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EXECUTIVE SUMMARY

This study assesses the global macroeconomic consequences of changes in climate risk. We explore three broad areas: (1) the macroeconomic impacts of physical climate risk due to chronic climate change associated with global temperature increases and climate-related extreme shocks; (2) the macroeconomic effects of climate policies designed to transition to net zero emissions by 2050 (transition risk); and (3) the potential macroeconomic consequences of changes in risk premia in financial markets associated with increasing concern over climate events.

To assess the macroeconomic consequences of climate change, we consider four widely used climate scenarios (Representative Concentration Pathways, or RCP), and identify the physical damage functions due to chronic climate risks from the literature. The chronic climate risks considered in this study include sea-level rise, crop yield changes, heat-induced impacts on labor, and increased incidence of diseases.

We also identify methodologies to estimate the future incidence of climate-related extreme events from previous studies. Based on climate variable projections under the climate scenarios, we obtain probabilistic estimates for the future incidence of droughts, floods, heat waves, cold waves, storms and wildfires. Using historical occurrence of the extreme events, we estimate their impacts on labor force, agriculture and electricity generation sectors.

After translating physical climate shocks into economic shocks to labor force and sectoral productivity, we investigate the macroeconomic consequences under the climate scenarios using the G-Cubed model. The results demonstrate that physical climate risk is likely to cause large economic losses in all the RCP scenarios, both through chronic climate change and extreme climate shocks.

We explore the impact of country-specific economy-wide carbon taxes as a representative policy action to drive the global economy to achieve net-zero emissions by mid-century. Transition risks vary according to the ambition and the design of policies to reduce emissions. We do not calcuate a distribution of transition risks by comparing the range of alternative policies that might be used to reduce emissions. However, the results for the particular example chosen demonstrate that there can be potentially significant costs associated with policies to reduce emissions, and the costs differ across sectors and across countries. As shown by Bang et al. (2020), the costs can vary greatly depending on the specific design of climate policy.

We also address whether changes in climate risk perceptions can significantly impact the real economy through changes in risk premia in financial markets. We calculate shocks to financial risk premia based on relationships between historical climate shocks and changes in financial market risk premia. We apply these shocks to risk premia under the RCP scenarios and find that the cost of rising risk premia can be of a magnitude consistent with historical

experience. The cost appears to be smaller than the economic costs of changes in physical climate risk.

We find that chronic climate change, extreme climate shocks, and economic policies implemented to reduce CO2 emissions can have significant economic consequences. Under RCP 2.6 scenario the GDP losses from physical climate risk range between 0.6% of GDP in Australia to 3.2% of GDP in developing countries by 2050. This rises under RCP 8.5 to between 1% for the ROCED economies and 5.7% of GDP for oil exporting countries by 2050. The costs could be amplified if financial markets re-price climate-related risks with additional GDP losses of between 0.5% to 1.5% per year for all countries except Russia which experiences larger GDP losses across all scenarios by 2030.

Keywords: Climate change, Extreme events, Climate shocks, Climate risk, Macroeconomics, DSGE, CGE, G-Cubed

JEL Codes: C51, C53, C54, C55, C68, F41, Q51, Q54

1. INTRODUCTION

Since the establishment of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992, climate change has been receiving increasing attention. Both academia and governments across the world have been involved in understanding the potential impacts of climate change. There is a broad consensus that climate change is the biggest global challenge that has ever confronted humans. The increasing awareness has catalyzed worldwide action against climate change, particularly in the last decade. Almost 200 countries joined the Paris Climate Agreement in December 2015, and 58 countries accounting for 54% of global GHG emissions have communicated net-zero carbon emissions around mid-century, including some of the largest emitters (Europe, Japan, Korea, China, and the US).[1] The worldwide commitment and action on decarbonization will significantly change the global economy in many ways. Economists and policymakers have long been discussing and investigating the economic impacts of various climate policies at the national and global levels. More recently, in the pandemic context, public investment in green energy has been extensively discussed as a win-win solution to boosting economies and mitigating climate change (e.g., Bang et al. (2020) and Jaumotte et al. (2021)). In addition to the impacts in real economies, the financial sector has been concerned about how climate change and policy might affect asset valuation and market behavior. Many Central Banks have also become increasingly involved in understanding the impact of climate-related risk on financial stability. Carney (2015) highlights the risk of sudden changes in significant fossil fuel-intensive asset valuation. The formation of the Network for Greening the Financial System (NGFS) has accelerated this push for considering the impact of climate risk on the economy (NGFS 2020).

Climate-related risks can be divided into two broad areas: physical risk and transition risk. Physical risks include chronic climate risks and climate-related extreme event risks. Chronic climate risks include the long-term gradual change in agricultural productivity, land stock (due to sea-level rise), human health, labor productivity, energy demand, etc. Climate-related extreme shocks include hurricanes, cyclones, floods, landslides, wildfires, droughts, heat and cold waves. Many studies that estimate the economic costs of climate risks focus on chronic risks which accumulate gradually but persistently over a long time (see Kompas et al. 2018). However, with future extreme weather events expected to become more frequent and intensive due to climate change, more studies have emerged to investigate their economic impacts.

Climate risks pose challenges not only in real economies but also through financial markets. Over the last decade, the financial sector has radically increased the discussion of how climate change might affect asset valuation and market behavior (Bolstad et al. 2020). Although few natural disasters have had moderate impacts on global financial markets, extreme climate shocks in the future may have significant effects on financial markets. The

[1] Net-zero Target Status | Explore Net-Zero Targets | Climate Watch Data

greater impact is likely given the damages from natural catastrophes worldwide are increasing, the exposure from the industrialization of developing nations, and the network of global industry and high-cost assets are growing (Mahalingam et al. 2018).

In addition to physical climate risks, the world is faced with transition risks from moving to a carbon-neutral world. There are numerous transition paths with different degrees of ambition, speed, coverage, and instruments for climate policy and regulation. There is also uncertainty with technology change, especially energy- and carbon-related technology change. Furthermore, policies can accelerate technology advances towards low carbon activities. The worldwide commitment and awareness may also promote public sentiment and preferences about climate protection, which would change individual behavior. The transition risk also depends on asymmetric possibilities of climate policy and technology progress across countries and can generate significant distributional effects across countries and sectors. An extensive literature investigates the impacts of climate policy, particularly of the Paris Agreement in the last several years (Liu et al. 2020). The world is now moving towards net-zero emissions, and it is timely to investigate the impacts of net-zero climate policies.

This paper explores climate-related risks and focuses on three aspects. Firstly, we assess the impact of physical climate risk on different sectors in different economies. We initially explore the effects on the labor supply and the productivity of the production sectors due to several chronic climate risks: rising sea levels, heat-induced impacts on the labor force, changes in the incidence of diseases and crop yield changes. We use the damage functions in the literature to create these shocks along with the climate variable projections under different climate scenarios. We then evaluate the historical impacts of climate-related extreme events on the labor force, agriculture- and energy-sector productivity. After estimating, using climate variables, the incidence of extreme events in the future, we estimate the economic shocks and their spill-over effects to other production sectors under the climate scenarios. These shocks together enable us to estimate the economic impact of climate change through the G-Cubed model.

Secondly, we explore the impact of transition risks on sectoral and aggregate outcomes in the global economy if countries implement effective policies to achieve zero net emissions by 2050. There are many ways that effective climate policy could be implemented. Each can have very different impacts on economies and sectors within economies. This paper uses a single policy example of a national carbon tax within each country to reach net-zero emissions in each region by 2050. The use of a carbon tax is purely illustrative of a wide range of different carbon policies that might be used in practice to reduce carbon emissions. While the quantitative estimates will change depending on the specific policies used to reduce emissions, the qualitative story will be broadly similar. We focus on the macroeconomic and sectoral adjustment over the decade commencing in 2021. The results illustrate the scale and distribution of transition risk faced by regions and by sectors across economies. We show that the adjustment can be significant for countries, particularly fossil-intensive economies and sectors. Many other policy packages would dramatically change this outcome. An example is the package of green infrastructure and energy subsidies and taxes explored in Bang et al. (2020) and Jaumott et al. (2021). There is enormous uncertainty about which policies, if any, governments might follow, which is why there is a considerable risk for different industries and countries.

Thirdly, we explore the impact of a reassessment for risk in financial markets of physical and transitional climate risks. What are the potential macroeconomic consequences if financial markets have not correctly priced the financial risks associated with climate change? As an illustration of how this might be evaluated, we use the information on the historical movements in global equity markets after surprise extreme event shocks to calculate the risk premia shocks and then adjust these shocks using the climate scenarios. The simulations of possible risk changes show how much more disruptive financial markets might become if participants re-price climate risk. The link between risk shocks and climate shocks is meant to indicate whether historical relationships between climate shocks and changes in financial markets when applied to the various climate scenarios can potentially be an additional cost associated with climate change.

The rest of this paper is organized as follows. Section 2 reviews previous studies on the economic impact of chronic climate change and extreme climate shocks over the coming century. Section 3 outlines the methodology for quantifying both chronic climate shocks and extreme climate shocks. Section 4 outlines the G-Cubed model and also illustrates how climate shocks are introduced into the model. Section 5 presents the simulation results focusing on GDP losses by region and changes in sectoral output from 2021 to 2100. Section 6 examines the economic impacts of transition risks. Section 7 explores the macroeconomic consequences of climate risk assessment changes in financial markets.

2. LITERATURE ON ECONOMIC IMPACTS OF CLIMATE RISKS

The purpose of estimating the effects of historical or hypothetic climate shocks is generally twofold: (1) post-hazard estimation of historical shocks, particularly of extreme climate shocks, for recovery and reconstruction plans and finance; and (2) pre-hazard estimation of hypothetical shocks to evaluate the preparedness and mitigation strategies (Okuyama and Santos 2014). While the importance of post-hazard assessment is self-evident, pre-hazard assessment is crucial for formulating sensible public policy to mitigate and prevent natural hazards. Given our paper contributes to the estimation of climate risks in the future, this section focuses on the literature on the pre-hazard estimation of climate risks.

Chronic climate change

There is extensive literature on chronic climate risks. Most modeling studies on climate risks are based on computable general equilibrium (CGE) models and integrated assessment models (IAM), where IAM models feed environmental damages into macroeconomic models. Earlier IAM models are often based on neoclassical growth models with an aggregate production sector (see Stern 2007 for a review). More recent IAM models allow multiple sectors such as DART (Deke et al. 2001), GTEM (Pant 2002), and ENVISAGE (Roson and van der Mensbrugghe 2012).

The studies on chronic climate risks consider various channels through which climate change affects economic systems. Jorgenson et al. (2004) examine the overall effect in the IGEM model on the US economy of predicted climate change impacts in key market activities including agriculture and forestry, energy services related to heating and cooling, commercial water supply, the protection of property and assets, livestock and fisheries, and also consider the costs associated with the increased storm, flood and hurricane events, as well as changes in labor supply and consumer demand due to climate-induced mortality and morbidity. They consider six scenarios where three levels of climate change (low, central, and high) are combined with two sets of market outcomes (optimistic and pessimistic) and provide several conclusions: (1) The impact of GDP ranges from -3% to 1% by 2100 across scenarios, where the economy can benefit from climate change because commodity prices declined in optimistic scenarios with higher temperatures and increased precipitation; (2) The effect on agriculture dominates the other market impacts; (3) Changes in human mortality and morbidity are small but essential determinants of the climate impacts.

In a series of studies, Bosello et al. (2006a, 2006b, 2007) apply a recursive version of the GTAP model (GTAP-E) to simulate climate change-induced effects on human health, tourism, and sea level, respectively, on the global economy up to 2050. Bosello et al. (2006a) estimate that most regions worldwide have labor productivity gains because vector-borne diseases are absent. The decrease in mortality and morbidity associated with cold stress-related diseases dominates heat stress-related diseases. Energy exporting countries and Africa experience lower labor productivity because of higher incidences of respiratory and gastro diseases in the former and higher incidences of malaria in Africa. The changes in labor productivity translate to GDP changes, with positive impacts ranging from 0.04 to -0.08% for countries with productivity gains and negative implications for energy-exporting countries and Africa -0.07% and -0.1%, respectively, by 2050.

Bosello et al. (2007) consider one sea-level rise scenario with two options for adaptation: coasts are unprotected with land loss, and coastal areas are fully protected. They show significant differences in both national and global welfare effects between the two options and argue that the optimal adaptation lies in between the two extremes. Eboli et al. (2010) apply another dynamic variant of the GTAP model (ICES) to analyze the effects of temperature change on global economic growth and wealth distribution. They find that macroeconomic effects are sizeable, but there are significant distributional effects at the regional and sectoral levels. Kjellstrom et al. (2009) estimate the impact of climate scenarios on labor productivity globally based on physiological evidence about the effects of heat, climate guidelines for safe work environments, climate modeling, and global distributions of the working population. Roson and der Mensbrugghe (2012) estimate the economic effects of climate change in the ENVISAGE model via a range of impact channels: sea level increases, agricultural productivity, water availability, human health, tourism, and energy demand. They show that climate impacts are highly varied across regions and impact channels. The most severe effect is labor productivity changes at the global level, which would induce 84% of the worldwide damage in 2050 (-1.8% of global GDP). The most seriously impacted region is the Middle East and North Africa, followed by East Asia. The former is suffering from direct labor productivity loss and the latter more from sea-level rise. The impacts on agriculture by 2050 are not dire, but as temperatures rise further, the adverse effects kick in and will be harsh overtime. Roson and Sartori (2016) estimate climate change damage functions for the above set of impact channels for 140 countries in the GTAP 9 database. Based on these damage functions, Kompas et al. (2018) focus on agricultural productivity, sea-level rise, and human health. They estimate their economic impacts for 140 countries until 2100 in an adapted GTAP model with forward-looking investment behavior.

