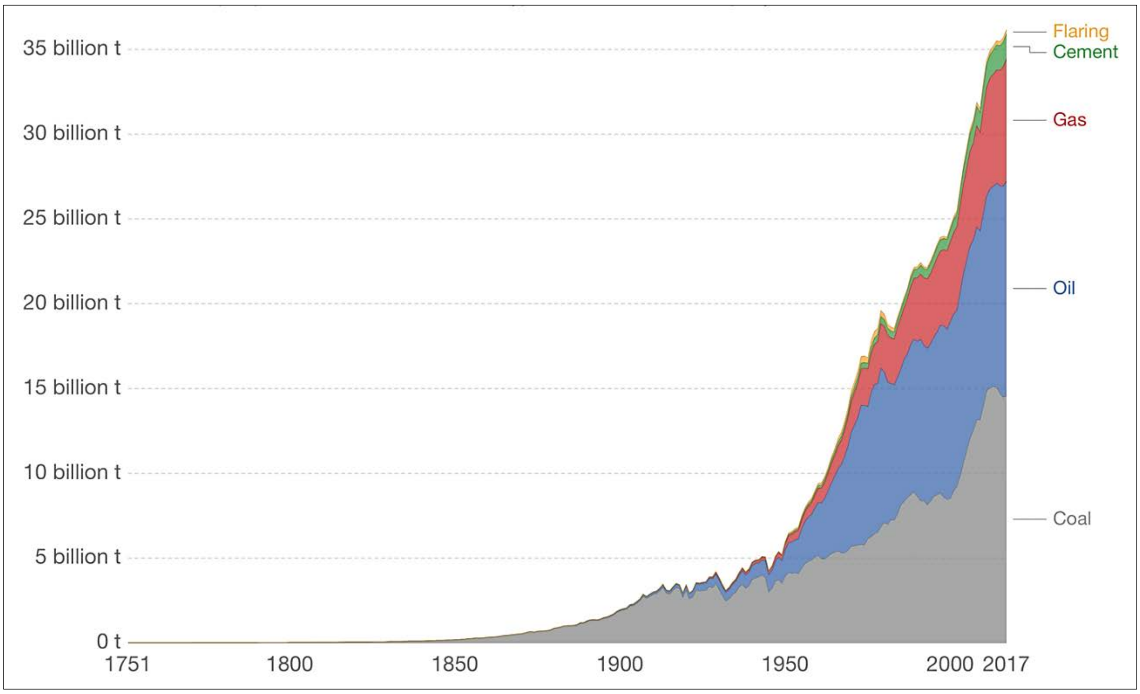
Country	CSCC (US$, 17th Percentile)	CSCC (US$, Median)	CSCC (US$, 83rd Percentile)
Afghanistan	–2.94	0.88	2.22
Armenia	–0.29	–0.08	0.04
Australia	1.20	5.89	7.53
Azerbaijan	–0.08	0.33	0.56
Bangladesh	7.57	10.33	11.68
Brunei Darussalam	–0.02	0.12	0.14
Bhutan	0.08	0.16	0.20
People's Republic of China	45.68	115.23	155.16
Fiji	0.03	0.04	0.05
Georgia	–0.10	0.08	0.19
Indonesia	15.24	25.64	29.92
India	76.31	116.98	131.53
Japan	0.61	10.41	14.35
Kazakhstan	–6.27	–2.03	0.01
Kyrgyz Republic	–1.53	–0.61	–0.13
Cambodia	0.47	0.88	1.04
Korea, Republic Of	–3.53	2.97	5.92
Lao People's Democratic Republic	0.37	0.52	0.60
Sri Lanka	1.12	1.90	2.23
Mongolia	–16.34	–6.03	–2.49
Malaysia	2.06	5.91	6.96
Nepal	1.32	1.68	1.92
New Zealand	–0.17	0.40	0.68
Pakistan	8.42	11.38	13.24
Philippines	5.45	8.34	9.59
Papua New Guinea	0.56	0.75	0.86
Solomon Islands	0.03	0.05	0.06
Thailand	3.95	8.41	9.96
Tajikistan	–0.25	0.10	0.28
Turkmenistan	0.35	0.71	0.88
Uzbekistan	0.27	1.29	1.82
Viet Nam	4.45	6.34	7.42
Vanuatu	0.02	0.04	0.04
Samoa	0.00	0.01	0.01

Source: Ricke et al. (2019).

