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The Effects of Climate Change on GDP by Country and the Global Economic Gains From Complying With the Paris Climate Accord

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Key Points:
- The global economic gains from complying with the Paris Climate Accord are shown to be substantial across 139 countries
- With the comparative case of RCP8.5 (4°C), the global gains from complying with the 2°C target (RCP4.5) are US$17,489 billion per year
- The relative damages from not complying with the 2°C target to Sub-Sahara Africa, India, and Southeast Asia are especially severe

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Abstract Computable general equilibrium (CGE) models are a standard tool for policy analysis and forecasts of economic growth. Unfortunately, due to computational constraints, many CGE models are dimensionally small, aggregating countries into an often limited set of regions or using assumptions such as static price-level expectations, where next period's price is conditional only on current or past prices. This is a concern for climate change modeling, since the effects of global warming by country, in a fully disaggregated and global trade model, are needed, and the known future effects of global warming should be included in forward-looking forecasts for prices and profitability. This work extends a large dimensional intertemporal CGE trade model to account for the various effects of global warming (e.g., loss in agricultural productivity, sea level rise, and health effects) on Gross Domestic Product (GDP) growth and levels for 139 countries, by decade and over the long term, where producers look forward and adjust price expectations and capital stocks to account for future climate effects. The potential economic gains from complying with the Paris Accord are also estimated, showing that even with a limited set of possible damages from global warming, these gains are substantial. For example, with the comparative case of Representative Concentration Pathway 8.5 (4°C), the global gains from complying with the 2°C target (Representative Concentration Pathway 4.5) are approximately US$17,489 billion per year in the long run (year 2100). The relative damages from not complying to Sub-Sahara Africa, India, and Southeast Asia, across all temperature ranges, are especially severe.

Plain Language Summary This work shows considerable global economic gains from complying with the Paris Climate Accord for 139 countries. For example, with the comparative case of a temperature increase of four degrees, the global gains from complying with the 2° target are approximately US$17,489 billion per year in the long run (year 2100). The relative damages from not complying to Sub-Sahara Africa, India, and Southeast Asia are especially severe.

1. Introduction

The cumulative effects of global climate change will depend on how the world responds to increasing emissions. The evidence indicates that climate change has already resulted in extreme weather events and sea level rises (SLRs), with added threats to agricultural production in many parts of the world (United Nations, 2018; World Bank, 2016). However, standard economic forecasts of the impact of climate change very considerably, with early estimates showing mild effects on the world economy (see, e.g., Nordhaus, 1991; Tol, 2002). Some of these views have softened subsequently (Nordhaus, 2007; Tol, 2012), but aggregate damages still remain relatively small for most temperature ranges.

Both Weitzman (2012) and Stern (2016), among others, have warned that current economic modeling may seriously underestimate the impacts of potentially catastrophic climate change and emphasize the need for a new generation of models that give a more accurate picture of damages. In particular, Stern (2016) has pointed out two key weaknesses of the current class of economic models: their limited spatial coverage, including averaged impacts across countries and regions, and unreasonable assumptions on the discount rate, which translate into a relative lack of forward-looking behavior in economic forecasts and resulting negative impacts on future generations.

Indeed, there have been relatively few attempts to examine the full global, disaggregated, and intertemporal effects of climate change on GDP using large-scale economic modeling, modeling that would capture all of the trading patterns, spillover effects, and economic linkages among countries in the global economic system over time. To date, given its computational complexity, computable general equilibrium (CGE) modeling has largely concentrated on individual country effects or on dynamic models with limited numbers of countries or regions and an absence of forward-looking behavior, that is, so-called recursive dynamic models with static or adaptive price-level forecasts. These recursive dynamic models have value, but the assumption that future price-level expectations are based only on current and past values is broadly incongruent with known future projections of various climate change outcomes and resulting trade effects (Kompas & Ha, 2017).

In this work, we extend the results of recent and innovative large-scale economic modeling, Global Trade Analysis Project (GTAP)-INT (Kompas & Ha, 2017), to account for the effects of various Representative Concentration Pathways (RCPs) and Shared Socioeconomic Pathways (SSPs) on global temperature, which result in a 1–4°C increase in global warming. Our model is fully disaggregated with forward-looking behavior, spanning across 139 countries and 57 broad commodity groups, with full computational convergence over a period of 200 years. In numerical simulations, we show the potential economic gains from following the Paris Climate Accord to the year 2100. It is important to note that we do not calculate the costs of implementing the Accord, but we do carefully measure the avoided damages (as potential losses in GDP) as the benefit of compliance.

As is well known, the Paris Accord targets to hold the increase in the global average temperature below 2.0°C above preindustrial levels and to pursue efforts to limit temperature increases to 1.5°C above preindustrial levels (United Nations, 2015). Following this agreement, United Nations members are committed to *intended nationally determined contributions* (INDCs), which provide estimates of their aggregate greenhouse gas (GHG) emission levels in 2025 and 2030. With the implementation of the INDCs, aggregate global emission levels would be lower than in pre-INDC trajectories (United Nations, 2016). The agreement also aims to further support the ability of countries to deal with the impacts of climate change (United Nations Framework Convention on Climate Change [UNFCCC], 2018a) and is seen as providing an essential road map for the human response to reduce emissions and build in further climate resilience.

Section 2 below provides a brief review of climate change agreements and the international framework. Section 3 highlights some of the previous literature on CGE modeling on the economic effects of climate change. Section 4 details our data, the model approach, and the results. Section 5 evaluates the long-term impacts by RCP scenario and the potential global economic gains of complying with the Paris Climate Accord. Section 6 provides some added discussion and a few closing remarks.

2. Climate Agreement and Scenario Context

Since 1850, the Earth's surface has become successively warmer and especially so over the past three decades. From 1880 to 2012, global average temperature (calculated with a linear trend for combined land and ocean surface temperature) shows a warming of 0.85 [0.65–1.06]°C (Intergovernmental Panel on Climate Change [IPCC], 2014). Emissions grew more quickly between 2000 and 2010, and carbon dioxide (CO_2) levels have increased by almost 50% since 1990. Under the effect of climate change, oceans have warmed, the amounts of snow and ice have diminished, and sea levels have risen. The global average sea level increased by 19 cm from 1901 to 2010 and is predicted to raise 24–30 cm by 2065 and 40–63 cm by 2100 (United Nations, 2018). The IPCC's Fifth Assessment Report (IPCC, 2014) has clearly confirmed human influence on the climate system. The report also indicates that the recent anthropogenic emissions of GHG are the highest in history and have already generated widespread impacts on human and ecological systems.

To counter these impacts, the past two decades have been marked by a sequence of international initiatives and agreements to stabilize GHG emissions. The UNFCCC, for example, was first introduced in 1992 to limit average global temperature increases. The UNFCCC is one of the three intrinsically linked Rio Conventions, adopted at the Rio Earth Summit in 1992. The other two Conventions are the UN Convention on Biological Diversity and the Convention to Combat Desertification (United Nations Framework Convention on Climate Change, 2018b). Since then, other major international climate change frameworks have progressed, including the Kyoto Protocol (1997), along with the Copenhagen Accord (2009), the Durban Platform for Enhanced

Action (2011), the adoption of the Doha Amendment to the Kyoto Protocol (2012), the IPCC Fifth Assessment Report (IPCC, 2014), and the adoption of the Paris Agreement in 2015 (based on United Nations Framework Convention on Climate Change, 2018c, 2018d).

According to the United Nations Framework Convention on Climate Change (2018b), the UNFCCC Convention (1994), developed from the Montreal Protocol (1987; one of the most successful multilateral environmental treaties at that time), binds member states to act in the interests of human safety, facing scientific uncertainty. The Convention aims to stabilize GHG emissions *at a level that would prevent dangerous anthropogenic (human-induced) interference with the climate system*. As such, targeted GHG emission levels "should be achieved within a time frame sufficient to allow ecosystems to adapt naturally to climate change, to ensure that food production is not threatened, and to enable economic development to proceed in a sustainable manner" (United Nations Framework Convention on Climate Change, 2018b). Following the Convention, the industrialized country members in the Annex I parties, countries belonging to the Organization for Economic Cooperation and Development, including 12 countries with *economies in transition* from Central and Eastern Europe, which are major sources of GHG emissions, are mandated to do the most to cut emissions. By the year 2000, the Annex I parties were expected to reduce emissions to 1990 levels (United Nations Framework Convention on Climate Change, 2018b).