Extreme climate shocks

In contrast to chronic climate change, there is a limited number of studies on extreme event risks from climate shocks.[2] Most economic studies estimating climate change impacts have paid little attention to extreme climate shocks (Narita, Tol & Anthoff 2009). Handmer et al. (2012) summarize several general conclusions on the economic effects of extreme climate shocks. First, global financial losses from climate-related disasters have increased, but with large spatial and temporal variability. Second, increasing exposure of people and economic assets has been the primary cause of long-term increases in economic losses. Still, climate change may increase the frequency and intensity of future extreme weather events. Third, economic costs associated with climate shocks are higher in developed countries, while fatality rates and GDP losses are higher in developing countries. Fourth, extreme shocks will significantly impact sectors with closer links to climate, such as water, agriculture and food security, forestry, health, and tourism.

Besides, there are a small number of specific modeling studies. Narita, Tol, and Anthoff (2009) evaluate the global economic impact of tropical cyclones due to climate change in the FUND model and show that the global economic damage would amount to 0.006% of world GDP in 2100. Other studies on tropical cyclones include Nordhaus (2006) and Pielke (2007). Narita, Tol, and Anthoff (2010) estimate the global economic impact of extratropical storms due to climate change in the FUND model and show that the global economic costs will increase by 38% in 2100. Several studies assess the economic impacts of extratropical storms due to climate change in a European context (Dorland et al. 1999; Hanson et al. 2004; Leckebusch et al. 2007; Pinto et al. 2007). A more recent study conducted by the AIR Worldwide Corporation (2020) assesses the impact of climate change on hurricane risks

[2] There is a large literature on estimating economic impacts of natural disasters which include extreme weather events but cover a much broader range of disastrous events (see, e.g., Okuyama 2007, Hallegatte and Przyluski 2010, Okuyama and Santos 2014), and most studies are post-hazard estimation.

and sea-level rise in the US. The study demonstrates that more intense hurricanes and sea-level rise could almost double the average annual losses currently experienced.

Schmitt et al. (2016) provide a review of economic evaluations of the adverse health effects from exposure to climate-related extreme shocks. Among the twenty studies surveyed, most studies focus on the US (nine studies) and Asia (seven studies), without studies on Africa, Latin America, and the Middle East or at the global level. Extreme temperatures account for a third of the studies (seven studies), followed by floods (six studies), without drought studies. While studies are heterogeneous in terms of objectives and methodology, they indicate that extreme shocks will become a pressing public health issue with significant welfare and distributional implications.

The above studies are based on real-economy models and abstract from financial markets. There is a small but growing literature investigating the impacts of climate extremes on financial markets through the channel of risk increase. Over the last decade, the financial sector has radically increased the discussion of how climate change might affect asset valuation and market behavior. Bolstad et al. (2020) find that corporate climate-risk disclosure has risen sharply in the last decade, with 60% of publicly traded firms disclosing climate risk in the US Securities and Exchange Commission based on the entire Russell 3000 and a sample of all US-issued municipal bonds. To date, few natural disasters have historically registered moderate impact on the shape of global financial markets. The costliest natural disaster of history, 2005's Hurricane Katrina, moved the New York Stock Exchange by less than a percentage point with its $150 billion in direct damages. Mahalingam et al. (2018) link a global general equilibrium model (GEM) to a financial investment model and explore natural catastrophes' potential to trigger financial market shocks and subsequent economic downturns. They demonstrate that natural disasters in the future can have significant effects on financial markets given the accrued damages from natural catastrophes worldwide are increasing, the exposure from the industrialization of developing nations, and the network of global industry and high-cost assets are growing.

Transition risk

An extensive literature investigates the effects of climate policy. Most of the studies investigate either the aggregate or sectoral or combined economic impacts of various climate policies at different geographic levels. Since 2015, almost 200 countries have signed and ratified the Paris Agreement on climate change, with the US rejoining the Agreement in February 2021. In the last several years, an emerging literature examines the impacts of the Paris Agreement. For example, Liu et al. (2020) explore the effects of the Paris Agreement on the global economy using the G-Cubed model. The paper also reviews the studies on the Agreement based on large-scale computational models, including CGE and IAM models. Although the Paris Agreement involves almost all countries, there is a consensus that the Agreement is not sufficiently ambitious to reach the 2-degree goal by the end of this century. Therefore, the international community has been proposing net-zero emissions by mid-century (IPCC 2018). So far, 58 countries have communicated net-zero carbon emissions by mid-century, including significant carbon emitters such as China, Japan, Korea, and the United Kingdom. The European Union has proposed to make the bloc carbon neutral by 2050, and US President Biden and Canadian Prime Minister Trudeau have agreed to work towards net-zero-emissions by 2050. This deep decarbonization will significantly affect the world economy with heterogeneous impacts across countries and sectors. The World Economic Outlook (Bang et al. 2020) simulates the effects of achieving global net-zero-emissions via carbon taxes.

Most recently, a few studies have focused on the transition risks from a financial perspective. Carney (2015) warns that the energy transition could give rise to financial risks. Some organizations, such as the European Systemic Risk Board, have recommended stress tests of financial sectors related to climate transition risks. Some central banks have proposed or conducted such tests (Vermeulen et al. 2018). van der Ploeg (2020) reviews pre-requisites to ensure a smooth transition to a carbon-free economy. He also reviews the empirical evidence for the effects of anticipated green transitions on asset returns and argues that the macro-financial policies should support the green transition. McKibbin et al. (2020) explore the interaction of monetary policy and climate change. They conclude that climate policy responses can have important implications for monetary policy. Monetary policy can also significantly affect the economic outcomes of climate policies. In light of ambitious climate action's urgency, the policy spheres should be brought together more explicitly, and more appropriate macroeconomic modeling frameworks should be developed.

3. ESTIMATION OF PHYSICAL CLIMATE SHOCKS

Climate scenarios

In this study, we first assess the global macroeconomic effects of climate risks up to 2100 under various climate scenarios. We use the four Representative Concentration Pathways (RCP) introduced by van Vuuren et al. (2011), namely RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5. The pathways' names indicate the additional radiative forcing levels achieved by the end of the century compared to the pre-industrial times due to greenhouse gas concentrations in the atmosphere. Table 1 summarizes the definitions of the RCP scenarios. Hereafter, we refer to RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 as the climate scenarios.

It is worth noting that we use these scenarios (particularly RCP 8.5) to obtain a range of estimates about the economic consequences of physical climate risks. We do not attribute any likelihood to any of the scenarios and do not assume any scenario to be "business-as-usual". Hausfather and Peters (2020) provide a detailed discussion on how best to interpret RCP scenarios in line with the most recent developments. We follow the literature to interpret RCP 8.5 as an upper bound of the estimates.

Table 1: RCP Scenarios

Scenario	Description
RCP 2.6	The peak in radiative forcing at ~3 W/m^2 (~490 ppm CO2 eq) before 2100 and then decline (the selected pathway decreases to 2.6 W/m^2 by 2100).
RCP 4.5	Stabilization without overshoot pathway to 4.5 W/m^2 (~650 ppm CO2 eq) at stabilization after 2100
RCP 6.0	Stabilization without overshoot pathway to 6 W/m^2 (~850 ppm CO2 eq) at stabilization after 2100
RCP 8.5	Rising radiative forcing pathway leading to 8.5 W/m^2 (~1370 ppm CO2 eq) by 2100.

Source: van Vuuren et al (2011). Approximate radiative forcing levels were defined as ±5% of the stated level in W/m^2 relative to pre-industrial levels. Radiative forcing values include the net effect of all anthropogenic GHGs and other forcing agents.

Climate variables

We use maximum temperature, minimum temperature, mean temperature, and precipitation as climate variables to determine the impact of climate risks. We obtain the historically observed climate variables and the projected climate variables under the climate scenarios from the Intersectoral Inter-model Intercomparison Project (ISIMIP) data portal (2021).[3]

The projected climate variables under the climate scenarios are available from 2006 to 2100 from four different models (the model ensemble): GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5.[4] We use the daily projections for the climate variables from the model ensemble to account for uncertainty in the model results. After aggregating the 0.5^0 x 0.5^0 gridded data across 193 countries, specified by the Database of Global Administrative Areas (GADM), we average the daily data to obtain the monthly means from 2006 to 2100.

Chronic climate risks

There is a broad range of long-term effects of climate change and an extensive body of literature discussing these effects. However, the availability of damage functions, which map the physical impacts of climate change onto economic variables, is minimal. Roson and Sartori (2016) review the literature on the damage functions and compile six damage functions for economic modeling assessments. These chronic risks include rising sea levels,

[3] ISIMIP, led by the Potsdam-Institute for Climate Impact Research, facilitates comprehensive, consistent, and comparable simulations from different climate impact models regarding the global impact from various climate scenarios by providing the international modeling community with a coherent framework.
[4] The models have been developed respectively by the Geophysical Fluid Dynamics Laboratory (GFDL), the Met Office Hadley Centre, the Pierre Simon Laplace Institute (IPSL), and the University of Tokyo Centre for Climate System Research, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology Frontier Research Centre for Global Change.

variation in crop yields, heat-induced impacts on labor productivity, changes in the occurrence of diseases, changes in tourism, and changes in household energy demand. Out of these, we focus on the first four chronic risks.

Roson and Sartori (2016) express the damage functions related to the chronic risks using climate variables' changes compared to a benchmark level. The damage functions then use the relative changes in the climate variables compared to the benchmark to derive the economic shocks. The benchmark variable primarily used in the damage functions is the average value of the climate variables from 1985 to 2005.

The damage functions we consider in this paper primarily use temperature and precipitation as the climate variables, and we use the projections for the climate variables under the climate scenarios from the model ensemble from 1979 to 2100 to derive the necessary benchmarks and the variations of the future climate variable from the benchmark. We then average the variations across the models for a given scenario for a given country. Using these variations, we use the damage functions to develop various economic shocks (see Section 4.4).

Climate extreme shocks

The International Disaster Database, maintained by the Centre for Research on the Epidemiology of Disasters (CRED), classifies disasters mainly as natural and technological disasters. Natural disasters are further classified as geophysical, meteorological, hydrological, climatological, biological, and extra-terrestrial disasters. The definitions of these natural disaster groups and the types of disasters falling under each group are presented in Table A1 in Appendix A.

Based on the classification, meteorological and climatological disasters are caused by short and long-term variability in the climate. This study focuses on two climatological disasters: droughts and wildfires, and two meteorological disasters: extreme temperature events and storms. In addition, despite being classified as a hydrological disaster, we also focus on floods due to the influence of climate variability on hydrological cycle. These five extreme climate shocks collectively account for 73% of extreme climate shocks reported by CRED. A historical summary of these extreme climate shocks categorized by the model regions is presented in Table A2.

As CRED reports, extreme events historically have led to 32.5 million lives lost and affected over 8 billion people in various forms (excluding deaths) from 1900 to 2019. The extreme climate shocks considered in this study have contributed to over 20 million deaths and affected almost 8 billion lives (excluding deaths). The breakdowns of historical fatalities and numbers of people affected by the extreme climate shocks aggregated across the model regions are presented in Table A3 and A4, respectively.

Furthermore, the extreme climate shocks considered in this study collectively account for $US 912 billion of insured losses (88% of total insured losses from all extreme events), and almost $US 4 trillion of total insured and non-insured indamages (74% of total insured and non-insured damages from all extreme events). Tables A5 and A6 present the historical breakdown of insured losses and total damages for the extreme events across the model regions.

Modeling and predicting weather and extreme climate shocks remains a challenge for the research community. Identifying the favorable initial state, large-scale drivers, local feedback processes, and stochastic processes are the underlying reasons for its complexity (Sillmann et al. 2017). However, an extensive literature survey demonstrates the possibility to use various monitoring tools to identify the occurrence and duration of weather and climate-related extreme conditions as close approximations for extreme climate shocks. These tools, discussed in depth below, require climate variables, specifically precipitation, maximum temperature, and minimum temperature.

Using the projections for the climate variables from the model ensemble for the climate scenarios and various approaches drawn from the literature, we approximate the frequency and duration of extreme climate shocks. Table 2 summarises the climate variables and the approaches. A detailed discussion of the estimations follows.

Table 2: Approaches to Identifying Extreme Climate Shocks

Extreme Event	**Approach**	**Climate Variables**
Drought	Standardized Precipitation Index	Daily Precipitation
Flood	Standardized Precipitation Index	Daily Precipitation
Extreme Temperature (Heat waves & Cold waves)	Heat/Cold Wave Magnitude Index	Daily Maximum/Minimum Temperature
Storms	Probabilistic econometric models	Daily Maximum Temperature
Wildfires	Probabilistic econometric models	Daily Maximum Temperature & Daily Precipitation

Source: Developed by the Authors.

(1) Droughts and floods

The Standardized Precipitation Index (SPI) by McKee et al. (1993) is a widely used indicator to identify droughts and extreme precipitation events. The SPI uses observed precipitation data to quantify a point observation's standardized deviation from a probabilistic distribution of historical precipitation data. Thus, the SPI values demonstrate the anomalies from the long-term mean and, based on the reference period at a given point of time, the SPI could be calculated for periods from 1-36 months. The index value could then be interpreted, as indicated in Table B1 in Appendix B.