4. MITIGATION

While the previous sections discussed projected physical and economic impacts of climate change, at the very heart of the problem is the fact that emissions of greenhouse gases have grown at a steady pace since the dawn of the industrial revolution. Figure 6 below shows the trajectory of emissions since 1751.

Figure 6: Global Emissions of CO_2



t = ton.

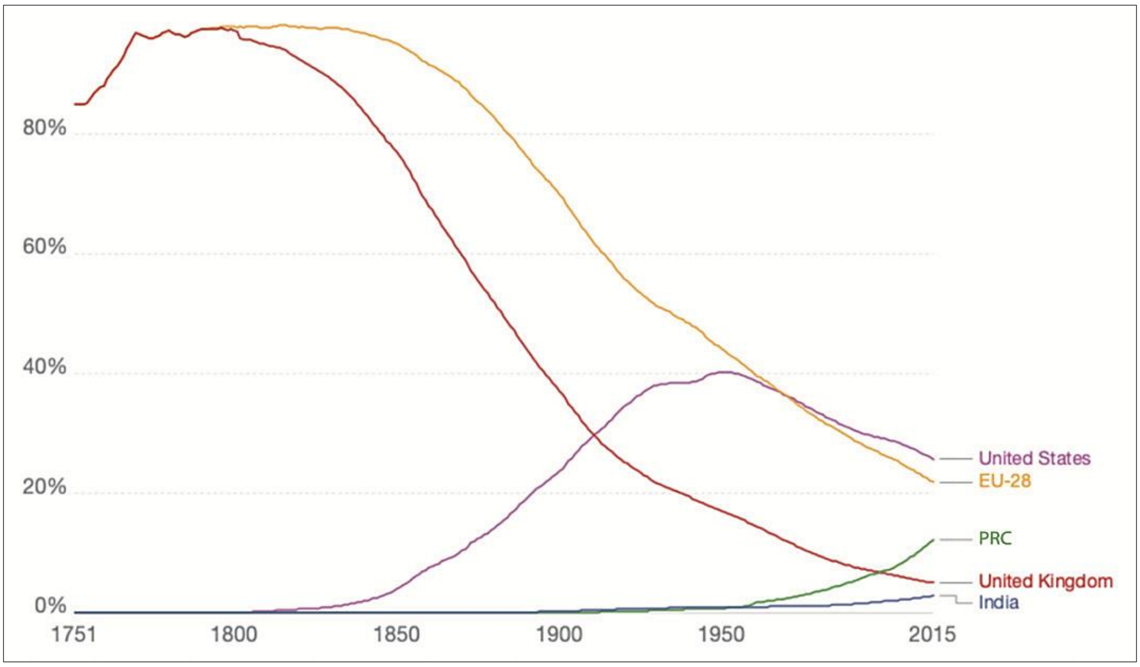
Source: Global Carbon Project (GCP); CDIAC.

The figure makes two points. First, the growth of emissions in the post-war period was massive. Annual emissions went from roughly 5 billion tons in 1950 to 35 billion tons in 2017, a sevenfold increase. The second aspect to notice is that global fuel mix has changed tremendously. While in the early parts of the 20th century the vast majority of emissions came from coal, today these account for less than half. Liquid fuels, largely driven by increases in transportation demand, are now the second biggest source of emissions, followed by natural gas.

Since CO_2 is a stock pollutant when using a human time horizon, one should ask who the biggest contributors to the stock of greenhouse gases in the atmosphere are by region. Figure 7 below breaks down the cumulative emissions for several countries and aggregates.

This figure provides two interesting insights. In the early days of industrial carbon emissions, the lion's share of emissions came from the home of the industrial revolution, the United Kingdom, with almost 100% of cumulative emissions. In the late nineteenth century, emissions in the United States started growing rapidly, and the US share in cumulative emissions rose to a peak of 40% by the end of World War 2. What one observes starting in the late twentieth century is the emergence of the PRC and India as major sources of annual emissions. The growth in emissions was so rapid that even though aggregate annual emissions were growing quickly during this period, the Chinese share in cumulative emissions broke 10% of total emissions, while India's is hovering around 5%. Maybe the most significant insight behind this figure is that the slope of the emissions trajectories for the US and the EU is declining and the share for the rapidly developing economies of India and the PRC is increasing, with the rate of change increasing.