In addition, the Kyoto Protocol, which was adopted in Kyoto in December 1997 and entered into force for many countries in February 2005, was a major climate change agreement that set internationally binding emission reduction targets. Under the principle of *common but differentiated responsibilities*, the Protocol places a heavier burden on developed nations, which are legally bound to emission reduction targets following two phases of commitment periods, given by 2008–2012 and 2013–2020 (United Nations Framework Convention on Climate Change, 2018e). The Paris Climate Accord (adopted in 2015 to which 175 parties have ratified to date) further intensifies the effort toward sustainable low-carbon development, requiring a worldwide response to climate change. In the Paris Accord, both developed and developing countries have committed to reducing emissions by 2030, using 2005 as the base year. As indicated, the Paris Accord is designed to keep global temperatures in this century to a rise "well below 2 degrees Celsius above preindustrial levels and to pursue efforts to limit the temperature increase even further to 1.5 degrees Celsius" (UNFCCC, 2018f, 2018a).

To assist with the understanding of future long-term socioeconomic and environmental consequences of climate change, along with the analysis of potential mitigation and adaptation measures, various future scenarios are widely used in climate change research (van Vuuren & Carter, 2014). The IPCC has used climate scenarios from 1990 forward (SA90) following IS92 and the Special Report on Emissions Scenarios in 2007. These scenarios were developed and applied sequentially from the socioeconomic factors that influence GHG emissions to atmospheric and climate processes. As is generally known, the sequential approach led to inconsistency and delays in the development of emission scenarios (Moss et al., 2010). From 2006, the climate research community initiated a new *parallel approach* to developing scenarios, where model development progresses simultaneously rather than sequentially (Moss et al., 2010; van Vuuren et al., 2014). The work of van Vuuren and Carter (2014) provides a summary of the new scenario framework comprising two key elements: (1) Four RCP scenarios representing the possible future development of GHG emissions and concentrations of different atmospheric constituents affecting the radiative forcing of the climate system and (2) five SSP scenarios providing narrative descriptions and quantitative prediction of possible future developments of socioeconomic variables. These two sets of scenarios provide an integrated framework, or a scenario matrix architecture, to account for the various possible effects of global warming (van Vuuren et al., 2014).

Since both sets of scenarios (i.e., the social development and radiative forcing) eventually lead to different surface temperature increases, they can be reconciled into similar groups with comparable temperature increases. As indicated, van Vuuren and Carter (2014) provide suggestions for such reconciliation of the new RCP and SSP scenarios, in which most of the SSP scenarios can be mapped with the four RCP scenarios (see van Vuuren & Carter, 2014, for the detailed discussion of scenarios and reconciliation tables).

The simulations in our own work thus fully examine the impact on the world economy of global warming in the range from 1 to 4°C, which roughly covers all four possible RCP scenarios from RCP2.6 to RCP8.5. Our individual simulations can be further mapped by comparing final temperature increases with the median temperature rise by RCP scenarios in IPCC (2014), using the reconciliation tables in van Vuuren and Carter (2014).

3. CGE Modeling and the Economic Effects of Climate Change

Climate change is a global and long-term phenomenon, which requires global coordination and a forward-looking policy approach. Global dynamic CGE models are, therefore, a natural candidate for climate change impact assessment and policy analysis. Rational, intertemporal responses cannot be made using naive static or adaptive price-level expectations, which are essentially backward looking, or with highly aggregated regional, rather than country-specific, approaches. Unfortunately, due to technical difficulties, current economic and CGE modeling of the effects of climate change lack both adequate time (forward-looking) and spatial (country-disaggregated) coverage.

As a whole, CGE models encompass standard policy analysis and forecasting approaches for GDP growth, incomes, and the global economic system. Since the pioneering work of Johansen (1960), with a basic one country model, CGE models have grown both in size and complexity. Modern CGE models are now (at least potentially) truly global with as many as 140 interactive regional economies (Aguiar et al., 2016; Corong et al., 2017; Hertel, 1997) and can be solved over a long time horizon in a recursive (e.g., Dixon & Rimmer, 2002; Ianchovichina & Walmsley, 2012) or intertemporal framework (e.g., Ha et al., 2017; McKibbin & Wilcoxen, 1999). With the implementation of time (intertemporal) and spacial (regional and country-specific) dimensions, the size of CGE models has grown exponentially posing a serious challenge to current computational methods. Current software packages such as GEMPACK or GAMS, which use a serial direct LU solver (see Ha & Kompas, 2016), are incapable of solving large intertemporal CGE models. Dixon et al. (2005) indeed has shown that with these models, using over 100 industries or commodity groups, it is only possible to solve the system simultaneously for a relatively small number of time periods.

Due to computational constraints, current CGE models are also normally limited to either static or recursive approaches. Static CGE models compare an economy over two discrete time points: the current period before an exogenous shock and either a short-run period or a long-run period after the shock is realized. The main difference between the short- and long-run cases is whether the capital stock is fixed or allowed to freely adjust (in response to an exogenous shock), designated by short- or long-run closure. Hertel et al. (2010) used such a static CGE-GTAP model to simulate the impact of climate change on the world economy in the year 2030 via shocks in agricultural production. Although the model can be used to analyze the impact of climate change in the long run, it cannot provide any intermediate and time path effects from climate change. It is also dimensionally constrained, that is, even with the comparison of only two time periods, Hertel et al.'s (2010) approach can only account for 34 countries/regions. In practice, it is rare to see CGE models, static or recursive, that are solved with a full countrywide database (up to 100 countries/regions or more).

In a search for a more comprehensive approach, recursive models extend the static CGE model beyond a one-period comparative analysis by solving the system recursively, year after year, over an unspecified but extended time horizon. Bosello et al. (2006, 2007), for example, used a variant of the CGE-GTAP model, GTAP-E, to simulate the impact of climate change-induced effects on human health (Bosello et al., 2006) and sea level increases (Bosello et al., 2007) to the world economy up to 2050. (The GTAP-E framework, Burniaux & Truong, 2002, is an extension of the GTAP model, Hertel, 1997, with more detailed energy inputs in the model's production structure.) The model is first run recursively to calibrate the baseline scenario from an initial calibration year to 2050; then shocks to labor productivity, expenditure for health services (public and private), and SLRs are introduced to form comparative effects of climate change-induced effects for human health in particular. For the expenditure on health services, Bosello et al. (2006) impose a shift in parameter values which would produce the required variation in expenditure if all prices and income levels remained constant. The model is simulated for eight regions of the world. An extension of the ICES model (Eboli et al., 2010), another modification of the GTAP-E model, is also a good example of a multiregion recursive dynamic modeling approach to analyze the effects of temperature change on economic growth and wealth distribution globally. In a more elaborate application, Roson and der Mensbrugghe (2012) use the recursive ENVISAGE model to simulate the economic impact of climate change via a range of impact channels: sea level increases, variations in crop yields, water availability, human health, tourism, and energy demand.

A key limitation of these recursive models is their lack of forward-looking behavior, relying instead on static or adaptive price-level expectations, and successive single period calculations. Economic agents, in other words, only respond to shocks in the current year (or past years) and ignore otherwise known future changes in, for example, climate conditions, no matter how severe they may be. In other words, responses in economic behavior only occur once the shocks are realized. In addition, even though recursive models are solved one period at a time, successively, they normally can only solved for a relatively small number of countries, regions, and sectors, given computational constraints. Thus, they cannot use the available and fully disaggregated country data to facilitate computation.

There have been a few attempts to breakout of the traditional recursive dynamic modeling approach, building instead a forward-looking, global intertemporal model for climate change analysis. McKibbin et al. (2009), for example, use their G-CUBED model (McKibbin & Sachs, 1991; McKibbin & Wilcoxen, 1999) to form an intertemporal global economy to predict future CO_2 emissions under different scenarios. The model in Dixon et al. (2005) is another approach, using rational expectations of future prices to model intertemporal behavior. These are valuable methods, but they too suffer from either limited dimension (McKibbin et al., 2009, with only 14 countries and 12 sectors in) or with difficulties guaranteeing convergence to a solution as in the case of the rational expectations approach.

Outside of the context of the CGE modeling of global intertemporal economies, there are a number of examples of economic assessments of the effects of climate change using more basic models, where damage functions range from low to extreme levels. Tol (2002), for example, estimated the impact of a 1°C warming on the world economy based on a suit of existing and globally comprehensive impact studies. Tol, 's estimations are somewhat inconclusive. The impacts on world GDP with a 1°C warming range from +2% to −3% depending on whether a simple sum or a global average value method is used. Using an estimated damage function for the U.S. economy and extrapolated to the world economy, Nordhaus (1991) also finds mild effects from climate change impacts of 1%, or at most 2%, on the global economy. These views have been modified more recently, as indicated above, but total damages are still relatively small.