A few recent studies using SPI to predict droughts and/or floods include Ekwezuo et al. (2020) for West Africa, Ali et al. (2020) for Pakistan Bhunia et al. (2020) for India, Golian et al. (2015) for Iran, Wang and Cao (2011) for China, and Manasta et al. (2010) for Zimbabwe.

Using the precipitation data obtained from ISIMIP for the model ensemble, we calculate 12-month SPI values from 2007 to 2100. We assume that 12-month SPI values below -2.00 for three or more months consecutively identify the future occurrence of droughts. We also assume that the occurrence of 12-month SPI values above 2.00 for three or more months sequentially identify a future occurrence of floods.

We then aggregate the frequency and duration of the droughts and floods across the model regions. For model regions containing more than two countries, we use the proportion of GDP of a given country in 2019 compared to the region to weigh the frequencies and durations of the events. By aggregating climate shocks using GDP weights, we better understand the relative vulnerability of different model regions to extreme climate shocks. We then obtain the average number of climate shocks across the model ensemble. Tables C1 and C2 in Appendix C presents the cumulative frequency and duration of droughts and floods, respectively, from 2020 to 2080 under the climate scenarios.

(2) Extreme temperature events: heat waves and cold waves

We follow the approach by Russo et al. (2014) to identify the possibilities of heat waves under the climate scenarios. Accordingly, we first construct a maximum temperature sample for a given day in a given year using the maximum temperature of the day up to 15 years before and after, and then, compare the maximum temperature with the ninetieth percentile of the sample. If there are six or more days consecutively recording maximum temperatures above the ninetieth percentile, those episodes are identified as possible heat waves.

To identify cold waves, we use daily minimum temperatures instead of maximum temperature and use the tenth percentile of the sample as the threshold to compare the minimum temperature of a given day in a given year. Six or more days of consecutive records of minimum temperature below the threshold are recognized as possible cold waves.

After identifying heat and cold waves, we take the GDP-weighted average of their frequencies and durations to obtain the occurrence of the events in the model regions. We then average the results from the model ensemble. Finally, we aggregate the averages to get the frequencies and durations of extreme temperature events under the climate scenarios. Table C3 presents the cumulative frequency and duration of extreme temperature events from 2020 to 2080 under the climate scenarios.

(3) Storms and wildfires

A growing body of literature demonstrates the impacts of climate change, or mostly global warming, on the changes in frequency and severity of wildfires and storms. The studies on wildfires mostly use the Keetch-Byram Drought Index (KBDI) to estimate the change in wildfire potential in different areas. However, due to the absence of information about land management practices in a range of countries needed for the KBDI, constructing the index at a global scale is challenging. Modeling storm frequency and duration changes requires additional variables such as wind speed, direction, pressure, and temperature and specialist modeling tools to predict storms. Given the absence of these tools, we use probabilistic regression techniques to derive the impact of maximum temperature on the occurrence of storms and wildfires.

We use the observed data on maximum temperature from ISIMIP from 1979 to 2019 and the historical data on the occurrence of storms and wildfires from CRED for the same period for the regression. After estimating the probability of occurrence for storms and wildfires for the climate scenarios, we obtain the GDP-weighted average of the number of events across the model regions. We then average the events across the model ensemble. Tables C4 and C5 present the cumulative frequency and duration of storms and wildfires under the climate scenarios from 2020 to 2080.

4. THE G-CUBED MODEL AND ECONOMIC SHOCKS

Overview of the G-Cubed model

The G-Cubed model is a multi-country, multi-sector, intertemporal general equilibrium model developed by McKibbin and Wilcoxen (1999, 2013). The model is designed to bridge the gaps between econometric general-equilibrium modeling, international trade theory, and modern macroeconomics. In the version of the model (version GGG20v154) used in this paper, there are ten regions and twenty sectors. The model regions are presented in Table 3. Appendix D shows the countries aggregated under the regions.

The sectors in the model are set out in Table 16. The G-Cubed sectors 1-12 are aggregated from 65 sectors of GTAP 10. We then further disaggregate the electricity sector into the electricity delivery sector (sector 1 in Table 4) and eight electricity generation sectors (sectors 13-20 in Table 4).

Model structure and features

The structure of the model is set out in McKibbin and Wilcoxen (2009; 2013). An illustration of the production structure is contained in Figure 1. CO2 emissions are measured through the burning of fossil fuels in energy generation.

Table 3: Regions in the G-Cubed Model

Region Code	Region Description
AUS	Australia
CHN	China
EUW	Europe
IND	India
JPN	Japan
OPC	Oil-Exporting developing countries
OEC	Rest of the OECD
ROW	Rest of the World
RUS	Russian Federation
USA	United States

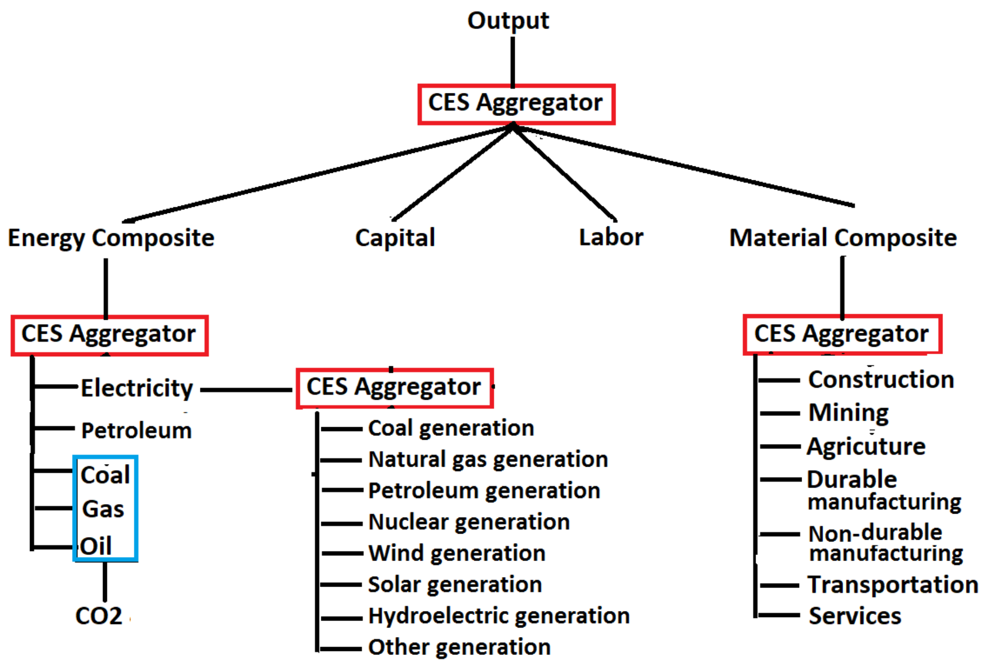
Source: G-Cubed Model (version GGG20v154).

Table 4: Sectors in the G-Cubed Model

Number	Sector Name	Notes
1	Electricity delivery	Energy Sectors Other than Generation
2	Gas extraction and utilities	
3	Petroleum refining	
4	Coal mining	
5	Crude oil extraction	
6	Construction	Goods and Services
7	Other mining	
8	Agriculture and forestry	
9	Durable goods	
10	Non-durable goods	
11	Transportation	
12	Services	
13	Coal generation	Electricity Generation Sectors
14	Natural gas generation	
15	Petroleum generation	
16	Nuclear generation	
17	Wind generation	
18	Solar generation	
19	Hydroelectric generation	
20	Other generation	

Source: G-Cubed Model (version GGG20v154).

Figure 1: Production Structure of Sectors 2 to 12 in the G-Cubed Model



Several key features of the standard G-Cubed model are worth highlighting here.

First, the model consistently accounts for stocks and flows of physical and financial assets. For example, budget deficits accumulate into government debt, and current account deficits accumulate into foreign debt. The model imposes an intertemporal budget constraint on all households, firms, governments, and countries. Thus, a long-run stock equilibrium obtains through the adjustment of asset prices, such as the interest rate for government fiscal positions or real exchange rates for the balance of payments. However, adjusting to each economy's long-run equilibrium can be slow, occurring over much of a century.

Second, agents in G-Cubed must use money issued by central banks for all transactions. Thus, central banks in the model set short-term nominal interest rates to target macroeconomic outcomes (such as inflation, unemployment, exchange rates, etc.) based on Henderson-McKibbin-Taylor monetary rules. These rules approximate actual monetary regimes in each country or region in the model. These monetary rules tie down the long-run inflation rates in each country and allow short-term policy adjustment to smooth fluctuations in the real economy.

Third, nominal wages are sticky and adjust over time based on country-specific labor contracting assumptions. Firms hire labor in each sector up to the point that labor's marginal product equals the real wage defined in terms of that sector's output price level. Any excess labor enters the unemployed pool of workers. Unemployment or the presence of excess demand for labor causes the nominal wage to adjust to clear the labor market in the long run. In the short-run, unemployment can arise due to structural supply shocks or aggregate demand changes in the economy.

Fourth, rigidities prevent the economy from moving quickly from one equilibrium to another. Rigidities include nominal stickiness caused by wage stickiness, lack of complete foresight in the formation of expectations, cost of adjustment in investment by firms with physical capital being sector-specific in the short run, monetary and fiscal authorities following particular monetary and fiscal rules. Short-term adjustment to economic shocks can be very different from the long-run equilibrium outcomes. The focus on short-run rigidities is essential for assessing the impact over the initial decades of demographic change.

Fifth, the model incorporates heterogeneous households and firms. Firms are modeled separately within each sector. There is a mixture of two types of consumers and two types of firms within each sector, within each country. One type bases its decisions on forward-looking expectations, and the other type follows more straightforward rules of thumb, which are optimal in the long run, but not necessarily in the short run.

The fiscal rule in the model varies across model versions. In this paper's version of the model, we assume governments levy lump-sum taxes on households adjusted to ensure fiscal sustainability. In the long run, the changes in interest servicing costs from any changes in revenue or expenditure exogenously imposed are offset through a lump sum tax on households. Thus, the government debt level can permanently change in the long run with the change in debt to GDP equal to the long-run fiscal deficit ratio to the economy's long-run real growth rate.

Baseline inputs and assumptions

We assume in the baseline that there are no additional climate policies other than those in place in 2018. The key inputs into the baseline are the initial dynamics from 2018 to 2019 and subsequent projections from 2019 onwards for sectoral productivity growth rates by sector and country. Sectoral productivity growth is driven by labor force growth and labor productivity growth.

(1) Labor force: We use the working-age population projections from the UN Population Prospects 2019 to calculate our economy-wide labor growth rates.

(2) Labor productivity: We use a catch-up model to generate labor productivity growth rates (labor-augmenting technological progress). The sectoral productivity projections follow the Barro approach, estimating that individual countries' average catch-up rate to the worldwide productivity frontier is 2% per year. We use the Groningen Growth and Development database to assess each sector's initial productivity level in the model and then take the initial productivity ratio to the US's equivalent sector (the frontier). Given this initial gap, we use the Barro catch-up model to generate long-term projections of the productivity growth rate of each sector within each country. Given that some regions are likely to catch up more quickly to the frontier due to economic reforms or more slowly to the frontier due to institutional rigidities, we vary the catch-up rate over time. The

calibration of the catch-up rate attempts to replicate each country's recent growth experiences and region in the model.

Given this global economy projection, we then implement a range of shocks to represent chronic climate shocks, extreme climate shocks, and a climate policy of achieving net-zero emission by 2050.

Economic shocks from chronic climate risks

As mentioned in Section 3.3, we focus on the economic impacts arising from chronic climate risks associated with rising sea levels, variation in crop yields, heat-induced effects on labor productivity, and changes in the occurrence of diseases. While the last two risks affect labor supply, the first two risks affect various economic sectors' productivity.

(1) Shocks to labor supply

Roson and Sartori (2016) present parameters to compute the heat-induced impacts on labor productivity in three main production sectors: agriculture, manufacturing, and services. We map these parameters to the model sectors: those for agriculture to coal mining, coal extraction, construction, mining, and agriculture; those for manufacturing to electric utilities, gas utilities, petroleum refining, durable manufacturing, non-durable manufacturing, and electricity generation sectors; and those for services to transportation and services. Based on the mean temperature variation in each country each year compared to the benchmark temperature for that country, we calculate the heat-induced reductions in labor productivity in the model sectors under each climate scenario.

Similar to the heat-induced impacts on labor supply, we estimate labor productivity changes due to climate-induced variations in the incidence of diseases. However, in contrast to the heat-induced impacts, we assume equal levels of exposure to the diseases across a given economy and apply the shock to the whole country. The diseases Roson and Sartori (2016) consider include malaria, dengue, and diarrhea.

(2) Shocks to productivity

Roson and Sartori (2016) derive damage functions to demonstrate the loss of land due to rising sea levels under various temperature increments from the benchmark. We use these estimates to calculate the percentage of land lost in each country each year under the climate scenarios. We then translate the loss of land into a productivity shock using the percentage reliance of each sector in each country on land compared to other inputs.