Figure 7: Cumulative CO_2 Emissions for a Subset of Countries and Aggregates

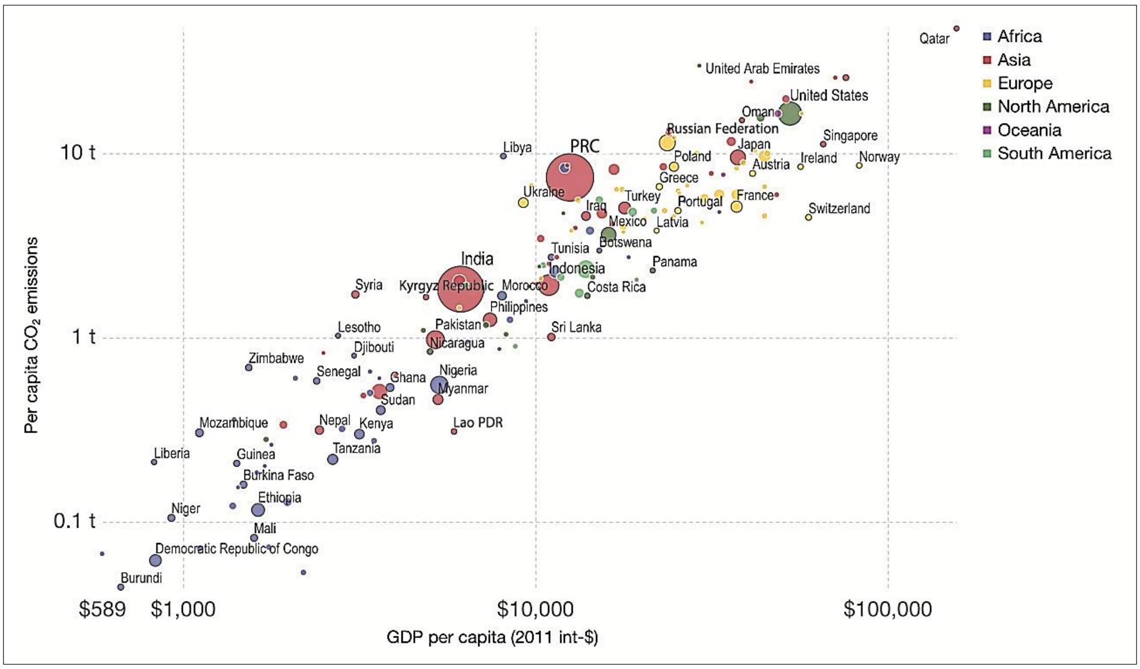


Source: Our World in Data based on Global Carbon Project (GCP).

The drivers of this growth are not surprising. In the climate literature, there is a simple decomposition of emissions called the KAYA identity. It hypothesizes that CO_2 emissions can be decomposed into a product of population, GDP per capita, energy intensity per unit of GDP, and carbon intensity (carbon per unit of energy consumed). If one takes this equation at face value, it suggests that more populous, richer, energy-intensive countries with a more carbon-intensive energy sector will have larger emissions. This is not surprising and has been confirmed in largely cross-sectional decomposition analyses. Taking a closer look at one part of this equation, the income emissions relationship is instructive. One common way to look at this is to plot the relationship between per capita emissions and per capita income, which compares measures per person across countries A snapshot of how average income and emissions correlate is provided in Figure 8 below for the year 2016.

It is important to note that this figure is plotted on a log-log scale. This suggests a highly nonlinear relationship between per capita emissions and income, higher incomes being consistent with significantly higher emissions. Sub-Saharan economies are shown to have a per capita GDP below $1,000 per person and emissions below 0.1 tons per year. The United States, whose GDP is approaching $60,000 per capita, has per capita emissions exceeding 10 tons per person year. That is a difference of two orders of magnitude. The sign of this effect is intuitive, as wealthier countries consume (and produce) more goods and services, and therefore have higher emissions.