Alternatively, Weitzman (2012) has warned that we might be considerably underestimating the welfare losses from climate change by using conventional quadratic damage functions and a *thin-tailed* temperature distribution and suggests severe limits on GHG levels to guard against catastrophic climate risks. A study by the Global Humanitarian Forum (2009) also provides a worrisome picture of the social impacts (e.g., on environment and health) of climate change in the developing world. The loss from global warming, here, includes climate-related deaths from worsening floods and droughts, malnutrition, the spread of malaria, and heat-related ailments. According to Global Humanitarian Forum (2009), the current global warming process already causes 300,000 deaths and US$125 billion in economic losses annually.

Our paper addresses the above weaknesses of current economic analysis and CGE modeling of the effects of climate change by applying new solution methods, developed for solving intertemporal CGE models with very large dimension (Ha & Kompas, 2016, 2014; Ha et al., 2017; Kompas & Ha, 2017), modifying and extending the preliminary results of the effects of climate change contained in Kompas and Ha (2017) to different RCP scenarios. As such, we provide the first example of a large-scale and intertemporal computational modeling of the economic effects of global warming, across all 139 countries in the GTAP database, for various temperature changes. The added, large-dimensional precision matters to the final estimates and disaggregation by country is especially important here. Although the effects of climate change on global average GDP may be large or small, depending on RCP scenario, the effects on individual countries can be enormous across various RCPs. Averaging across such countries into regions severely masks these effects.

4. GTAP-INT Model Framework, Data, and Climate Change Results

The modeling approach applied in this study is an intertemporal CGE version of the GTAP model, termed GTAP-INT in Ha et al. (2017). GTAP is a global economic model that estimates the interactions of economic activities and effects among countries or regions under various exogenous shocks (Hertel, 1997).

We use GTAP version 6.2 to be consistent with our previous research (Ha et al., 2017). We are aware of the publication of GTAP version 7, where commodities and activities are separated so that a single producer can produce more than one product (Corong et al., 2017). However, in the most recent GTAP database (version 9), which we employ, a producer can produce only one product (see Aguiar et al., 2016). Therefore, we expect no substantive difference in our work between GTAP version 6.2 and version 7 simulation results with the current database.

The intertemporal version of GTAP model consists of blocks of supply and demand equations for producers, households, investment demand, and governments, indexed by country and at each point in time. Producers use inputs, or factors of production, such as land, labor and capital, and other intermediate goods, to deliver commodities which are sold on international and domestic markets. Households make decisions between savings and the consumption of various commodities, foreign and domestic, from their income, less taxes. In an individual economy, the total demand for a product (from international and domestic sources) equals the supply of that product, with corresponding price linkages and market clearing conditions. Global savings, investment, and transportation is also modeled (Ha et al., 2017; Hertel, 1997).

The GTAP model, in its current form, is run either as a static model or as a recursive dynamic model with assumed static or adaptive price-level expectations (Kompas & Ha, 2017). A key benefit of the GTAP-INT model is that it allows producers, in particular, to look forward, to choose how much to invest in capital stocks over time to maximize profits in the long run. A fully defined intertemporal version of the GTAP model was first developed in Ha et al. (2017), where fixed capital formation and given allocations of investment across regional blocks of countries are replaced by long-run profit conditions. The version of GTAP-INT in Kompas and Ha (2017) extends this work to very large dimensions using a new solution method and allowing for multiple countries and time periods. In the context of climate change, GTAP-INT allows producers to respond to foreseeable climate change impacts immediately, in terms of how they invest and the choice over what they produce, rather than waiting for climate change impacts to be actually realized and then enter their forecasts for prices and other key variables. In recursive models, alternatively, producers only respond to climate change impacts once they actually occur. The structural equations for GTAP-INT are detailed in Ha et al. (2017) and are not repeated here, save for the key intertemporal condition for profit (dividend) maximization, given by two motion equations for capital accumulation and its shadow price:

$$\dot{k}_{r,t} = I_{r,t} - \delta_r k_{r,t} \tag{1}$$

$$\dot{\mu}_{r,t} = \mu_{r,t}[r_t + \delta_r] - \frac{\phi_{r,t}}{2}\left(\frac{I_{r,t}}{k_{r,t}}\right)^2 p^I_{r,t} - p^k_{r,t} \tag{2}$$

where $k_{r,t}$ is the capital stock in region r at time t (hereafter we supress the indices r and t where appropriate for simplicity), r_t is the world interest rate, $I_{r,t}$ is increment in capital (i.e., investment), δ_r is the depreciation rate, $\mu_{r,t}$ is the shadow price of capital, and $\phi_{r,t}$ is the investment coefficient, which shows how much extra money we must invest in order to obtain a dollar increase in the capital stock; $p^I_{r,t}$ is the price of capital goods; and $p^k_{r,t}$ is the rental price of capital. To solve the model, we use the GTAP model equations to link all global economies over time using forward-backward equations (i.e., equations (1) and (2)) for each country in the GTAP model, given an initial condition (fixed initial capital $k_{r,0}$) and one terminal condition: $\dot{\mu}_{r,T} = 0$ (Kompas & Ha, 2017). As usual in intertemporal models, we take a state steady benchmark as the baseline or as *business as usual*. We then compare this baseline path to parametric changes across different climate change scenarios. This is standard in an intertemporal framework and indeed is the only technical option available to facilitate our large-dimensional modeling.

4.1. Database and Climate Change Damage Functions

As indicated, the database employed in this work is GTAP Data Version 9 (Aguilar et. al., 2016; GTAP, 2017), which consists of 140 countries and regions (we drop one country, Benin, for numerical stability) and 57 commodities with 2011 as the base year. The data set requires the addition of damage functions, which aim to estimate the economic impacts of global warming, in general, and, in particular, in CGE and GTAP modeling. The climate change damage functions applied in this paper largely follow, with some qualifications, Roson and Sartori (2016), where climate change parameters for damages are estimated from a series of meta-analyses for each of the 140 countries and regions in the GTAP version 9 data set. The damage functions applied include the effects of SLR, losses in agricultural productivity, temperature effects on labor productivity and human health, energy demands, and flows of tourism (Roson & Sartori, 2016).

The background for all of this is straightforward. For SLR impacts, following the Fifth IPCC Assessment Report (IPCC, 2014), Roson and Sartori (2016) note that a large number of studies find a connection between global warming and sea level increases. SLR affects the total stock of land and causes erosion, inundation, or salt intrusion along the coastline. As a consequence, the share of land which may be lost depends on several country-specific characteristics. In Roson and Sartori (2016), the relationship between SLR (in meters) and the increase in global mean surface temperature (in degrees Celsius), at the time intervals 2046–2065 and 2080–2100, is based on IPCC (2014), with an added emphasis on land losses in agriculture.

Indeed, economic studies of climate change appear to focus predominantly on agricultural impacts. According to Roson and Sartori (2016), climate change is expected to bring about higher temperatures, a higher carbon concentration, and different patterns in regional precipitation, all of which affect crop yields and agricultural productivity. In Roson and Sartori (2016), in particular, the climate change damage function for agricultural productivity is based on a meta-analysis provided in IPCC (2014), which provides central estimates for variations in the yields of maize, wheat, and rice. Roson and Sartori (2016) elaborate on these results to get estimates of productivity changes for these three crops, in all 140 regions and for the five levels of temperature increase, from 1 to 5°C. The estimation distinguishes between tropical and temperate regions and identifies a nonlinear interpolation function for all cases. Roson and Sartori (2016) also apply the work by Cline (2007) for the estimation of productivity changes for the entire agricultural sector in various regions. In this approach, the variation in agricultural output per hectare is expressed as a function of temperature, precipitation, and carbon concentration.

Estimation of labor productivity loss due to heat stress in Roson and Sartori (2016) is based on a study by Kjellstrom et al. (2009), which produced a graph of *work ability* as the maximum percentage of an hour that a worker should be engaged working. Roson and Sartori (2016) define work ability (a proxy for productivity) as a function of *wet bulb globe temperature*. The heat exposure index, using wet bulb globe temperature (units in °C), is a combination of average temperature and average absolute humidity (Roson & Sartori, 2016). As developed from Kjellstrom et al. (2009), Roson and Sartori (2016) estimate the effect of global warming for different increments in temperatures (ranging from 1 to 5°C) for three labor sectors (agriculture, manufacturing, and services) in each of the GTAP countries.