We also use the damage function parameters estimated by Roson and Sartori (2016) to estimate the changes in crop yields for maize, rice, and wheat for temperature variations from the benchmark. We then compute the yield changes for each of the crops under the climate scenarios for each country in each year. We map the estimates for maize, rice, and wheat on eight of the fourteen agriculture sub-sectors in the GTAP 10 database. The excluded sub-sectors account for livestock, forestry, and fisheries. We assume similar impacts to rice on vegetables and fruits, sugar cane and sugar beet, and plant-based fibers. We also assume a similar impact on wheat on oilseeds and other crops. Based on these assumptions, we derive total impact on agricultural productivity from climate chronic risks . We then calculate the productivity impacts on other sectors based on their reliance on inputs from the agriculture sector.

Economic shocks from extreme climate shocks

There are several channels through which extreme climate shocks could affect economic activities. These channels include the impacts of extreme climate shocks on labor force and the disruption to production processes. The change in country risk depends on the vulnerability to extreme climate shocks. There could also be changes in production sectors' equity risk premia depending on their exposure to extreme climate shocks. These issues are discussed in Section 5. We detail below the approaches to formulating shocks along with various data sources.

(1) Shocks to labor supply

Exposure to extreme climate shocks could lead to deaths and other physical and mental effects, reducing current and potential workforce's ability to contribute to an economy (Javadinejad et al. 2020; Bell et al. 2018; Schmitt et al. 2016; Ebi & Bowen 2016). We create mortality and morbidity shocks to labor supply to represent the future effects of extreme climate shocks on populations. While the mortality shock permanently reduces current and future economic contribution from affected individuals, the reduction in economic contribution due to the morbidity shock is temporary.

When estimating the mortality shock, we use CRED data to calculate the average number of deaths caused by historical extreme climate shocks in each country and average them across the model regions. We then use the averages to estimate the likely number of deaths caused by future extreme climate shocks under the climate scenarios. The historical average number of deaths caused by extreme climate shocks across the model regions is presented in Table 5.

Table 5: Historical Average Deaths Caused by Extreme Climate Shocks

Model Region	Droughts	Extreme Temperature	Floods	Storms	Wildfires
AUS	55	73	6	3	13
CHI	89,835	28	21,782	562	40
EUW	-	435	19	6	9
IND	265,645	300	245	826	8
JPN	-	66	238	191	-
OPC	2	28	119	19	8
OEC	-	83	1	7	5
ROW	4,707	62	66	442	7
RUS	200,000	2,758	12	27	7
USA	-	145	16	48	17

Source: CRED.

When estimating the morbidity shock, we first use CRED data on the number of affected individuals from historical extreme climate shocks and the duration of those. Using the data, we calculate the average number of affected individuals per day over the period of an extreme event. We then use the averages to estimate the number of individuals affected by future extreme climate shocks under the climate scenarios. Since the affected individuals would not contribute to economic activities during the duration of extreme climate shocks, we then calculate the number of working days lost from a 256-day working year. The morbidity shock is obtained as the proportion of the days lost from the working year. Table 6 presents the average number of individuals affected from historical extreme climate shocks.

Table 6: Average Individuals Affected by Historical Extreme Climate Shocks

Model Region	Droughts	Extreme Temperature	Floods	Storms	Wildfires
AUS	643,636	657,541	5,089	38,465	2,455
CHI	13,589,744	5,801,429	6,886,578	1,599,088	7,227
EUW	187,500	354	20,610	11,823	2,539
IND	87,502,563	12	2,983,325	708,048	-
JPN	-	12,513	160,239	47,098	222
OPC	1,783,192	25,458	82,537	53,920	7,560
OEC	7,857	29	4,345	357	8,808
ROW	1,247,730	74,999	240,276	195,823	30,878
RUS	1,000,000	36,152	30,012	1,211	4,647
USA	-	-	65,724	155,950	13,268

Source: CRED.

(2) Shocks to productivity

Extreme climate shocks affect both short-term and long-term productivity of economic sectors via their impacts on biodiversity, ecosystems, agriculture, and infrastructure (Sheng & Xu 2019). Thus, we first estimate the exposure of agricultural and energy productivities to historical extreme climate shocks. We then obtain other sectors' exposure to extreme climate shocks based on their dependencies on agriculture and energy sectors.

To assess agricultural productivity exposure to extreme climate shocks, we first obtain data on production of 175 crops across 224 countries from 1961 to 2018 from the Food and Agriculture Organization (FAO 2021). We categorize the crops into eight agricultural sectors following the GTAP 10 sectors: paddy rice, wheat, cereal grains, vegetables, fruit and nuts, oilseeds, sugar cane and sugar beet, plant-based fibers, and other crops. We then summarize the crops' production in tonnes and the total area cultivated in hectares, and obtain aggregate yield for each agricultural sector, before estimating the sensitivity of the agricultural yields to climate shocks. Based on the sensitivity estimates and each agricultural sectors' contribution to the agricultural sector in the model, we derive agricultural productivity's sensitivity to future extreme climate shocks. Table 7 presents the impact of extreme climate shocks on agricultural productivity for the model regions.

Table 7: Percentage Reduction in Agricultural Productivity due to Extreme Climate Shocks

Model Region	Droughts	Extreme Temperature	Floods	Storms	Wildfires
AUS	-1.96	-1.88	-0.40	-0.22	-2.60
CHI	-2.49	-1.95	-0.43	-0.21	-3.04
EUW	-1.96	-1.89	-0.36	-0.22	-2.70
IND	-1.83	-1.88	-0.41	-0.21	-2.54
JPN	-1.73	-1.89	-0.38	-0.20	-2.43
OPC	-1.94	-1.83	-0.47	-0.25	-2.57
OEC	-1.98	-1.86	-0.39	-0.24	-2.62
ROW	-1.77	-1.88	-0.40	-0.21	-2.39
RUS	-1.97	-1.86	-0.40	-0.24	-2.62
USA	-1.97	-1.89	-0.36	-0.22	-2.62

Source: Calculations by the Authors.

To assess the impacts of extreme climate shocks on electricity generation, we use the World Bank (2021) data on electricity production using oil, gas and coal, renewable resources, and nuclear energy. We obtain data for 227 countries from 1965 to 2015 and econometrically estimate electricity generation changes in response to extreme climate shocks. Based on the composition of the electric utility sector from different electricity generation sectors, we estimate the impact of extreme climate shocks on the electric utility sector. We then derive the effects on other sectors, due to disruptions to electric utilities from extreme climate shocks, based on their reliance on electric utilities. Table 8 summarizes the impacts on electric utilities across the model regions.

Table 8: Percentage Reduction in Electricity Generation due to Extreme Climate Shocks

Model Region	Droughts	Extreme Temperature	Floods	Storms	Wildfires
AUS	-0.20	-0.20	-1.13	-2.57	-2.00
CHI	-0.23	-0.26	-1.14	-2.52	-2.00
EUW	-0.49	-0.90	-1.06	-2.08	-2.00
IND	-0.22	-0.25	-1.13	-2.54	-2.00
JPN	-0.14	-0.49	-0.93	-2.59	-2.00
OPC	-0.06	-0.06	-1.07	-2.78	-2.00
OEC	-1.14	-1.36	-1.48	-1.19	-2.00
ROW	-0.34	-0.43	-1.15	-2.36	-2.00
RUS	-0.05	-0.11	-1.04	-2.77	-2.00
USA	-0.23	-0.57	-0.98	-2.46	-2.00

Source: Calculations by the Authors.

5. ECONOMIC IMPACTS OF CLIMATE RISKS

Tables 9 through 12 show the change in real GDP for each country and region relative to the baseline on average for each decade from 2021 to 2100. Each table is related to a specific RCP scenario. For example, the results show that US GDP in the decade from 2021-2030 is 0.48% lower than it otherwise would be due to climate change. This compares with more significant losses of 2.97% for China and 3.74% of GDP loss for ROW, which consists of emerging and developing economies. As the RCP scenarios increase in warming potential, the GDP losses tend to rise (except for the RCP 6.0 scenario, which has lower GDP loss than the RCP 4.5 scenario). The changes in GDP across time and scenarios reflect different responses of economic agents to rising shocks. Investment in various sectors is a good example. Suppose a higher temperature impact is anticipated in a particular RCP scenario. In that case, the more significant investment may be undertaken, which can cause GDP to vary due to the response of agents and the shocks' size. The apparent anomalies in some results show that there need not be a simple linear relation between temperature changes, the size of economic shocks (when there are a variety of shocks) and the economic outcomes. This outcome is driven by the changes in households and firms' behaviour in response to the shocks. This variation in results demonstrates the advantage of using a large-scale model with behavioural responses rather than a simple linear extrapolation when modeling climate change's economic consequences.

Table 9: Percentage Deviation from Baseline GDP by Decade under RCP 2.6

Model Region	2021-2030	2031-2040	2041-2050	2051-2060	2061-2070	2071-2080	2081-2090	2091-2100
AUS	-0.52	-0.70	-0.61	-0.55	-0.52	-0.46	-0.50	-0.66
CHI	-2.97	-2.71	-2.37	-2.01	-2.05	-1.99	-2.05	-1.81
EUW	-1.08	-1.00	-1.02	-0.95	-0.98	-0.93	-0.94	-0.92
IND	-1.04	-1.04	-0.87	-0.59	-0.67	-0.49	-1.03	-0.38
JPN	-1.98	-2.68	-2.46	-2.23	-2.69	-2.51	-2.31	-3.30
OPC	-1.83	-2.03	-2.00	-1.69	-1.73	-1.35	-1.10	-1.00
OEC	-1.06	-1.32	-1.07	-0.96	-0.89	-0.80	-0.78	-0.74
ROW	-3.74	-3.54	-3.14	-2.88	-2.77	-2.49	-2.36	-2.27
RUS	-1.54	-2.08	-1.92	-1.99	-1.81	-1.94	-1.92	-1.68
USA	-0.48	-0.60	-0.63	-0.49	-0.47	-0.49	-0.45	-0.57

Source: Results from G-Cubed Model Simulations.

Table 10: Percentage Deviation from Baseline GDP by Decade under RCP 4.5

Model Region	2021-2030	2031-2040	2041-2050	2051-2060	2061-2070	2071-2080	2081-2090	2091-2100
AUS	-0.74	-0.63	-0.76	-0.79	-0.97	-1.02	-0.81	-1.19
CHI	-2.42	-2.72	-2.67	-3.68	-4.05	-4.02	-5.14	-5.64
EUW	-1.10	-1.10	-1.11	-1.16	-1.21	-1.23	-1.19	-1.24
IND	-1.15	-1.36	-1.72	-2.31	-3.29	-2.97	-3.08	-3.56
JPN	-1.55	-2.03	-2.95	-3.74	-4.69	-4.31	-5.84	-5.11
OPC	-2.08	-2.83	-3.39	-4.00	-4.18	-4.27	-4.05	-4.03
OEC	-1.40	-1.23	-1.08	-0.95	-1.05	-1.05	-1.02	-0.93
ROW	-3.56	-3.53	-3.83	-4.23	-4.59	-4.76	-4.66	-4.96
RUS	-1.72	-1.98	-1.79	-1.93	-2.42	-2.06	-2.21	-2.48
USA	-0.49	-0.65	-0.76	-0.98	-1.13	-1.12	-1.15	-1.31

Source: Results from G-Cubed Model Simulations.

Table 11: Percentage Deviation from Baseline GDP by Decade under RCP 6.0

Model Region	2021-2030	2031-2040	2041-2050	2051-2060	2061-2070	2071-2080	2081-2090	2091-2100
AUS	-0.59	-0.66	-0.64	-0.84	-1.04	-1.07	-1.34	-1.50
CHI	-2.39	-1.98	-2.61	-2.58	-3.39	-4.86	-6.66	-9.74
EUW	-1.04	-1.03	-1.02	-1.11	-1.17	-1.30	-1.35	-1.34
IND	-1.49	-1.01	-1.53	-0.98	-1.77	-2.74	-2.99	-4.52
JPN	-1.19	-1.67	-1.96	-2.39	-3.81	-5.58	-7.22	-9.00
OPC	-2.21	-2.47	-2.99	-3.23	-3.86	-4.85	-6.12	-6.68
OEC	-1.02	-1.11	-1.08	-1.11	-1.11	-1.13	-1.07	-0.92
ROW	-3.49	-3.28	-3.46	-3.63	-4.18	-5.28	-6.21	-6.73
RUS	-1.39	-1.83	-1.98	-1.96	-2.05	-2.28	-2.55	-2.83
USA	-0.43	-0.48	-0.67	-0.70	-1.02	-1.20	-1.81	-1.98

Source: Results from G-Cubed Model Simulations.

Table 12: Percentage Deviation from Baseline GDP by Decade under RCP 8.5

Model Region	2021-2030	2031-2040	2041-2050	2051-2060	2061-2070	2071-2080	2081-2090	2091-2100
AUS	-0.76	-0.91	-1.27	-1.75	-2.09	-2.85	-4.11	-4.13
CHI	-2.57	-3.34	-4.47	-6.56	-10.65	-11.26	-3.01	-1.07
EUW	-1.11	-1.17	-1.24	-1.42	-1.65	-1.77	-1.71	-1.47
IND	-1.42	-1.65	-2.74	-3.84	-6.37	-8.72	-13.23	-17.42
JPN	-1.56	-2.46	-4.16	-6.20	-10.92	-16.32	-21.49	-13.18
OPC	-2.48	-3.85	-5.64	-8.02	-10.48	-11.88	-10.06	-8.22
OEC	-1.22	-1.23	-1.03	-1.35	-1.28	-1.33	-1.39	-1.66
ROW	-3.82	-4.40	-5.44	-7.24	-9.82	-11.52	-12.54	-12.60
RUS	-1.75	-1.89	-1.68	-2.52	-2.90	-2.96	-2.25	-1.27
USA	-0.54	-0.64	-1.14	-1.98	-2.89	-3.89	-2.69	-0.31

Source: Results from G-Cubed Model Simulations.