Figure 8: Per Capita CO2 Emissions Plotted Against Per Capita GDP



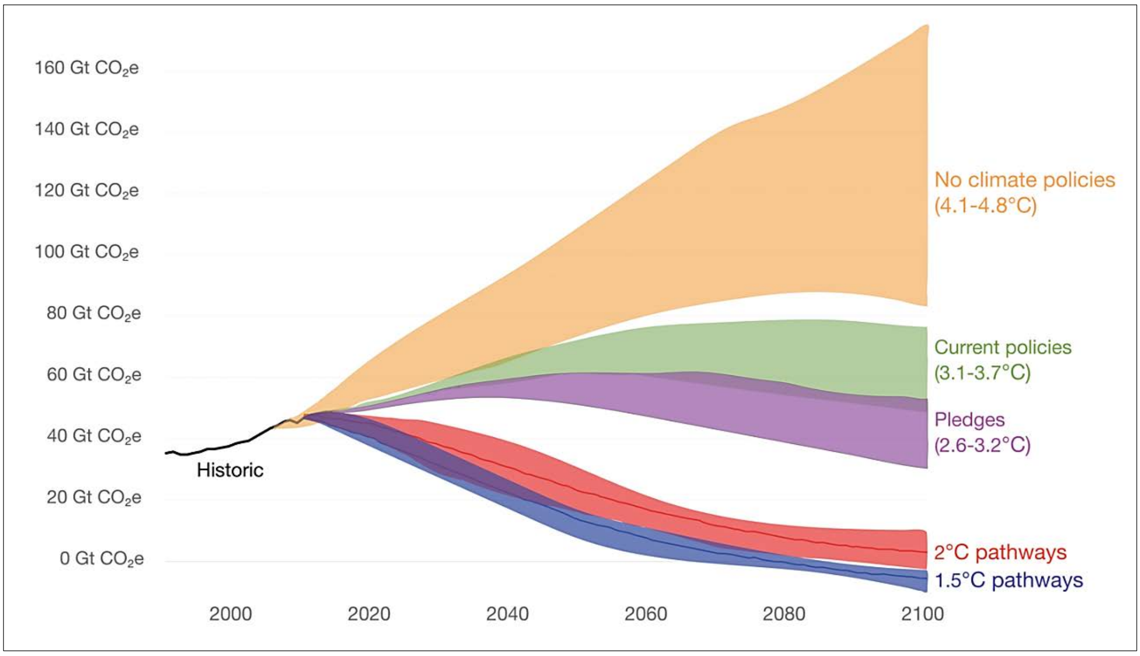
Source: Global Carbon Project, Maddison (2017).

The cross-sectional figure below ignores what happens over time. The questions we need to ask are what will happen to the countries located at the bottom left on this graph as time goes on? Will they migrate to the top right quadrant, which means they would be wealthier—which is arguably a good thing, but also producing significantly higher emissions per person? The real question is what will happen to the energy intensity and carbon intensity of economies across the board? Will lower carbon intensity decrease overall emissions? Will improved energy efficiency be instrumental in driving down emissions? In a dream world, one would produce an ever-increasing amount of goods and services at rapidly declining levels of resource intensity, which is more than just decreasing carbon emissions.

There is a set of emissions scenarios that provide climate modelers with an idea of different ‘states of the world’, as emissions are a key input in the GCMs. Emissions for the next 80 years are the usual time horizon. Figure 9 below shows possible future emissions trajectories at the global level.

These worlds are, of course, extremely different. The top (yellow) fan indicates a world without climate policies, consistent with 4.1–4.8°C warming. The reported figures of warming here are for the global average temperature. Averages, as any statistician knows, are often misleading. In the context of climate change, we think that warming near the poles will be much higher than near the equator. This is, of course, problematic, as the poles are covered by ice. Hot temperatures make ice melt, which is especially problematic at the South Pole, as that ice is sitting on land. If it melts, it will result in a significant degree of sea level rise. The same is true for the Greenland ice sheet. The green trajectory in Figure 9 above indicates a world with current policies, assuming that they are implemented and enforced, which will, of course, require significant commitment by regulators, politicians, and environmental authorities across roughly 200 countries. Note that if we just stick with current policies, we will likely experience warming of 3.1–3.7°C, which is significantly above the targeted 2°C warming scenario which is thought to help us avoid the worst consequences of climate change. The purple scenario incorporates pledges made by individual countries under the Paris Agreement, which I discuss in more detail below. If countries implement policies consistent with their pledges, which is an ambitious goal, this would reduce expected warming to 2.6–3.2°C, which is still above the target of 2°C. In order to get to 2°C, the red emission pathway needs to be met. This pathway is a significant challenge. It requires actual reductions in greenhouse gas emissions now. Given the continued growth of emissions, this is a tall order that I think is unrealistic. Given that CO_2 is a stock pollutant, one could shift reduction across time, but there is not much room to maneuver. Finally, the figure displays an ambitious goal of limiting warming to 1.5°C, which I think is unattainable from an economic point of view, since the reductions required are massive.