In Roson and Sartori (2016), estimation of the GTAP human health damage function is developed from Bosello et al. (2006), which, based partly on Tol (2002), develops estimates of the association between temperature increments and a number of added cases of mortality and morbidity of selected diseases, considering, in particular, the direct effect of incremental temperatures for vector-borne diseases (e.g., malaria and dengue), heat- and cold-related diseases, and diarrhea. Given the lack of data, supporting evidence and the scope of the analysis, Roson and Sartori (2016) do not include other diseases mentioned in IPCC (2014), such as hemorrhagic fever, plague, Japanese and tick-borne encephalitis, air quality and nutrition-related and allergic diseases, nor other impact categories mentioned in World Health Organization (2014) such as heat-related mortality in elderly people, or mortality associated with coastal flooding, and so on (Roson & Sartori, 2016).

Given our purposes, we disregard the climate damage functions for tourism and energy demand, also estimated by Roson and Sartori (2016). In terms of tourism, Roson and Sartori (2016) estimate travel flows following Hamilton et al. (2005) of which flows of international tourism are regressed as a function of temperature, land area, length of coastline, and per capita income. However, tourism flows in Roson and Sartori (2016) are regressed simply as an exponential function of temperature with a constant term (for a country's specific condition). This seems inadequate for our otherwise nonlinear specifications. Also, Roson and Sartori (2016) did not consider the other key drivers of tourism flows, including the attractions of natural landscapes, cultural and historical attributes, and, most importantly, the distinction between tourism and other forms of migration for climate change-related movements. Moreover, transforming the tourism effect into a CGE framework, which is based on GDP, implies no difference of income spending between nationals and foreigners inside a country's border and therefore is largely inappropriate.

The climate change effect on household's energy consumption in Roson and Sartori (2016) is estimated and adjusted from De Cian et al. (2013) of which the key drivers are season, sources of energy, and a country's climatic condition. However, for GTAP modeling, other drivers such as the elasticity of fuel use and income, the fuel mix in each country, and variations in standards of living among rich and poor nations matter a great deal. Since these are not included, we suspend this effect, for now, pending the development of a GTAP-E version of GTAP-INT. In any case, the temperature elasticities in De Cian et al. (2013), which are estimated for current climate conditions, would change considerably under various global warming scenarios, and this needs to be analyzed separately and comprehensively and not simply adjusted.

From the above damage function estimations, we design shocks to the GTAP-INT model to simulate the climate change impacts. First, the SLR impact will be simulated as a negative shock to the supply of land, a nonmobile factor of production in GTAP-INT. The shock is region specific, as in Roson and Sartori (2016). Next, negative agricultural productivity will be simulated by a percentage change shock to output-augmenting technical change in agricultural sectors. The shock is also sector and region specific. We aggregate and simulate labor productivity loss and human health damages via a negative labor productivity loss. Again, the labor productivity loss will be region and sector specific. With all the shocks, we assume a linear gradual increase from the current year (2017) with the highest shock occurring in 2100. After 2100, the size of the shock is assumed to remain constant (at the 2100 level), and the model is run forward for 200 years to ensure convergence to a new steady state, which the latter interpreted as long-run losses or impacts. With the time horizon of the model at 200 years, we apply a variable time grid to reduce the dimension of the model (see for details on intertemporal solution methods ; Dixon et al., 1992). Nevertheless, with multiple periods and the full regional and country-specific GTAP model, the size of the model is very large, and we solve the model using only the one-step Johansen method (see for details on the Johansen solution method; Dixon et al., 1992).

4.2. The Economic Effect of Global Warming

Following Riahi et al. (2017), different SSP narratives are characterized by assumptions on future economic growth, population change, and urbanization. As indicated above, Riahi et al. (2017) provide an overview of the main characteristics of five SSPs and related integrated assessment scenarios. The scenario analysis in our work, as discussed in section 2, is based on four different scenarios where the world surface temperature increases from 1 to 4°C to 2100, with RCPs (Moss et al., 2010) mapped to our scenarios by using the predictions of global surface temperature increases in IPCC (2014). As SSPs can also be mapped with RCPs (van Vuuren & Carter, 2014), our scenarios can be seen as a potential realization of scenarios from the Scenario Matrix Architecture (van Vuuren et al., 2014) and are valuable for analyzing climate change and mitigation policies.

For our GTAP-INT results, the dynamic effect of global warming is measured as the change in real GDP in all regions for different global warming scenarios in the range from 1 to 4°C. With lower emissions, for example, global warming is approximated by an increase of 0.85°C as in RCP2.6, where the climate change damage parameters for the 1°C case in Roson and Sartori (2016) can be (approximately) applied. In the extreme case of RCP8.5, without mitigation action (i.e., with *Rocky Road* [SSP 3] and strong *Fossil-Fueled Development* [SSP5] scenarios; Ria et al., 2017), global warming could increase temperatures by as much as 4°C, or perhaps more, by 2100.

For our current purposes, we first focus on *Middle of the Road* (SSP2) as the most likely or *business as usual* scenario. In this case, the path of the world's social, economic, and technological trends does not shift markedly from historical patterns (Riahi et al., 2017). As such, climate change is likely to be RCP6.0 and our scenario with a global warming of 3°C by 2100 can be applied. The results from GTAP-INT on GDP are given in percentage changes in Table 1 (which, with Figure 1, qualify and extend the preliminary results in Kompas & Ha, 2017). The value losses in GDP caused by global warming over the medium and long term for selected countries are contained in Table A1. Table A2 also details the global warming effects decomposed by economic sectors. As indicated, it is important to note that the model is run forward for 200 years, our *long run* for convenience and computational convergence. After the year 2100 no additional shocks are introduced to the model so that convergence is guaranteed. GDP estimates in Table A2 and the calculation of the gains from complying with the Paris Accord are based on outcomes to the year 2100 only.

The results clearly show that the effects of global warming vary by time, region, and economic sectors but tend to increase over time and become much worse in relatively poor African and Asian nations, where the loss in GDP here and in all countries near the equator is most severe (see Table 1 and Figure 1). But, indeed, over the medium term, despite some minor gains in a few European countries, the losses from global warming (at 3°C) dominate a major part of the world (Figure 1).

Using the value of GDP in 2017 from IMF (2018) as the base year, our GTAP-INT results, and economic growth forecasts from SSP2 (Crespo Cuaresma, 2017; International Institute for Applied Systems Analysis, 2018), the approximate global potential loss is estimated to be US$9,593.71 billion or roughly 3% of the 2100 world GDP for 3°C global warming (see Table A1). At 4°C, losses from global warming increase significantly to US$23,149.18 billion. The largest losses in all cases, and for all temperature increases, occur in Sub-Saharan Africa, India, and Southeast Asia.

Table 1
Impacts of Global Warming (3°C) on the World GDP (% Change/Year)

Country	2027	2037	2047	2067	Long run
Australia	−0.051	−0.107	−0.172	−0.326	−1.083
New Zealand	0.043	0.073	0.087	0.073	−0.798
Rest of Oceania	−0.452	−0.924	−1.422	−2.470	−5.171
China	−0.205	−0.438	−0.692	−1.247	−2.918
Hong Kong	−0.356	−0.765	−1.216	−2.205	−5.288
Japan	−0.042	−0.100	−0.173	−0.356	−1.335
South Korea	−0.025	−0.071	−0.136	−0.313	−1.498
Mongolia	−0.214	−0.415	−0.631	−1.105	−2.710
Taiwan	−0.535	−1.121	−1.740	−3.034	−5.978
Rest of East Asia	−0.819	−1.752	−2.752	−4.849	−9.490
Brunei Darussalam	−0.372	−0.815	−1.308	−2.385	−5.563
Cambodia	−1.175	−2.439	−3.758	−6.482	−12.101
Indonesia	−1.242	−2.594	−4.020	−6.973	−13.267
Laos	−1.039	−2.164	−3.342	−5.765	−10.621
Malaysia	−1.091	−2.293	−3.568	−6.229	−12.118
Philippines	−1.206	−2.592	−4.093	−7.275	−14.798
Singapore	−0.905	−1.958	−3.106	−5.562	−11.652
Thailand	−0.766	−1.605	−2.500	−4.401	−9.243
Vietnam	−0.802	−1.636	−2.500	−4.276	−7.959
Rest of Southeast Asia	−1.342	−2.767	−4.237	−7.234	−12.924
Bangladesh	−0.854	−1.671	−2.491	−4.142	−7.591
India	−1.023	−2.099	−3.222	−5.532	−10.351
Nepal	−0.505	−1.012	−1.537	−2.628	−5.731
Pakistan	−0.483	−1.001	−1.557	−2.753	−6.435
Sri Lanka	−1.129	−2.320	−3.569	−6.154	−11.716
Rest of South Asia	−1.081	−2.105	−3.133	−5.206	−9.606
Canada	0.062	0.111	0.151	0.203	−0.218
United States of America	−0.015	−0.037	−0.067	−0.147	−0.622
Mexico	−0.029	−0.076	−0.147	−0.363	−2.277
Rest of North America	0.015	−0.003	−0.033	−0.127	−0.902
Argentina	−0.061	−0.137	−0.228	−0.450	−1.583
Bolivia	−0.194	−0.388	−0.592	−1.028	−2.332
Brazil	−0.319	−0.658	−1.018	−1.782	−3.843
Chile	0.008	0.001	−0.021	−0.112	−1.158
Colombia	−0.452	−0.916	−1.401	−2.425	−5.532
Ecuador	−0.183	−0.380	−0.594	−1.061	−2.599
Paraguay	−0.630	−1.304	−2.012	−3.482	−6.729
Peru	−0.174	−0.348	−0.526	−0.902	−1.934
Uruguay	−0.055	−0.135	−0.234	−0.482	−1.776
Venezuela	−0.309	−0.636	−0.982	−1.712	−3.614
Rest of South America	−0.028	−0.075	−0.141	−0.321	−1.545
Costa Rica	−0.585	−1.277	−2.038	−3.673	−7.871
Guatemala	−0.215	−0.442	−0.684	−1.206	−2.798
Honduras	−1.025	−2.151	−3.337	−5.802	−11.126
Nicaragua	−1.187	−2.449	−3.757	−6.435	−11.673
Panama	−0.870	−1.823	−2.838	−4.958	−9.580
El Salvador	−0.338	−0.719	−1.136	−2.048	−4.957