The impacts on individual sectors across countries and regions on average between 2021 and 2050 are presented in Tables 13-16. Each table contains results for a particular RCP scenario. A shorter time period is chosen to simplify the presentation of results. Note that, as with the aggregate GDP outcomes, the impact of climate change varies across countries and across sectors. The largest impacts tend to be on agriculture in many countries.

Table 13: Percentage Deviation in Sector Outputs from 2021-2050 under RCP 2.6

Sector	AUS	CHI	EUW	IND	JPN	OPC	OEC	ROW	RUS	USA
Electricity delivery	-2.41	-4.15	-4.84	-1.51	-4.71	-4.19	-5.59	-7.18	-4.99	-2.42
Gas extraction and utilities	-0.17	-2.64	-0.15	-0.76	-3.20	-1.24	-0.32	-1.63	-0.47	-0.17
Petroleum refining	-0.80	-3.17	-1.61	-1.17	-2.57	-1.75	-1.17	-3.36	-2.08	-0.89
Coal mining	-0.11	-3.60	5.02	-0.93	-2.90	-1.25	0.62	-1.59	-0.36	1.86
Crude oil extraction	-2.05	-1.73	-2.37	-1.48	-9.80	-1.84	-1.48	-4.17	-3.41	-0.65
Construction	-1.24	-3.34	-1.61	-1.14	-8.23	-3.28	-1.82	-5.52	-3.45	-1.27
Other mining	-2.26	-2.92	-1.99	-2.02	-6.13	-1.98	-2.96	-4.13	-2.84	-2.64
Agriculture and forestry	-3.69	-5.55	-5.69	-1.87	-8.83	-4.83	-5.27	-8.76	-5.52	-3.52
Durable goods	-1.46	-3.00	-1.90	-1.27	-4.82	-2.27	-2.27	-4.63	-2.70	-1.33
Nondurable goods	-2.11	-4.43	-2.46	-1.47	-4.43	-3.09	-3.12	-5.79	-3.25	-1.43
Transportation	-0.34	-1.93	-0.62	-0.65	-1.61	-0.99	-0.92	-1.96	-1.34	-0.51
Services	-0.08	-1.05	-0.22	-0.37	-0.91	-0.62	-0.03	-1.19	-0.62	-0.18

Source: Results from G-Cubed Model Simulations.

Table 14: Percentage Deviation in Sector Outputs from 2021-2050 under RCP 4.5

Sector	AUS	CHI	EUW	IND	JPN	OPC	OEC	ROW	RUS	USA
Electricity delivery	-2.78	-4.13	-5.03	-2.03	-4.18	-5.50	-6.00	-7.46	-4.78	-2.53
Gas extraction and utilities	-0.19	-2.75	-0.25	-1.27	-3.92	-2.01	-0.39	-1.95	-0.44	-0.25
Petroleum refining	-1.05	-3.49	-1.75	-1.94	-2.81	-2.72	-1.25	-3.67	-2.06	-1.03
Coal mining	-0.31	-3.48	5.24	-1.59	-2.66	-2.55	-0.09	-1.97	-0.67	1.55
Crude oil extraction	-2.22	-1.47	-2.52	-2.02	-8.68	-2.63	-1.65	-4.21	-3.69	-0.75
Construction	-1.60	-3.70	-1.78	-1.91	-8.16	-5.36	-1.98	-6.25	-3.34	-1.55
Other mining	-2.62	-2.94	-2.41	-2.77	-6.48	-3.29	-3.56	-4.64	-3.33	-3.22
Agriculture and forestry	-4.00	-5.22	-5.96	-2.46	-8.10	-5.86	-5.84	-8.93	-5.50	-3.61
Durable goods	-1.84	-3.15	-2.30	-1.87	-5.21	-3.68	-2.63	-5.22	-2.90	-1.64
Nondurable goods	-2.20	-4.13	-2.58	-1.92	-4.03	-3.89	-3.41	-5.91	-3.08	-1.46
Transportation	-0.41	-1.94	-0.67	-1.06	-1.59	-1.49	-0.99	-2.09	-1.31	-0.60
Services	-0.08	-0.96	-0.22	-0.59	-0.76	-1.07	0.00	-1.25	-0.56	-0.22

Source: Results from G-Cubed Model Simulations.

Table 15: Percentage Deviation in Sector Outputs from 2021-2050 under RCP 6.0

Sector	AUS	CHI	EUW	IND	JPN	OPC	OEC	ROW	RUS	USA
Electricity delivery	-2.51	-3.57	-4.86	-1.86	-3.35	-5.15	-5.41	-7.15	-4.60	-2.14
Gas extraction and utilities	-0.14	-2.46	-0.11	-1.16	-2.40	-1.69	-0.31	-1.57	-0.38	-0.15
Petroleum refining	-0.91	-3.18	-1.61	-1.72	-2.25	-2.47	-1.08	-3.37	-1.96	-0.88
Coal mining	-0.17	-3.00	5.28	-1.42	-1.39	-2.24	0.08	-1.55	-0.57	1.72
Crude oil extraction	-2.00	-1.26	-2.36	-1.93	-5.99	-2.33	-1.46	-3.86	-3.47	-0.59
Construction	-1.36	-3.17	-1.60	-1.68	-5.71	-4.78	-1.73	-5.67	-3.27	-1.22
Other mining	-2.25	-2.46	-2.16	-2.52	-4.91	-2.90	-3.13	-4.16	-3.06	-2.70
Agriculture and forestry	-3.63	-4.90	-5.72	-2.47	-6.94	-5.65	-4.91	-8.57	-5.27	-3.38
Durable goods	-1.57	-2.66	-2.07	-1.68	-3.97	-3.27	-2.30	-4.71	-2.75	-1.36
Nondurable goods	-2.03	-3.84	-2.44	-1.91	-3.37	-3.72	-2.94	-5.63	-2.92	-1.33
Transportation	-0.36	-1.72	-0.61	-0.96	-1.18	-1.39	-0.85	-1.93	-1.20	-0.51
Services	-0.08	-0.84	-0.19	-0.56	-0.49	-0.98	0.00	-1.14	-0.50	-0.16

Source: Results from G-Cubed Model Simulations.

Table 16: Percentage Deviation in Sector Outputs from 2021-2050 under RCP 8.5

Sector	AUS	CHI	EUW	IND	JPN	OPC	OEC	ROW	RUS	USA
Electricity delivery	-3.24	-5.18	-5.13	-2.72	-4.95	-7.27	-5.59	-8.62	-4.09	-2.65
Gas extraction and utilities	-0.39	-3.76	-0.43	-1.95	-6.34	-3.36	-0.58	-3.43	-0.46	-0.55
Petroleum refining	-1.62	-4.88	-1.95	-3.10	-3.63	-4.19	-1.24	-4.91	-1.97	-1.35
Coal mining	-0.82	-5.46	5.00	-2.44	-4.13	-4.82	-1.92	-3.76	-1.46	0.60
Crude oil extraction	-2.86	-2.07	-2.70	-2.59	-11.0	-3.91	-1.88	-5.28	-4.32	-1.11
Construction	-2.66	-5.47	-2.04	-3.03	-11.2	-8.62	-2.00	-8.88	-3.67	-2.12
Other mining	-3.77	-4.30	-3.23	-3.94	-9.31	-5.33	-4.68	-6.44	-4.46	-4.66
Agriculture and forestry	-4.42	-6.12	-6.13	-3.04	-9.55	-7.41	-5.71	-10.1	-5.22	-3.81
Durable goods	-2.87	-4.59	-3.03	-2.73	-7.46	-5.85	-3.10	-7.18	-3.45	-2.25
Nondurable goods	-2.45	-4.95	-2.68	-2.37	-4.74	-5.13	-3.29	-6.88	-2.66	-1.58
Transportation	-0.62	-2.73	-0.73	-1.67	-2.03	-2.25	-1.01	-2.76	-1.22	-0.80
Services	-0.14	-1.41	-0.21	-0.91	-0.89	-1.74	0.07	-1.79	-0.43	-0.30

Source: Results from G-Cubed Model Simulations.

6. TRANSITION RISKS

The previous section explores the impact of climate shocks on economic activity. This section focuses on transition risk for economies. Transition risk occurs when there are changes in climate policies that have economic impacts. It is important to stress that there are many ways to implement climate policies, including market-based mechanisms like cap-and-trade, carbon taxes and hybrid policies. There are also direct regulatory policies and a range of subsidies to support non-fossil industries. This section explores a carbon tax and how this approach affects countries differently and sectors within countries differently.

The policy we focus on is a pure carbon tax implemented separately in each economy and is designed to reach zero net carbon emissions by 2050. The tax is designed to be implemented in 2021, and then the tax increases by 7% per year until 2050. We search for an initial tax rate in each country, such that CO2 emissions from energy use are 80% lower relative to 2050. This contribution of energy to achieving economy-wide zero net emissions assumes that policies outside the energy sector would reach 20% of the additional emissions reduction. We do not model the emissions reductions outside the energy sector following Bang et al. (2020) and based on the existing literature.

Figure 2 shows the carbon tax required in each economy to reach zero net emissions by 2050. We assume that the revenue from the carbon tax is rebated as a lump sum to households. As shown in McKibbin et al. (2015), the assumption about how revenue is recycled does have a significant impact on the policy's macroeconomic outcomes. Note in Figure 2 that the carbon tax starts at a different level in each economy. We assume there is no international trading of emissions reduction, which would improve economic efficiency, but we have argued elsewhere (McKibbin et al. 2014) it is not politically plausible.

The results for GDP across all countries in the model are shown next in Figure 3. Countries that rely on fossil fuels in energy generation in domestic production or receive substantial income flows from selling fossil fuel or fossil fuel-intensive products overseas have the most significant negative impacts on GDP. The higher costs are transparent for the case of Russia, OPC, and the rest of the world. Other countries, such as India and the ROECD region, experience a reduction in GDP, relative to baseline, close to 4% by 2032. Note that this is a reduction relative to what it would otherwise have been, not an absolute reduction in GDP. China and Australia have very similar losses by 2032 of roughly 2% of GDP.

Figure 4 shows the carbon tax impact on each energy sector's output within the US economy. The energy sectors are coal, gas, petroleum refining, and electricity generation. A complete set of results for all countries are contained in Appendix E.

Figure 5 contains the impact of the global carbon tax on the non-energy sectors in the US. As for all regions, there is a substantial reduction in coal output in the United States by 2032 well before. This decline in coal production occurs because coal has higher CO2 emissions per unit of energy generated, and therefore the carbon tax falls most heavily on coal. Other sectors such as gas and oil are also impacted but to a much lesser extent. Mining is the most impacted non-energy sector , followed by durable manufacturing. The results for durable manufacturing output reflect that once the carbon taxes are announced and believed to be credibly committed to being implemented over the following 30 years, investment drops substantially in fossil fuel-intensive industries. This investment, undertaken using goods produced by the durable goods sector for durable goods globally, will tend to contract due to the tax on CO2. Transportation is also impacted because there is a substantial amount of petroleum as an input into the transportation sector. With the price of oil increasing, there is a rise in costs in that sector. The construction sector also faces a decline in demand from the mining and energy sectors. Construction also faces a drop in demand due to the fall in investment in the capital-intensive fossil fuel sectors. Some sectors, however, do expand as a result of the global carbon tax. For example, services output is above baseline by 2032 as there is substitution on the demand side away from fossil fuel-intensive industries towards non-fossil-fuel intensive industries.

Figure 6 contains results for the different electricity generation technologies. The increase in the price of coal leads to a substantial reduction in coal use for generating electricity. Simultaneously, renewable technologies such as wind, solar and hydro in electricity generation rise substantially over the next decade. The introduction of the carbon tax is insufficient to drive the substantial increase in these technologies needed for a more rapid energy transformation in the next decade without additional policies such as a subsidy on renewable energy generation which further shifts relative price away from coal and towards renewables.