Figure 9: Possible Future Scenarios of Greenhouse Gas Emissions for the Next 100 Years



Note: Based on data from the Climate Action Tracker (CAT). The data visualization is available at OurWorldinData.org. There you find research and more visualizations on the topic.

5. GLOBAL POLICY

Countries across the world have actively engaged in designing a global agreement which will drive down greenhouse gas emissions to help avoid the worst scenarios of climate change. The first sign of this was the Rio Earth Summit in 1992, which ended in a general agreement by most countries to study what it would take to deal with the climate change problem. This resulted in the 1997 Kyoto Agreement, which had very little impact on global emissions as the two largest emitters were not required to reduce their emissions. The 2015 Paris Agreement was the first global agreement which specified emissions targets for almost all countries—with the exception of the United States, which spectacularly withdrew from the agreement under President Trump a few years after signing. At the time of writing of this paper, all countries in Asia have signed the agreement and the major emitters have joined the agreement, which is the first positive step forward. This signals intent to do something about the problem among higher and lower income countries alike.

This begs the question of what was different about the Paris Agreement from previous attempts to bring together the countries of the world to engage in emissions reductions? I think this worked because individual countries came to the table with their own emissions reduction plans and targets, called Intended Nationally Determined Contributions (INDCs). These INDCs essentially stated what each country's plans were post-2020 to reduce emissions. The word 'intended' is removed once countries submit their ratification. For example, the PRC's INDC stated that its emissions will peak by 2030 or earlier, with a 60%–65% reduction in emissions intensity per unit of GDP. India's commitment is a 33%–35% reduction in the emissions intensity of its GDP by 2030 compared to the 2005 level. Specific links to the individual countries' INDCs can be found on the World Resource Institute's CAIT Climate Data Explorer.[5]

6. A PATH FORWARD

Stating a willingness to do something about a problem is very different from actually doing something about it. This is very similar to the problem of an overweight person trying to lose weight: even with the best intentions one often falls short. But there are rays of hope on the horizon. The choice facing each country is what tools to use to achieve their more or less ambitious goals. The basic choice available to each country is a set of command and control strategies, or incentive-based tools, or a mix of both.

Command and control strategies usually come in three flavors: emissions standards, input standards, or technology standards. Emissions standards require individual firms, for example, to meet a specific emissions target. If firm A currently emits 1,000 tons of CO_2, an emissions standard could require it to reduce its emissions to, for example, 800 tons or pay a fine. If the fine is larger than the cost of reducing emissions, the firm will reduce its emissions. The advantage of this approach is that if the fines are large enough and institutions can enforce a standard, one's abatement goal can be reached. The disadvantage is that an emissions standard will almost always not achieve emission reductions at least cost, since it does not take into account the marginal cost of abatement, which is likely to differ across firms. In order to minimize the cost of abatement, the marginal cost of abatement should be equal across firms at the final level of emissions, which is called the equimarginal principle. Input standards differ from emissions standards in that they require firms to use a specific input to production. The simplest example one can think of is to require coal-fired power plants to use low sulfur coal instead of high sulfur coal. The advantage of this method is that it will likely lead to reductions in emissions if the new input is well chosen. However, input standards have been criticized along two dimensions: firstly, they offer very little incentive for emission reduction R&D, as firms will likely do what they are told and not look for lower cost options to reduce emissions using alternative technology; secondly, the government chooses the 'correct' input, which relies on regulators being able to pick the best input along technical and possibly cost dimensions. Furthermore, input standards will likely violate the equimarginal principle. Finally, technology standards prescribe a specific technology for either emissions reduction or production. Examples of this are catalytic converters, which were widely implemented in cars, or the NO_x scrubbing technology prescribed for many power plants across the planet. The advantage of this approach is that it will almost certainly lead to emissions reductions, yet ex ante quantifying how much emissions will be reduced by is difficult, making it hard to predict specific reductions. The two disadvantages are similar to those affecting input standards. Technology standards

[5] The CAIT Climate Data Explorer can be found at http://cait.wri.org. Another good resource is the Climate Watch Data website, which can be found at https://www.climatewatchdata.org.

require governments to pick a technology, which they may not be well suited to do. Furthermore, they provide low to no incentive for technological improvements and likely violate the equimarginal principle.