Table 1 *(continued)*

Country	2027	2037	2047	2067	Long run
Rest of Central America	−1.163	−2.391	−3.665	−6.285	−11.646
Dominican Republic	−0.522	−1.150	−1.855	−3.400	−7.934
Jamaica	−0.616	−1.287	−1.999	−3.492	−6.940
Puerto Rico	−0.458	−0.995	−1.587	−2.870	−6.527
Trinidad and Tobago	−0.503	−1.136	−1.842	−3.371	−7.357
Caribbean	−0.771	−1.610	−2.492	−4.320	−8.207
Austria	0.055	0.107	0.151	0.200	−0.486
Belgium	0.043	0.081	0.108	0.128	−0.540
Cyprus	0.025	0.042	0.049	0.024	−0.816
Czech Republic	0.086	0.165	0.231	0.312	−0.567
Denmark	0.037	0.068	0.092	0.112	−0.393
Estonia	0.018	0.028	0.028	−0.008	−0.750
Finland	0.060	0.117	0.165	0.231	−0.254
France	0.048	0.088	0.117	0.141	−0.455
Germany	0.044	0.083	0.112	0.140	−0.415
Greece	0.108	0.200	0.281	0.402	−0.275
Hungary	0.064	0.122	0.168	0.217	−0.590
Ireland	0.055	0.108	0.152	0.196	−0.748
Italy	0.070	0.136	0.190	0.255	−0.588
Latvia	0.060	0.111	0.152	0.196	−0.394
Lithuania	0.092	0.178	0.251	0.353	−0.394
Luxembourg	0.054	0.101	0.138	0.171	−0.600
Malta	0.066	0.130	0.181	0.225	−1.261
Netherlands	0.054	0.101	0.135	0.169	−0.467
Poland	0.074	0.139	0.192	0.253	−0.514
Portugal	0.044	0.083	0.113	0.140	−0.460
Slovakia	0.100	0.193	0.273	0.382	−0.470
Slovenia	0.041	0.071	0.091	0.097	−0.512
Spain	0.044	0.078	0.102	0.113	−0.575
Sweden	0.039	0.074	0.102	0.131	−0.349
United Kingdom	0.034	0.063	0.085	0.101	−0.422
Switzerland	0.016	0.028	0.034	0.029	−0.355
Norway	0.003	0.008	0.007	−0.022	−0.646
Rest of EFTA	0.057	0.111	0.154	0.205	−0.421
Albania	−0.054	−0.114	−0.185	−0.365	−1.461
Bulgaria	0.063	0.115	0.153	0.187	−0.590
Belarus	0.089	0.147	0.191	0.240	−0.249
Croatia	0.010	0.015	0.015	−0.007	−0.454
Romania	0.041	0.076	0.099	0.112	−0.483
Russian Federation	−0.011	−0.016	−0.027	−0.081	−0.936
Ukraine	0.057	0.107	0.149	0.204	−0.250
Rest of Eastern Europe	0.175	0.311	0.432	0.639	0.370
Rest of Europe	0.104	0.198	0.280	0.401	−0.206
Kazakhstan	−0.031	−0.058	−0.089	−0.173	−0.820
Kyrgyzstan	0.009	0.006	−0.011	−0.083	−0.930
Rest of Former Soviet Union	0.012	0.019	0.017	−0.015	−0.564
Armenia	−0.040	−0.079	−0.126	−0.249	−1.350

Table 1 *(continued)*

Country	2027	2037	2047	2067	Long run
Azerbaijan	−0.174	−0.350	−0.538	−0.953	−2.638
Georgia	−0.025	−0.060	−0.106	−0.231	−1.035
Bahrain	−0.281	−0.630	−1.031	−1.939	−5.138
Iran	−0.167	−0.350	−0.558	−1.047	−3.516
Israel	−0.198	−0.410	−0.632	−1.102	−2.317
Jordan	−0.158	−0.342	−0.555	−1.052	−3.254
Kuwait	−0.218	−0.508	−0.851	−1.639	−4.488
Oman	−0.210	−0.478	−0.786	−1.477	−3.780
Qatar	−0.357	−0.829	−1.387	−2.674	−7.304
Saudi Arabia	−0.378	−0.831	−1.332	−2.422	−5.449
Turkey	0.007	−0.008	−0.045	−0.180	−1.540
United Arab Emirates	−0.457	−1.007	−1.630	−3.024	−7.684
Rest of Western Asia	−0.248	−0.507	−0.783	−1.381	−3.306
Egypt	−0.354	−0.714	−1.086	−1.867	−4.000
Morocco	−0.200	−0.415	−0.640	−1.120	−2.436
Tunisia	−0.227	−0.473	−0.735	−1.303	−3.052
Rest of North Africa	−0.211	−0.417	−0.630	−1.080	−2.394
Burkina Faso	−1.576	−3.278	−5.076	−8.829	−17.058
Cameroon	−0.980	−1.989	−3.031	−5.162	−9.396
Cote d'Ivoire	−1.972	−3.988	−6.034	−10.164	−17.528
Ghana	−2.000	−3.999	−6.028	−10.124	−17.571
Guinea	−0.980	−1.939	−2.932	−4.991	−9.896
Nigeria	−1.674	−3.422	−5.217	−8.874	−15.723
Senegal	−1.270	−2.565	−3.905	−6.666	−13.001
Togo	−2.338	−4.553	−6.787	−11.276	−19.032
Rest of Western Africa	−2.334	−4.091	−5.860	−9.409	−15.566
Central Africa	−0.376	−0.783	−1.223	−2.173	−4.977
South Central Africa	−0.289	−0.587	−0.896	−1.549	−3.320
Ethiopia	−0.759	−1.476	−2.197	−3.656	−6.704
Kenya	−0.744	−1.492	−2.254	−3.813	−7.238
Madagascar	−0.726	−1.486	−2.270	−3.881	−7.212
Malawi	−0.983	−1.995	−3.028	−5.133	−9.266
Mauritius	−0.650	−1.359	−2.113	−3.700	−7.458
Mozambique	−0.837	−1.738	−2.681	−4.639	−8.878
Rwanda	−0.766	−1.531	−2.309	−3.888	−7.047
Tanzania	−0.737	−1.479	−2.237	−3.785	−6.988
Uganda	−0.635	−1.268	−1.912	−3.232	−6.328
Zambia	−0.407	−0.831	−1.272	−2.189	−4.414
Zimbabwe	−0.428	−0.849	−1.283	−2.187	−4.423
Rest of Eastern Africa	−0.874	−1.750	−2.644	−4.461	−8.099
Botswana	−0.148	−0.322	−0.523	−0.993	−3.047
Namibia	−0.088	−0.190	−0.310	−0.610	−2.404
South Africa	−0.130	−0.278	−0.443	−0.823	−2.464
Rest of South African Customs Union	−0.192	−0.407	−0.644	−1.172	−3.045
Rest of the World	−0.078	−0.177	−0.294	−0.577	−1.918

Note. Source: Authors' GTAP-INT calculation.