Figure 2: Carbon Tax per Unit of CO2

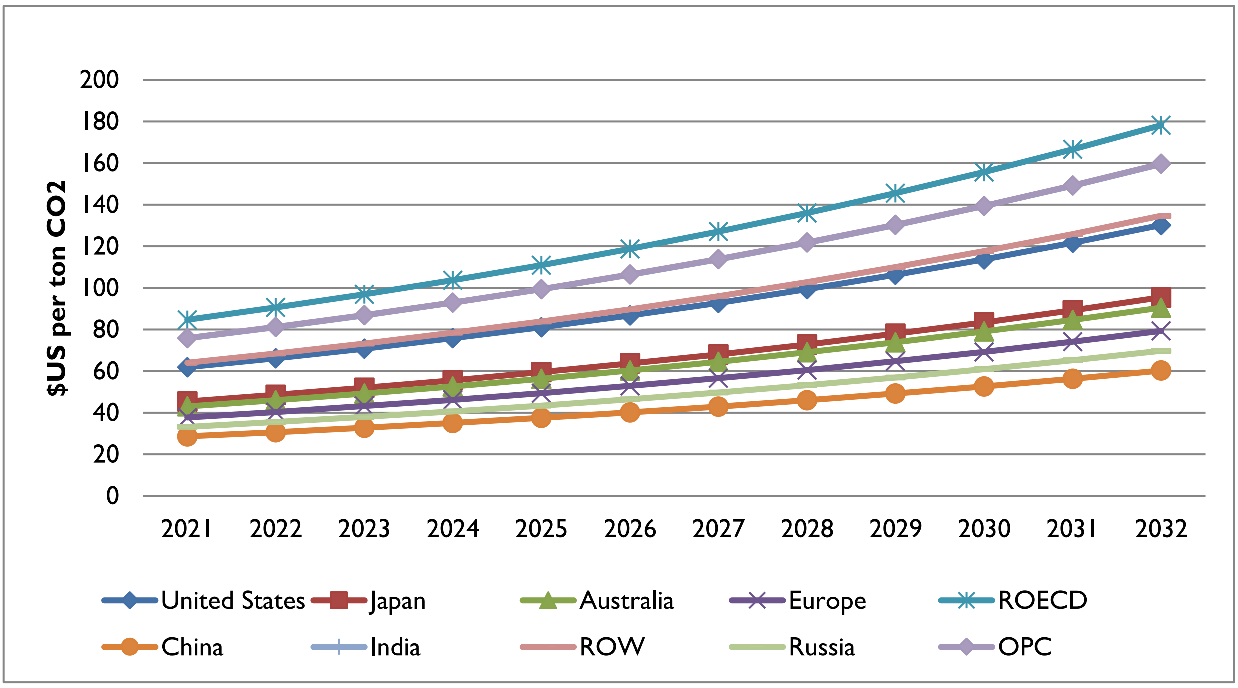


Figure 3: Global Change in GDP (2021-2032)

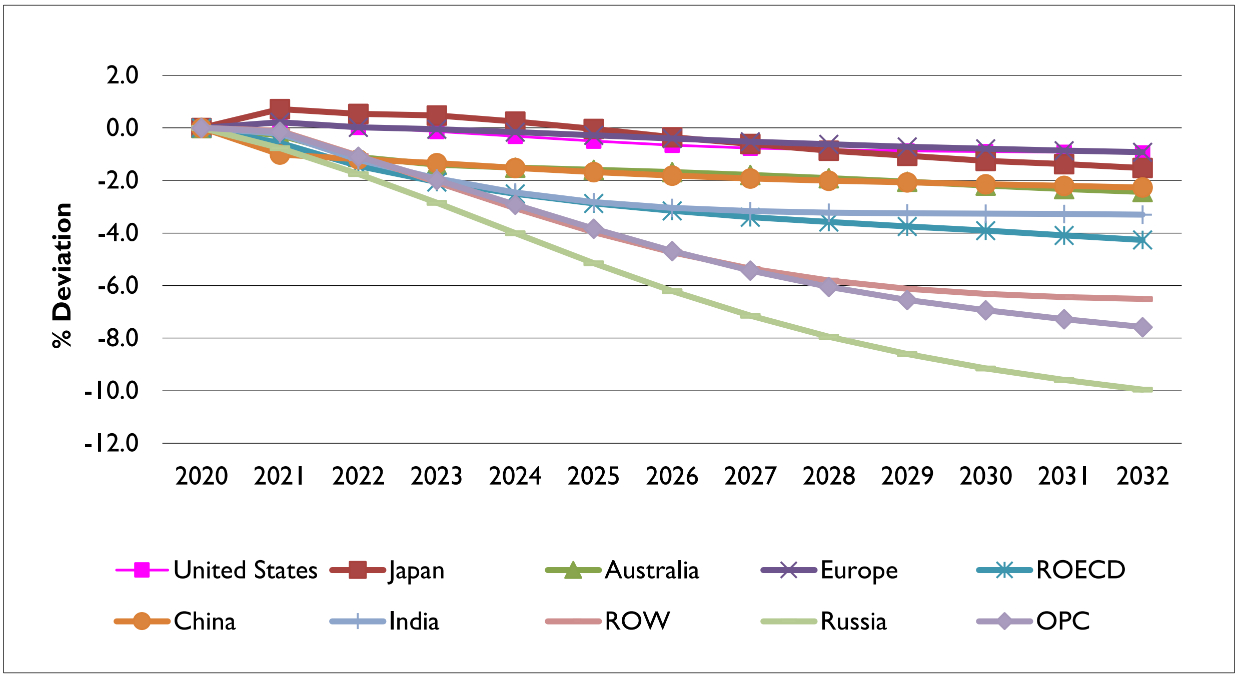


Figure 4: Changes in the Energy Sectors' Output in the US under a Global Carbon Tax

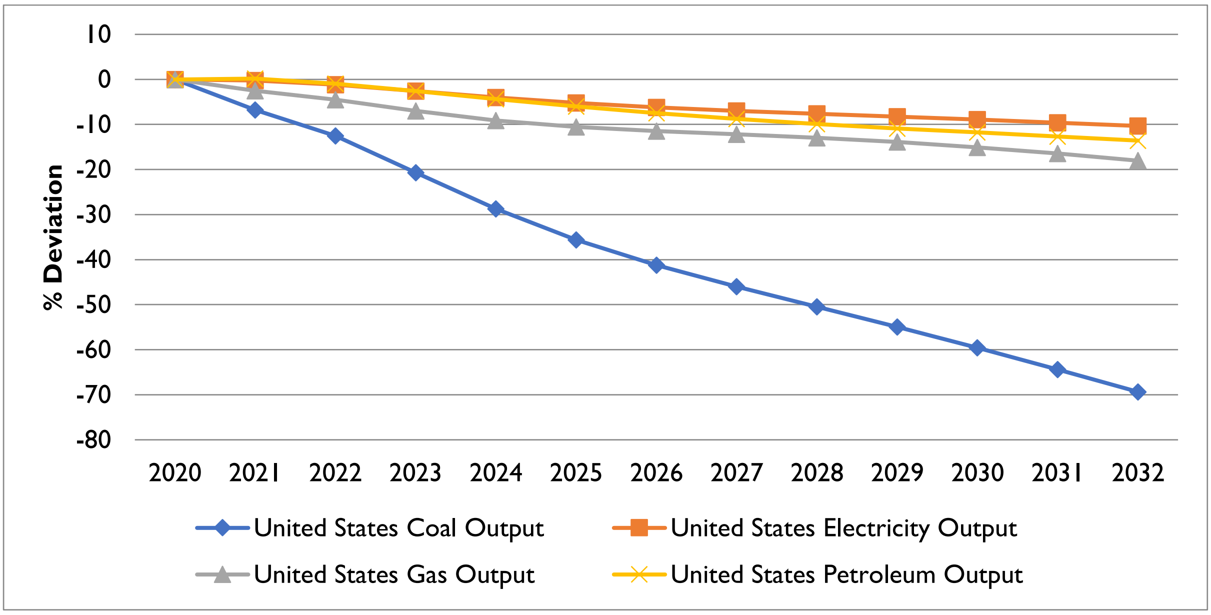
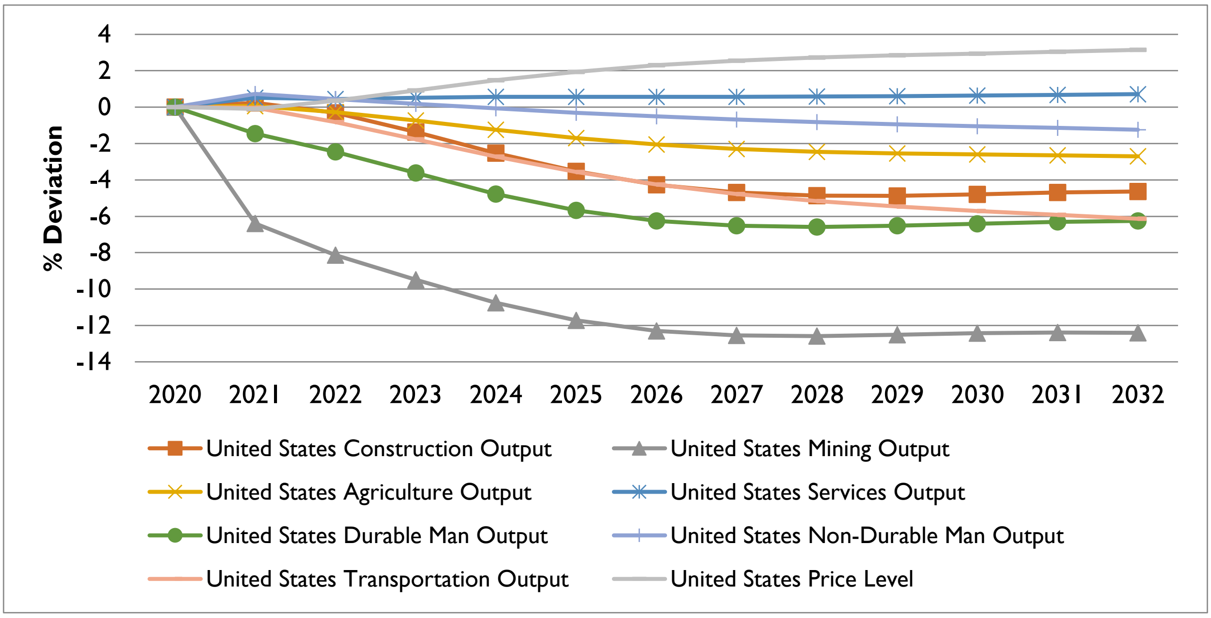
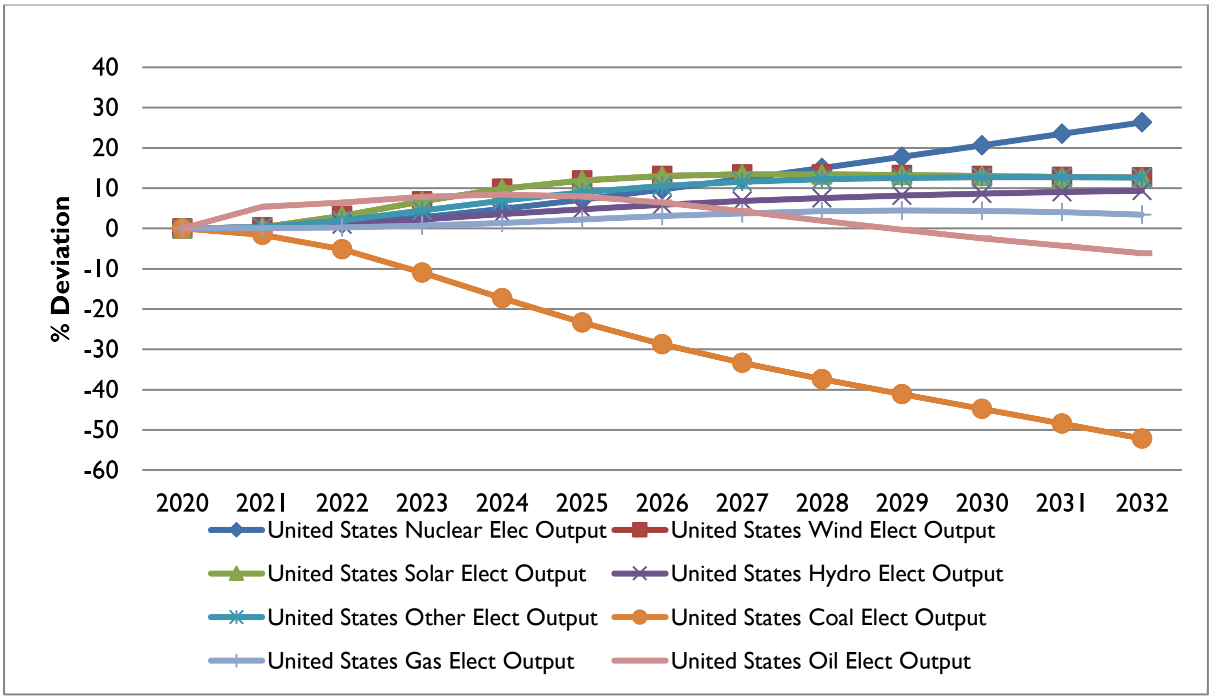


Figure 5: Changes in the Non-energy sectors' Output in the US under a Global Carbon Tax



Whether renewable energy technologies can replace the electricity generation by coal more quickly is explored further in Bang et al. (2020). This result that coal generation falls by more than renewables generation can increase, causing electricity output to fall, driven by the model's investment functions' properties. Costs are quadratic in the rate of investment. This assumption implies that it is difficult to quickly expand a small sector due to the rapidly rising costs of a high investment rate.