Incentive-based methods come in essentially three types: taxes, tradeable permit systems, and subsidies (which are essentially a negative tax). These are economists' preferred policy tools. Taxes, going back to Pigou, follow a simple goal—internalizing the negative externality generated by the production of a good. If a ton of CO_2 at the optimal emissions level causes $50 in damages, one should impose a tax of $50 per ton of carbon emitted. The insight behind this is a thing of beauty. If a firm is charged $50 per ton in addition to the private costs of input to production, the firm has an incentive to reduce its emissions, since costs have gone up. It will reduce its emissions until it is more expensive to reduce emissions compared to paying the tax. At that point, the firm pays the full damage its marginal ton causes. This policy has many advantages. Firstly, it reduces emissions to the socially optimal amount, assuming that the tax rate is set correctly. Furthermore, it provides significant incentives for firms to engage in emissions-related R&D to reduce their abatement costs. The tax also satisfies the equimarginal principle, since all firms will reduce to the point where their marginal abatement costs are equal to the tax rate. Finally, a carbon tax generates significant revenue for governments, which can either be returned to producers and consumers, or used to fund other government programs, such as social security or health care.

Tradeable permit systems work on a different dimension. The regulator chooses what the total desired amount of emissions is and issues a number of permits, equivalent to the total amount of desired emissions, which is hopefully below current emissions. Firms are allocated these certificates based on a number of possible criteria. Furthermore, there is a market for these permits. Firms will sell permits if they find it cheaper to reduce emissions than the market value of a permit. Firms will buy permits if they find it more expensive to reduce emissions than the price of a permit. In equilibrium, then, all firms produce at a point where marginal abatement costs are identical across firms, and if the number of permits is chosen correctly, the permit price will equate to the external cost of emissions. This system has many advantages. Firstly, total desired emissions reductions are achieved, as the number of permits dictates total emissions. Secondly, the equimarginal principle is again met. Thirdly, this system provides significant incentives for firms to innovate in terms of lower cost abatement technologies. Finally, the policy tool generates significant revenue for governments, if initial permits are auctioned off. In practice, some permits are usually given away to get some industries on board. While this may not be optimal from a government revenue point of view, it may just be from a political economy view. What are the disadvantages of this policy tool? The devil is in the detail here. There are issues with permit banking, allocation, and how long the permits last. Also, there are significant incentives for manipulating these markets. Also, from an ethical point of view, one may object to issuing a right to pollute. Finally, subsidies provide payments for adopting things. This could be low emissions technologies, in our case. If we believe that a new technology needs a little 'push' to be successful in the marketplace, one might want to subsidize this technology initially (e.g., electric vehicle subsidies). The advantage is that these subsidies lower the purchase price of the desired technology and result in higher adoption. The disadvantage is that governments have to pick what to subsidize and by how much. This is hard to do. Finally, taking away subsidies is politically as feasible as imposing new taxes.

In reality, governments across the world are implementing a mix of both types of tool at the same time. California, the world's fifth largest economy with one of the most aggressive emissions reduction goals, is a good example. The state has a cap and trade system, which covers a number of large sectors. Furthermore, it has a low carbon fuel standard, which is targeted at increasing the share of low carbon fuels in the transportation sector. It has a renewable portfolio standard designed to increase the share of renewables in electricity generation. It has some of the world's most aggressive energy efficiency standards—and the list goes on. The cost of these emissions reduction goals ranges from negligible (energy efficiency) to wildly expensive (low-carbon fuel standard). Economists have pointed out repeatedly that one should at least attempt to achieve desired emissions reductions at the lowest cost. Unfortunately, the situation in California and in Europe is not even close to that, given the implementation of multiple emissions reduction tools at the same time.

That said, there is a glimmer of hope on the horizon in many Asian economies, the most significant of which may be the design of a tradable emissions system covering the electricity sector in the PRC. This would, for the first time, put a price on carbon at the national level for the world's largest emitter. While this effort does not cover all sectors and many details remain to be worked, this signifies an important first step on a hopefully rapid and impactful journey toward a world with limited climate change.

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