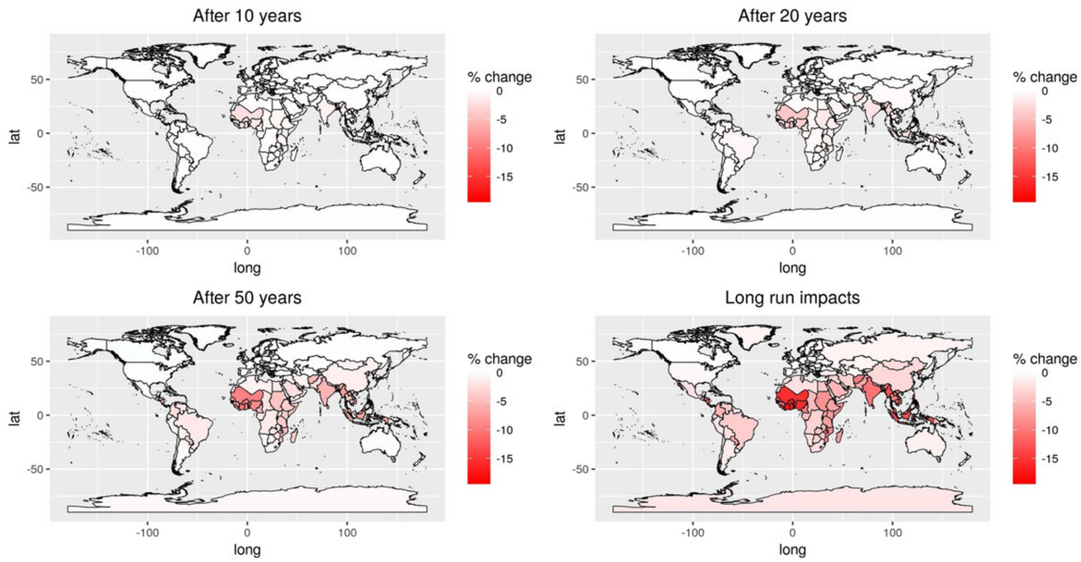

Figure 1. Dynamic impacts of global warming (3°C) on the world GDP (% change/year).

5. Long-Term Potential Impacts by RCP Scenario and Gains From Complying With the Paris Accord

This section compares the long-term impact by different temperature changes from global warming or equivalently different RCPs so that the avoided losses from various responses to climate change can be analyzed and the gains from complying with the Paris Accord can be calculated. Table 2 presents the long-run impacts of different global warming scenarios (1–4°C), which correspond to different RCPs in Moss et al. (2010). The measure is the change in GDP. It is clear that falls in GDP for countries near the equator are especially dramatic.

Indeed, it is interesting to compare our results with the findings of Roson and der Mensbrugghe (2012), using their ENVISAGE model. Although comparable, it is important to note that the model context here is different. Roson and der Mensbrugghe (2012) use a recursive dynamic approach, with adaptive expectations, and their results are only for 15 regions, which will necessarily average outcomes. Our intertemporal approach is dimensionally larger, for 139 countries, and drops the damage functions for tourism and energy use. That said, Roson and der Mensbrugghe (2012) find that the developing and poorer countries in the *rest of Asia* and the *Middle East and North Africa* lose 10.3% to 12.6% of their GDP when the global temperature increases by 4.79°C in 2100. Our larger dimensional model shows, instead, that if global surface temperature increases by 4°C, countries in South East Asia can lose up to 21% of their GDP per year. The picture for developing countries in Africa is even more grim with the GDP losses as high as 26.6% per year (Table 2).

From the above GDP damages, it is possible to calculate the gains from complying with the Paris Climate Accord. Following van Vuuren et al. (2011), we can map our scenarios in terms of their implications for the following climate change policies.

1. The case of 1°C is likely to reflect the lowest emission scenario with the most stringent mitigation policies (or approximately RCP2.6).
2. Implementation of a climate change agreement (e.g., the Paris Accord) would slow global warming to around 2°C by 2100 (or approximately RCP4.5).
3. A medium baseline case with less stringent mitigation policies will push global surface temperatures up to 3°C by 2100 (approximately RCP6).
4. Without any countervailing action to reduce emissions, global warming could increase up to 4°C (or approximately RCP8.5).

The successful achievement of the Paris Accord, which aims to keep global warming at roughly 2°C (or RCP4.5), or less, allows us to calculate the potential benefit of the Accord as the difference in losses between the 4, 3, and 2°C scenarios. Based on the full version of Table 2 from our GTAP-INT simulation results, and Table A1, which represents the value of annual GDP losses in 2100, we can calculate the differences.

10.1029/2018EF000922

Table 2
Long-Run Impacts of Climate Change Scenarios on the World GDP (% Change/Year)

Country	1°C	2°C	3°C	4°C
Australia	−0.287	−0.642	−1.083	−1.585
New Zealand	−0.144	−0.413	−0.798	−1.269
Rest of Oceania	−1.015	−2.627	−5.171	−8.553
China	−0.755	−1.694	−2.918	−4.597
Hong Kong	−1.314	−3.082	−5.288	−7.655
Japan	−0.182	−0.595	−1.335	−2.412
South Korea	−0.211	−0.731	−1.498	−2.666
Mongolia	−0.789	−1.664	−2.710	−3.981
Taiwan	−1.597	−3.560	−5.978	−8.552
Rest of East Asia	−2.389	−5.709	−9.490	−13.710
Brunei Darussalam	−1.202	−3.134	−5.563	−8.173
Cambodia	−3.509	−7.572	−12.101	−17.183
Indonesia	−3.347	−7.980	−13.267	−19.040
Laos	−3.369	−6.795	−10.620	−15.759
Malaysia	−3.084	−7.145	−12.118	−17.339
Philippines	−4.113	−9.185	−14.798	−20.986
Singapore	−2.729	−6.923	−11.652	−16.566
Thailand	−2.541	−5.749	−9.243	−13.269
Vietnam	−2.223	−4.862	−7.959	−11.641
Rest of Southeast Asia	−3.811	−8.110	−12.924	−18.573
Bangladesh	−2.285	−4.755	−7.591	−11.237
India	−2.922	−6.434	−10.351	−14.622
Nepal	−1.012	−2.881	−5.731	−9.859
Pakistan	−1.901	−3.994	−6.435	−9.338
Sri Lanka	−2.989	−6.941	−11.716	−17.437
Rest of South Asia	−2.778	−6.002	−9.606	−13.880
Canada	−0.096	−0.158	−0.218	−0.321
United States of America	−0.182	−0.392	−0.622	−0.885
Mexico	−0.506	−1.178	−2.277	−3.985
Rest of North America	−0.231	−0.539	−0.902	−1.292
Argentina	−0.360	−0.872	−1.583	−2.610
Bolivia	−0.650	−1.442	−2.332	−3.356
Brazil	−0.615	−1.910	−3.843	−6.829
Chile	−0.323	−0.709	−1.158	−1.674
Colombia	−1.104	−2.714	−5.532	−9.325
Ecuador	−0.741	−1.627	−2.599	−3.801
Paraguay	−1.604	−3.873	−6.729	−10.142
Peru	−0.509	−1.169	−1.934	−2.768
Uruguay	−0.471	−1.023	−1.776	−2.785
Venezuela	−0.649	−1.794	−3.614	−6.339
Rest of South America	−0.459	−0.937	−1.545	−2.446
Costa Rica	−1.407	−4.047	−7.871	−12.928
Guatemala	−0.694	−1.553	−2.798	−4.533
Honduras	−2.751	−6.492	−11.126	−16.521
Nicaragua	−3.020	−6.898	−11.673	−17.264
Panama	−2.197	−5.367	−9.580	−14.457
El Salvador	−0.986	−2.498	−4.957	−8.438