Figure 6: Changes in Electricity Generation by Fuel Type in the US



7. CHANGE IN FINANCIAL RISK ASSESSMENT

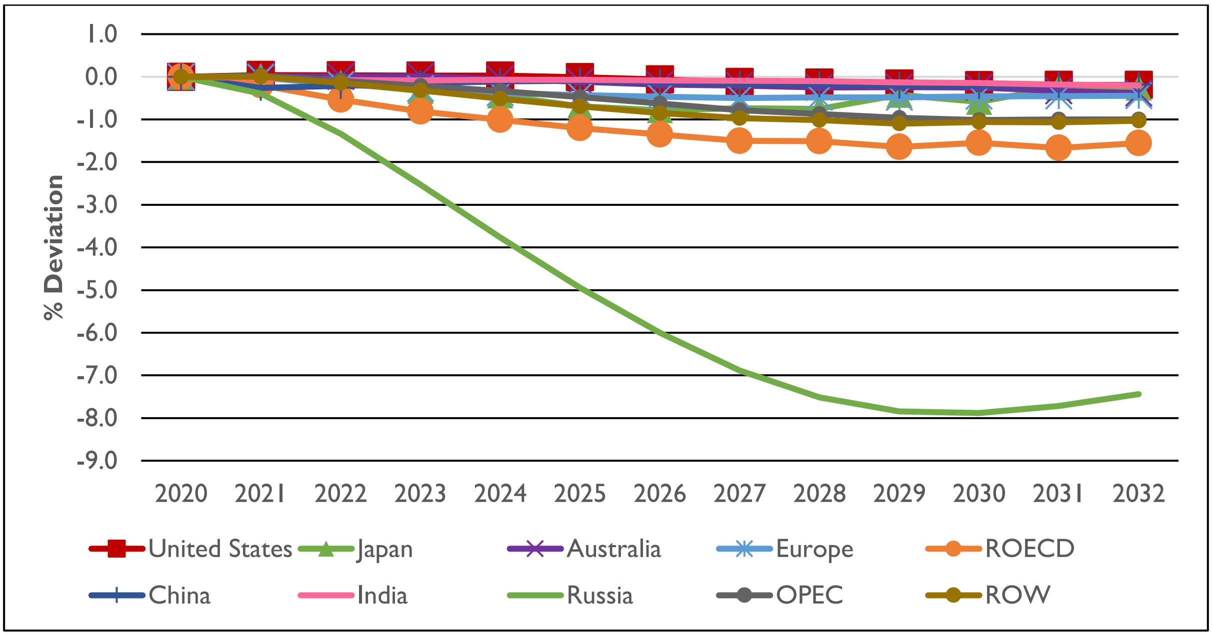
This section explores the impact of climate shocks on risk assessment in different economic sectors. Extreme climate shocks cause investors to be less attracted to countries and production sectors that are more vulnerable to climate shocks. The model captures the direct impact on physical returns to investment in sectors. What is not captured is how risk premia might also respond to climate shocks. These relative changes in country and sector risks are likely to be reflected in financial markets.

To estimate the sensitivity of stock indices to the incidence of extreme climate shocks, we first obtain data on the monthly value of a country's leading stock index for 72 countries since the inception of stock markets in the particular country from the Thomson-Reuters' Datastream Database (2021). We also obtain the monthly yield on long-term government bonds for the same countries for the same period. We then calculate the monthly risk premium attributable to investments in stocks compared to risk-free government bonds. We regress the risk premia against the incidence of the extreme climate shocks to estimate the changes in equity risk premia of production sectors in response to extreme climate shocks.

A complete set of results for all countries is contained in Appendix F. Here we focus on the results for the RCP 8.5 scenario, which is the upper bound of the climate scenarios. All of the results in Section 7 are the additional changes in variables due to the changes in risk premia resulting from the climate shocks. These results do not include the climate shocks explored in previous sections. Figure 7 contains the additional GDP changes when we map the extreme climate shocks into a change in sector risk premium. This approach is highly speculative and is based on the historical experience of extreme climate shocks. It is possible that the realised future changes in risk premia could be much larger than the shocks we model. Nonetheless, Figure 7 shows that for most countries, the loss in economic activity each year could be up to 2% of GDP per year in the worst-case scenario considered. In Russia's case, the risks shocks are dramatically accentuated because the climate shocks have significant impacts on Russia, which are then magnified in financial markets.

In Appendix F, we show results for each country's GDP and sectoral output over the next decade just from the changes in financial risk premia. Future shocks to risk premia have short term impacts because of the forward-looking nature of asset markets in the G-Cubed model. A change in risk over the century is captured in financial markets in the short run, and the consequences evolve. This forward-looking assumption causes significant adjustment over the next decade. In each country, GDP is permanently lower in the long run with a permanently higher risk. However, in the short run, in some cases (i.e. the United States), GDP rises before it falls. This initial increase in GDP is because, despite falls in some asset price, a rise in real investment in some sectors in response to expected future changes in real activity can temporarily stimulate GDP. Also, a fall in real interest rates due to lower expected future growth can temporarily increase private consumption in the short term through a temporary rise in expected future income due to a fall in the interest rate used to discount future income. This transitory effect of the impact of a fall in real interest rates on expected future income is discussed in detail in Liu et al. (2020).

Figure 7: GDP Change under RCP 8.5



8. CONCLUSION

This paper has explored the global macroeconomic consequences of climate risk, focusing on three broad areas: the economic impact of physical climate risk such as chronic climate change due to temperature increases and extreme climate shocks; the economic effects of transition risk (change in climate policies); and scenarios where greater awareness of climate shocks on individual sectors in the economy may lead to changes in risk perceptions within financial markets.

We find that even under relatively modest assumptions about temperature changes (represented by the RCP 2.6 scenario), there can be significant economic costs associated with physical climate risks by the end of the century. This result is consistent with the results of other studies, including Kompas et al. (2018).

It should be stressed that there is enormous uncertainty in the analysis in this paper. We have drawn extensively from other researchers' work in a range of disciplines in designing the economic analysis. We have not explored the sensitivity of other assumptions that might be made outside our study, nor have we presented a wide range of results reflecting the uncertainty in modeling the global economy. We have explored a central illustrative case that shows potentially high economic costs in not taking action on climate change. These risks involve physical risk from gradual temperature change and risk from extreme climate shocks. We have also shown that, depending on how policies are designed, there can be significant transition risk to induvial sectors and countries in the global economy when moving to net zero emissions by 2050. These risks vary across countries and sectors. It will also vary across economic and other implemented policies to reduce carbon dioxide emissions by the end of the century. If anything, we underestimate the potential impact of financial risk adjustment by using historical relationships between change in financial prices and extreme climate events.

There is a great deal more research required to understand the risks from climate change better and understand future outcomes' sensitivity to key assumptions. The paper aims to show how existing economic models can be used to explore various scenarios about future climate change and explore alternative pathways for achieving significant action against future climate risks. There is still a large amount of research required to understand better the critical issues explored in this paper.

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APPENDIX A: CLIMATE SHOCK ESTIMATION

Table A1: Classification of Natural Disasters by CRED

Disaster Category	Disasters
Geophysical: A hazard originating from solid earth. This term is used interchangeably with the term geological hazard.	Earthquake, Mass Movement (dry), Volcanic activity
Meteorological: A hazard caused by short-lived, micro- to meso-scale extreme weather and atmospheric conditions that last from minutes to days.	Extreme Temperature (Heat waves / Cold waves), Fog, Storm
Hydrological: A hazard caused by the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater.	Flood, Landslide, Wave action
Climatological: A hazard caused by long-lived, meso- to macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variability.	Drought, Glacial Lake Outburst, Wildfire
Biological: A hazard caused by the exposure to living organisms and their toxic substances (e.g. venom, mold) or vector-borne diseases that they may carry. Examples are venomous wildlife and insects, poisonous plants, and mosquitoes carrying disease-causing agents such as parasites, bacteria, or viruses (e.g., malaria).	Epidemic, Insect infestation, Animal Accident
Extra-terrestrial: A hazard caused by asteroids, meteoroids, and comets as they pass near-earth, enter the earth's atmosphere, and/or strike the earth, and by changes in interplanetary conditions that affect the earth's magnetosphere, ionosphere, and thermosphere.	Impact, Space weather

Source: CRED.

Table A2: Historical Occurrence of Extreme Events from 1900 to 2019

Model Region	Drought	Extreme Temperature	Flood	Storm	Wildfire	Total
AUS	11	7	64	108	41	231
CHI	39	14	304	312	8	677
EUW	32	205	447	485	82	1,251
IND	16	60	306	202	4	588
JPN	1	16	57	183	1	258
OPC	29	11	424	68	11	543
OEC	7	7	84	58	25	181
ROW	590	220	3,319	2,235	164	6,528
RUS	6	21	83	26	25	161
USA	16	36	189	651	86	978
Total	747	597	5,277	4,328	447	11,396

Source: CRED.

Table A3: Historical Deaths due to Extreme Events from 1900 to 2019

Model Region	Drought	Extreme Temperature	Flood	Storm	Wildfire	Total
AUS	600	509	322	248	533	2,212
CHI	3,503,534	384	6,621,627	175,037	314	10,300,896
EUW	-	89,029	8,148	2,793	683	100,653
IND	4,250,320	17,975	74,910	166,769	30	4,510,004
JPN	-	1,048	13,513	34,918	-	49,479
OPC	58	302	50,334	1,280	80	52,054
OEC	-	580	82	367	119	1,148
ROW	2,776,867	13,511	215,855	985,948	1,006	3,993,187
RUS	1,200,000	57,914	973	692	169	1,259,748
USA	-	5,201	3,023	30,843	1,437	40,504
Total	11,731,379	186,453	6,988,787	1,398,895	4,371	20,309,885

Source: CRED.

Table A4: Affected Individuals due to Extreme Events 1900 to 2019

Model Region	Drought	Extreme Temperature	Flood	Storm	Wildfire	Total
AUS	7,080,000	4,602,784	325,719	4,154,264	100,638	16,263,405
CHI	530,000,000	81,220,002	2,093,519,672	498,915,572	57,816	3,203,713,062
EUW	6,000,000	72,599	9,212,865	5,734,080	208,186	21,227,730
IND	1,400,041,000	700	912,897,512	143,025,632	-	2,455,964,844
JPN	-	200,214	9,133,631	8,618,995	222	17,953,062
OPC	51,712,565	280,037	34,995,885	3,666,582	83,159	90,738,228
OEC	55,000	200	364,954	20,697	220,207	661,058
ROW	736,160,929	16,499,748	797,477,022	437,663,634	5,063,924	1,992,865,257
RUS	6,000,000	759,198	2,491,000	31,489	116,174	9,397,861
USA	-	31	12,421,772	101,523,302	1,141,079	115,086,184
Total	2,737,049,494	103,635,513	3,872,840,032	1,203,354,247	6,991,405	7,923,870,691

Source: CRED.

Table A5: Insured Losses due to Extreme Events from 1900 to 2020 (Constant 2019 $US 1000)

Model Region	Drought	Extreme Temperature	Flood	Storm	Wildfire	Total
AUS	-	-	6,828,661	13,244,956	3,005,857	23,079,474
CHI	1,769,439	1,899,894	3,593,955	1,448,455	-	8,711,742
EUW	-	1,089,252	34,401,672	77,384,804	464,653	113,340,381
IND	431,458	-	3,839,327	1,393,554	-	5,664,339
JPN	-	-	5,208,905	69,437,123	-	74,646,028
OPC	-	273,300	917,760	829,925	-	2,020,985
OEC	-	-	3,626,327	3,869,416	4,122,839	11,618,582
ROW	-	232,091	17,201,423	53,447,128	409,272	71,289,913
RUS	-	-	55,062	-	23,449	78,511
USA	20,934,566	4,638,202	21,415,735	512,025,923	42,831,012	601,845,439
Total	23,135,463	8,132,739	97,088,827	733,081,284	50,857,082	912,295,394

Source: CRED.

Table A6: Total Losses due to Extreme Events from 1900 to 2020 (Constant 2019 $US 1000)

Model Region	Drought	Extreme Temperature	Flood	Storm	Wildfire	Total
AUS	29,154,096	-	20,571,764	38,813,196	7,567,687	96,106,743
CHI	50,264,545	27,147,238	393,459,694	145,960,456	247,501	617,079,434
EUW	39,774,318	21,621,335	214,131,368	174,911,001	15,965,379	466,403,401
IND	9,534,655	898,153	101,177,100	52,350,890	4,922	163,965,720
JPN	-	-	33,082,280	159,165,358	-	192,247,638
OPC	5,465,493	1,730,903	39,405,656	7,485,167	945,965	55,033,184
OEC	17,952,075	4,152,265	14,069,024	10,067,126	15,875,496	62,115,987
ROW	63,978,249	7,114,553	275,134,751	361,612,741	23,512,650	731,352,943
RUS	2,910,832	1,778,227	12,766,746	526,092	2,961,383	20,943,280
USA	52,433,420	40,234,826	172,858,428	1,162,261,138	72,929,700	1,500,717,512
Total	271,467,682	104,677,501	1,276,656,810	2,113,153,165	140,010,683	3,905,965,841

Source: CRED.

APPENDIX B: STANDARD PRECIPITATION INDEX

Table B1: SPI Values and their Interpretations

Index Value	Interpretation
Above 2.00	Exceptionally wet
Between 1.60 and 1.99	Extremely wet
Between 1.30 and 1.59	Severely wet
Between 0.80 and 1.29	Moderately wet
Between 0.51 and 0.79	Abnormally wet
Between 0.50 and -0.50	Near normal
Between -0.79 and -0.51	Abnormally dry
Between -1.29 and -0.80	Moderately dry
Between -1.59 and -1.30	Severely dry
Between -1.99 and -1.60	Extremely dry
Below -2.00	Exceptionally dry

Source: McKee et al. (1993).

APPENDIX C: FREQUENCY AND DURATION OF THE FUTURE EXTREME CLIMATE SHOCKS

Table C1: Cumulative GDP-weighted Frequency and Duration (Months) of Droughts from 2020 to 2080

Model Region	GDP-weighted Frequency of Droughts				GDP-weighted Duration of Droughts			
	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
AUS	9	9	14	9	14	16	24	9
CHI	7	10	16	8	9	11	22	8
EUW	61	61	60	61	63	64	63	61
IND	8	15	10	10	15	25	16	10
JPN	18	18	15	19	25	29	20	19
OPC	39	41	30	29	51	51	38	29
OEC	54	54	50	52	56	57	51	52
ROW	61	61	61	61	61	61	61	61
RUS	8	9	8	2	10	14	9	2
USA	16	15	15	13	36	23	22	13

Source: Calculations by the Authors.