Table 2 *(continued)*

Country	1°C	2°C	3°C	4°C
Rest of Central America	−1.675	−5.603	−11.646	−18.231
Dominican Republic	−1.850	−4.406	−7.934	−12.171
Jamaica	−1.485	−3.696	−6.940	−10.813
Puerto Rico	−1.269	−3.297	−6.527	−10.536
Trinidad and Tobago	−1.690	−4.150	−7.357	−10.905
Caribbean	−1.864	−4.529	−8.207	−12.605
Austria	−0.122	−0.287	−0.486	−0.728
Belgium	−0.151	−0.330	−0.540	−0.788
Cyprus	−0.194	−0.462	−0.816	−1.481
Czech Republic	−0.169	−0.352	−0.567	−0.842
Denmark	−0.127	−0.252	−0.393	−0.573
Estonia	−0.230	−0.476	−0.750	−1.087
Finland	−0.067	−0.153	−0.254	−0.383
France	−0.139	−0.285	−0.455	−0.662
Germany	−0.118	−0.254	−0.415	−0.608
Greece	−0.048	−0.149	−0.275	−0.708
Hungary	−0.197	−0.390	−0.590	−0.884
Ireland	−0.184	−0.436	−0.748	−1.125
Italy	−0.144	−0.342	−0.588	−0.906
Latvia	−0.140	−0.259	−0.394	−0.564
Lithuania	−0.179	−0.288	−0.394	−0.587
Luxembourg	−0.137	−0.343	−0.600	−0.896
Malta	−0.275	−0.691	−1.261	−2.083
Netherlands	−0.118	−0.275	−0.467	−0.694
Poland	−0.166	−0.332	−0.514	−0.774
Portugal	−0.120	−0.275	−0.460	−0.684
Slovakia	−0.129	−0.285	−0.470	−0.706
Slovenia	−0.139	−0.310	−0.512	−0.764
Spain	−0.147	−0.341	−0.575	−0.871
Sweden	−0.095	−0.211	−0.349	−0.516
United Kingdom	−0.122	−0.260	−0.422	−0.613
Switzerland	−0.094	−0.214	−0.355	−0.522
Norway	−0.160	−0.377	−0.646	−0.967
Rest of EFTA	−0.097	−0.242	−0.421	−0.634
Albania	−0.395	−0.857	−1.461	−2.360
Bulgaria	−0.090	−0.294	−0.590	−0.999
Belarus	−0.176	−0.214	−0.249	−0.617
Croatia	−0.083	−0.216	−0.454	−0.946
Romania	−0.171	−0.329	−0.483	−0.754
Russian Federation	−0.266	−0.568	−0.936	−1.405
Ukraine	−0.153	−0.219	−0.250	−0.382
Rest of Eastern Europe	0.011	0.160	0.370	0.492
Rest of Europe	−0.089	−0.150	−0.205	−0.318
Kazakhstan	−0.371	−0.592	−0.820	−1.137
Kyrgyzstan	−0.377	−0.614	−0.930	−1.500
Rest of Former Soviet Union	−0.239	−0.392	−0.564	−0.888
Armenia	−0.739	−1.050	−1.350	−1.777
Azerbaijan	−0.756	−1.563	−2.638	−4.025

Table 2 *(continued)*

Country	1°C	2°C	3°C	4°C
Georgia	−0.393	−0.680	−1.035	−1.769
Bahrain	−1.440	−3.192	−5.138	−7.303
Iran	−0.894	−2.044	−3.516	−5.365
Israel	−0.743	−1.514	−2.317	−3.416
Jordan	−0.982	−1.998	−3.254	−4.835
Kuwait	−1.315	−2.795	−4.488	−6.387
Oman	−0.996	−2.248	−3.780	−5.482
Qatar	−2.091	−4.618	−7.304	−10.358
Saudi Arabia	−1.650	−3.457	−5.449	−7.773
Turkey	−0.342	−0.842	−1.540	−2.479
United Arab Emirates	−2.207	−4.799	−7.684	−10.976
Rest of Western Asia	−0.829	−1.879	−3.306	−4.985
Egypt	−1.083	−2.377	−4.000	−6.143
Morocco	−0.770	−1.525	−2.436	−3.487
Tunisia	−0.871	−1.836	−3.052	−4.609
Rest of North Africa	−0.653	−1.415	−2.394	−3.639
Burkina Faso	−5.229	−10.894	−17.058	−23.586
Cameroon	−2.276	−5.528	−9.396	−14.480
Cote dIvoire	−4.710	−10.742	−17.528	−25.252
Ghana	−4.857	−10.815	−17.571	−24.983
Guinea	−2.712	−6.093	−9.896	−14.689
Nigeria	−4.528	−9.689	−15.723	−22.250
Senegal	−3.859	−8.189	−13.001	−18.544
Togo	−5.597	−12.221	−19.032	−26.556
Rest of Western Africa	−4.432	−9.769	−15.566	−21.938
Central Africa	−1.013	−2.430	−4.977	−8.362
South Central Africa	−0.961	−2.066	−3.320	−4.894
Ethiopia	−1.862	−4.238	−6.704	−9.416
Kenya	−2.331	−4.706	−7.238	−10.506
Madagascar	−1.976	−4.286	−7.212	−10.993
Malawi	−2.277	−5.683	−9.266	−13.609
Mauritius	−1.829	−4.399	−7.458	−11.245
Mozambique	−2.411	−5.311	−8.878	−12.989
Rwanda	−2.107	−4.490	−7.047	−9.819
Tanzania	−1.546	−4.130	−6.988	−10.825
Uganda	−1.743	−3.652	−6.328	−10.404
Zambia	−1.097	−2.616	−4.414	−6.720
Zimbabwe	−1.261	−2.726	−4.423	−6.502
Rest of Eastern Africa	−2.112	−4.750	−8.099	−11.862
Botswana	−0.710	−1.659	−3.047	−4.873
Namibia	−0.673	−1.464	−2.404	−3.616
South Africa	−0.740	−1.570	−2.464	−3.433
Rest of South African Customs Union	−0.890	−1.923	−3.045	−4.390
Rest of the World	−0.587	−1.227	−1.918	−2.671

Note. Source: Authors' GTAP-INT calculation.

As indicated above, we calculate world GDP in 2100 using 2017 world GDP in US$ (IMF, 2018, from the World Economic Outlook database) and economic growth from the corresponding SSPs (SSP1 for 2 °C, SSP2 for 3°C and SSP5 for 4°C; Crespo Cuaresma, 2017; International Institute for Applied Systems Analysis, 2018). Because the economic forecasts in the SSPs are for a 10-year period, we apply a linear interpolation method to approximate the missing forecasts for the years between and any two predicted time points (similarly for the GDP damage ratios from our simulation results). The results for GDP damages in US$ are available from 2017 to 2100, but only 2100 results are shown in Table A1.

In total, the avoided global GDP losses for the case of 3°C (or equivalently RCP6.0) compared to 2°C are US$3,934.25 billion a year in terms of 2100 GDP. For the case of RCP8.5, or a global warming of 4°C, the avoided global losses in GDP between 4 and 2°C are much larger or US$17,489.72 billion a year in the long run (also in terms of GDP in 2100).

6. Discussion and Concluding Remarks

GHG emission growth and its global warming consequences are a significant threat to the Earth's future. Assessing climate change impacts to the global economy and national incomes, and the potential benefit of climate change agreements, however, is complex, requiring large-scale modeling to even approach a comprehensive answer. For economists, the standard tool is CGE modeling. But, here, save for a few valuable country studies and some dynamic recursive modeling efforts, current models are either dimensionally too small or bound by myopic forecasting rules to be completely useful or compelling. The extension of the GTAP-INT model used in this work fills that gap, providing estimates of global warming damages on GDP and its rate of change for 139 countries in the GTAP database, by various temperature changes, as well as by measures of the benefits of complying with a trade agreement, such as the Paris Climate Accord.

Although GTAP-INT is country detailed and uses forward-looking approaches to forming price and profit expectations, there are a number of significant caveats to be aware of and considerable scope for future research. First, the model dimension does not computationally allow for random shocks or any of the usual jump-diffusion characteristics of a stochastic process that may impact both technology or living standards in the economy, among many other things. This lack of randomness is a serious shortcoming of all CGE modeling, except those with very small dimensions, and it needs to be worked on. There are ways forward, but it will require very large dimensional modeling and the use of parallel processing techniques, at the least, as in the GTAP-INT model and related work (Ha & Kompas, 2016; Ha et al., 2017; Kompas & Ha, 2017).

Second, given the lack of a random component, it is not possible to include the effects of natural disasters or more extreme weather events that occur year to year in the model. The costs of these can be considerable. For now, all that is captured is the effects of SLR, changes in agricultural productivity, and key health effects. Indeed, some of the significant effects of actions concomitant with global warming, such as the effects of air pollution, losses in biodiversity, the spread of invasive species, changes in energy mix, and the costs of significant migration, are also not included. Capturing natural disaster shocks and these other effects is possible in GTAP modeling, but it has not been done for the global economy to date, and this too needs to be worked on.

Third, and finally, although the extension of GTAP-INT to full climate change effects does allow for forward-looking estimates of the possible effects of global warming, the informational requirements here are profound and will not nearly be met in every circumstance or by every producer and consumer. Practically speaking, some forecasts fail to account not only for projected changes in the local and global economy but also for all of the other unpredictable changes that occur. Including randomness in the model framework would help with this, but as it stands the model is benchmarked to perfect foresight settings as a comparator. Designing models with mixed information requirements, that is, ranges of forward-looking forecasts combined over a set of elements with more myopic forecasting rules, is possible, but that work too needs to be done. It is clear, however, that models with only static price forecasting rules are clearly inadequate when climate change is considered. We know that at least some economic agents look forward and endeavor to incorporate this information in their price forecasting. We also know that economic agents revise their forecasts given exogenous shocks at any moment in time, calling again for some stochastic process in the CGE/GTAP model framework.

With all of the above caveats in mind, the estimates from GTAP-INT do indicate substantial damages and losses in national income from global warming, providing at least a means of comparison across different temperature ranges and countries, regardless of the range of information that is available, perfect or otherwise. The losses in GDP and the gains from complying with the Paris Accord, even in this limited framework, are substantial, as indicated. What is perhaps as equally disturbing is how the percentage fall in GDP varies across the world and is most severe in many of the poorest countries (Table 2). Notable in the list are the dramatic falls in GDP by decade and in the long term, especially, of course, for the 4°C outcome, for Ghana, Nigeria, Cote D'Ivoire, Togo, Honduras, Nicaragua, the Phillipines, Cambodia, and Laos, among others. But Indonesia, Bangladesh, India, Singapore, Central America, East Asia, Thailand, and Vietnam also experience fairly substantial falls. Complying with the Paris Climate Accord would benefit these relatively poor countries, especially so.

It is important to note that the results above also assume that the United States remains in the Paris Accord and that all countries that have agreed to emission reduction targets honor their commitments. This is all questionable.

One final point. The often severe falls in GDP in the long term will put many governments in fiscal stress, since tax revenues are tied to GDP or national income levels. In addition, if global warming is tied to increases in the frequency of weather events and other natural disasters, which invoke significant emergency management responses and expenditures, the pressure on government budgets will be doubly severe. It would be good to form estimates of the extent of these budget pressures.

Appendix A: Impacts of Climate Change on the Global Economy

In this appendix we detail estimates of the long-term losses in GDP per year under various global warming scenarios to the year 2100. We also indicate the long-run impacts of global warming on the economic sectors (or commodity groups) contained in the GTAP database.

Table A1
Estimation of Long-Term GDP Loss per Year Under Global Warming Scenarios (US$ Billion/Year) to the Year 2100

	4°C	3°C	2°C
World total	−23,149.18	−9,593.71	−5,659.47
Sub-Saharan Africa	−8,073.68	−2,889.66	−1,927.78
India	−4,484.96	−2,070.06	−1,149.36
Southeast Asia	−4,158.88	−2,073.09	−1,166.23
China	−1,716.91	−701.75	−394.59
Latin America	−1,371.81	−576.65	−259.82
Rest of South Asia	−1,157.92	−469.98	−283.78
Middle East and North Africa	−1,032.27	−451.96	−241.12
United States of America	−697.77	−223.83	−168.48
Japan	−253.18	−54.43	−23.02
Mexico	−127.70	−55.79	−20.88
Australia	−117.42	−36.87	−23.72
South Korea	−81.44	−14.72	−7.86
Rest of Oceania	−39.65	−14.97	−6.96
Russian Federation	−24.49	−10.88	−6.53
Rest of Former Soviet Union	−9.93	−5.31	−3.85
EFTA	−8.72	−3.01	−2.16
New Zealand	−4.19	−0.77	−0.09
East Asia	−3.35	−1.27	−0.78
Rest of Eastern Europe	1.49	1.28	0.18
Rest of Europe	3.15	1.38	0.63

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Table A1 *(continued)*

	4°C	3°C	2°C
World total	−23,149.18	−9,593.71	−5,659.47
United Kingdom	17.78	4.06	0.35
Germany	23.85	5.38	2.46
France	26.92	7.11	1.80
Italy	32.42	12.20	7.26
Canada	45.29	11.40	5.20
Rest of EU25	64.19	18.47	9.68

Note. The numbers are calculated on the value of predicted GDP to 2100 from data in IMF (2018), International Institute for Applied Systems Analysis (2018), and Crespo Cuaresma (2017).

Table A2
Long-Run Impacts of Global Warming (3°C) on the World's Economic Sectors (% Change)

Economic Sectors	2017	2027	2037	2067	Long run
Paddy rice	−0.026	−0.532	−1.056	−2.687	−4.857
Wheat	0.006	−0.339	−0.699	−1.843	−3.582
Cereal grains nec	−0.012	−0.358	−0.718	−1.859	−3.554
Vegetables, fruit, nuts	−0.012	−0.398	−0.797	−2.040	−3.723
Oil seeds	−0.010	−0.501	−1.012	−2.618	−4.875
Sugar cane, sugar beet	0.015	−0.450	−0.939	−2.493	−4.812
Plant-based fibers	0.182	−0.432	−1.081	−3.144	−6.240
Crops nec	0.001	−0.348	−0.720	−1.914	−3.763
Bovine cattle, sheep and goats, horses	−0.015	−0.293	−0.588	−1.539	−3.102
Animal products nec	−0.007	−0.308	−0.625	−1.646	−3.293
Raw milk	−0.017	−0.334	−0.666	−1.720	−3.362
Wool, silkworm cocoons	−0.090	−0.423	−0.772	−1.877	−3.562
Forestry	−0.020	−0.300	−0.608	−1.645	−3.632
Fishing	−0.008	−0.303	−0.616	−1.619	−3.162
Coal	−0.003	−0.162	−0.345	−0.985	−2.365
Oil	0.006	−0.112	−0.253	−0.763	−1.987
Gas	0.018	−0.021	−0.079	−0.347	−1.431
Minerals nec	−0.018	−0.202	−0.418	−1.200	−3.061
Bovine meat products	−0.002	−0.265	−0.539	−1.421	−2.893
Meat products nec	0.002	−0.204	−0.422	−1.130	−2.384
Vegetable oils and fats	−0.006	−0.384	−0.783	−2.052	−3.980
Dairy products	−0.002	−0.170	−0.348	−0.945	−2.141
Processed rice	−0.029	−0.468	−0.926	−2.363	−4.363
Sugar	−0.016	−0.324	−0.649	−1.693	−3.381
Food products nec	−0.001	−0.201	−0.414	−1.113	−2.369
Beverages and tobacco products	−0.003	−0.158	−0.327	−0.900	−2.073
Textiles	0.003	−0.188	−0.398	−1.107	−2.501
Wearing apparel	0.006	−0.131	−0.282	−0.804	−1.942
Leather products	−0.002	−0.167	−0.346	−0.950	−2.176
Wood products	0.013	−0.063	−0.161	−0.563	−1.907
Paper products, publishing	−0.003	−0.104	−0.221	−0.650	−1.767
Petroleum, coal products	0.003	−0.105	−0.233	−0.703	−1.876
Chemical, rubber, plastic products	−0.002	−0.147	−0.315	−0.914	−2.326
Mineral products nec	−0.020	−0.176	−0.360	−1.053	−2.921
Ferrous metals	−0.024	−0.201	−0.409	−1.174	−3.112

Table A2 *(continued)*

Economic Sectors	2017	2027	2037	2067	Long run
Metals nec	−0.028	−0.224	−0.449	−1.252	−3.084
Metal products	−0.028	−0.162	−0.319	−0.909	−2.515
Motor vehicles and parts	0.013	−0.096	−0.230	−0.745	−2.236
Transport equipment nec	−0.025	−0.203	−0.409	−1.148	−2.894
Electronic equipment	0.011	−0.139	−0.319	−0.994	−2.720
Machinery and equipment nec	0.007	−0.118	−0.271	−0.865	−2.561
Manufactures nec	−0.015	−0.190	−0.389	−1.092	−2.700
Electricity	0.000	−0.115	−0.249	−0.740	−2.006
Gas manufacture, distribution	0.018	−0.132	−0.303	−0.920	−2.440
Water	−0.016	−0.143	−0.288	−0.811	−2.093
Construction	−0.007	−0.132	−0.290	−0.917	−2.829
Trade	−0.004	−0.156	−0.327	−0.934	−2.341
Transport nec	−0.006	−0.142	−0.298	−0.861	−2.248
Water transport	−0.004	−0.204	−0.433	−1.238	−2.972
Air transport	0.000	−0.118	−0.255	−0.747	−1.940
Communication	0.001	−0.101	−0.221	−0.668	−1.880
Financial services nec	0.001	−0.108	−0.237	−0.708	−1.927
Insurance	0.000	−0.097	−0.208	−0.606	−1.591
Business services nec	0.012	−0.042	−0.112	−0.407	−1.495
Recreational and other services	0.004	−0.096	−0.210	−0.623	−1.675
Public Administration, Defense, Education, Health	0.000	−0.104	−0.218	−0.603	−1.420
Dwellings	−0.003	−0.068	−0.160	−0.569	−2.158

Note. Source: Authors' GTAP-INT calculation.

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