Table C2: Cumulative GDP-weighted Frequency and Duration (Months) of Floods from 2020 to 2080

Model Region	GDP-weighted Frequency of Floods				GDP-weighted Duration of Floods			
	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
AUS	16	12	12	10	36	26	24	10
CHI	12	7	14	13	26	15	27	13
EUW	60	61	58	57	60	62	60	57
IND	18	11	9	12	36	20	20	12
JPN	17	10	15	23	35	14	25	23
OPC	25	35	26	21	30	40	35	21
OEC	56	56	55	56	61	66	60	56
ROW	61	61	61	61	62	61	62	61
RUS	14	10	2	2	25	17	2	2
USA	13	13	12	10	20	22	21	10

Source: Calculations by the Authors.

Table C3: Cumulative GDP-weighted Frequency and Duration (Months) of Extreme Temperature Climate Shocks from 2020 to 2080

Model Region	GDP-weighted Frequency				GDP-weighted Duration			
	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
AUS	56.25	58.25	58.00	58.75	11.25	11.65	11.60	11.75
CHI	62.25	61.00	59.50	60.25	12.45	12.20	11.90	12.05
EUW	51.13	57.11	55.32	58.77	12.75	12.10	12.15	12.18
IND	43.50	56.50	53.25	57.25	8.70	11.30	10.65	11.45
JPN	55.25	57.25	51.75	57.75	11.05	11.45	10.35	11.55
OPC	59.11	60.74	59.91	60.65	12.68	12.20	12.15	12.20
OEC	59.77	60.44	60.54	60.56	13.28	12.20	12.20	12.20
ROW	54.49	56.72	55.19	58.10	13.75	12.48	12.65	12.33
RUS	54.75	61.00	59.25	60.50	10.95	12.20	11.85	12.10
USA	55.50	61.00	60.25	60.75	11.10	12.20	12.05	12.15

Source: Calculations by the Authors.

Table C4: Cumulative GDP-weighted Frequency and Duration (Months) of Storms from 2020 to 2080

Model Region	GDP-weighted Frequency				GDP-weighted Duration			
	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
AUS	4.39	4.39	4.39	4.39	0.18	0.18	0.18	0.18
CHI	4.37	4.37	4.37	4.38	0.18	0.18	0.18	0.18
EUW	4.38	4.38	4.38	4.38	0.18	0.18	0.18	0.18
IND	4.39	4.39	4.39	4.39	0.18	0.18	0.18	0.18
JPN	4.39	4.39	4.39	4.39	0.18	0.18	0.18	0.18
OPC	4.09	4.10	4.10	4.10	0.18	0.18	0.18	0.18
OEC	4.39	4.39	4.39	4.39	0.18	0.18	0.18	0.18
ROW	4.39	4.39	4.39	4.39	0.18	0.18	0.18	0.18
RUS	4.08	4.08	4.08	4.08	0.18	0.18	0.18	0.18
USA	4.39	4.39	4.39	4.39	0.18	0.18	0.18	0.18

Source: Calculations by the Authors.

Table C5: Cumulative GDP-weighted Frequency and Duration (Months) of Wildfires from 2020 to 2080

Model Region	GDP-weighted Frequency				GDP-weighted Duration			
	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
AUS	1.31	1.31	1.30	1.32	0.06	0.06	0.06	0.06
CHI	1.26	1.26	1.25	1.26	0.06	0.06	0.06	0.06
EUW	1.26	1.26	1.26	1.26	0.06	0.06	0.06	0.06
IND	1.31	1.32	1.30	1.32	0.06	0.06	0.06	0.06
JPN	1.27	1.27	1.26	1.27	0.06	0.06	0.06	0.06
OPC	1.21	1.21	1.22	1.21	0.06	0.06	0.06	0.06
OEC	1.31	1.32	1.30	1.32	0.06	0.06	0.06	0.06
ROW	1.30	1.30	1.29	1.30	0.06	0.06	0.06	0.06
RUS	1.21	1.21	1.22	1.22	0.06	0.06	0.06	0.06
USA	1.27	1.27	1.27	1.27	0.06	0.06	0.06	0.06

Source: Calculations by the Authors.

APPENDIX D: COUNTRY AGGREGATION IN THE G-CUBED MODEL

Europe:
Germany, France, Italy, Spain, Netherlands, Belgium, Bulgaria, Croatia, Czech Republic, Estonia, Cyprus, Lithuania, Latvia, Hungary, Malta, Poland, Romania, Slovenia, Slovakia, Luxemburg, Ireland, Greece, Austria, Portugal, Finland, United Kingdom, Norway, Sweden, Switzerland, Denmark

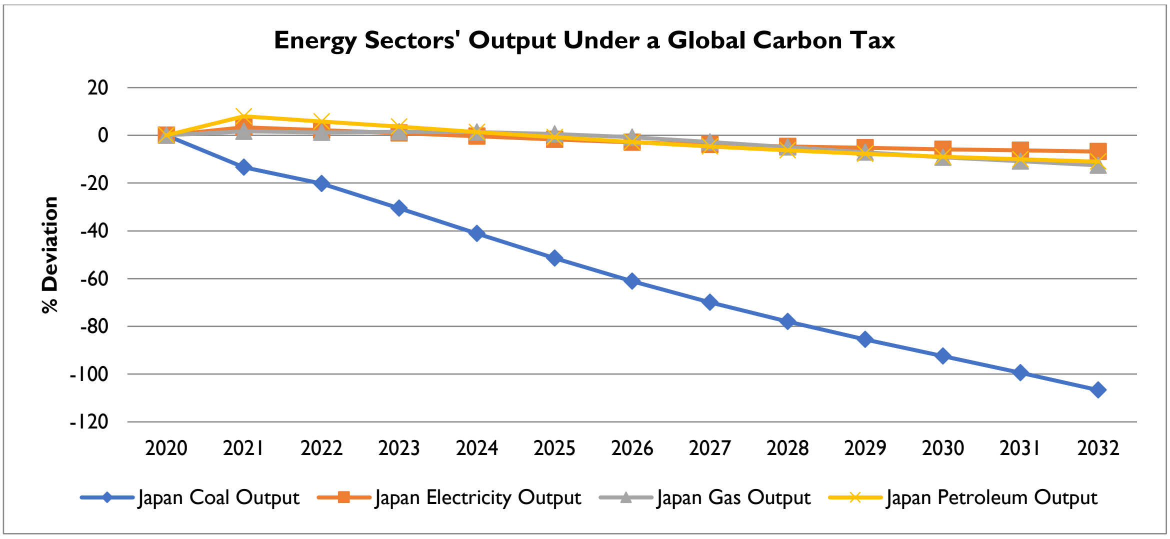
Rest of Advanced Economies:
Canada, New Zealand, Iceland, Liechtenstein

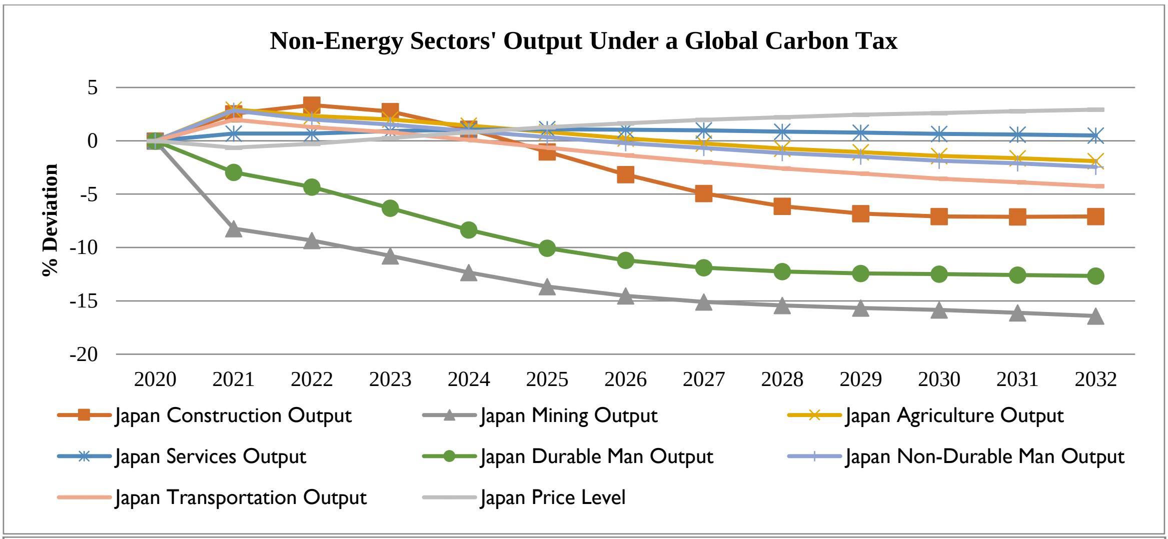
Oil-Exporting and the Middle East:
Ecuador, Nigeria, Angola, Congo, Iran, Venezuela, Algeria, Libya, Bahrain, Iraq, Israel, Jordan, Kuwait, Lebanon, Palestinian Territory, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, United Arab Emirates, Yemen

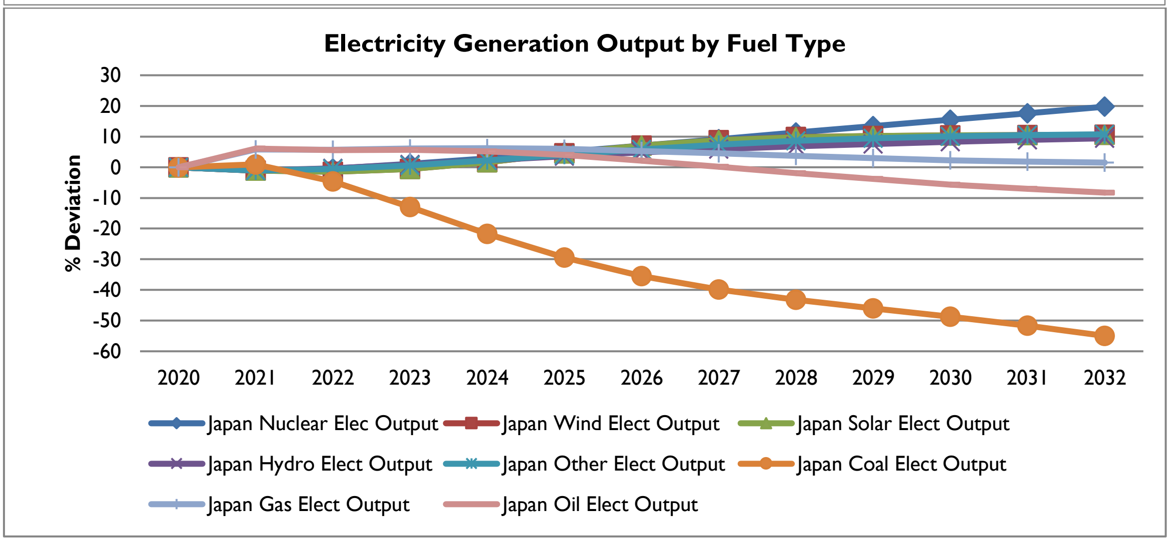
Rest of World:
All countries not included in other groups.

APPENDIX E: TRANSITION DYNAMICS FOR ALL COUNTRIES

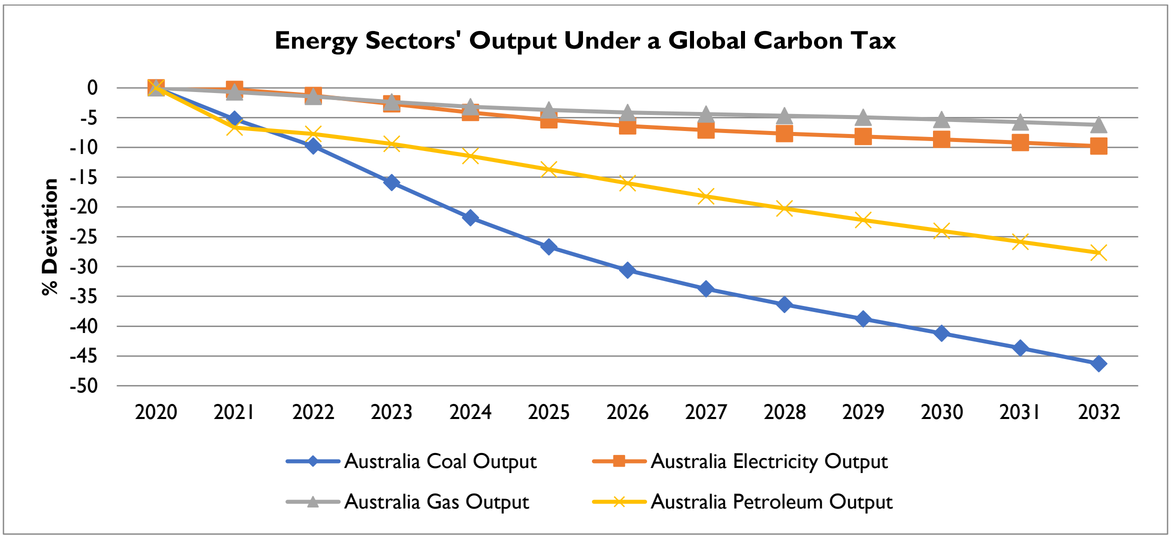
E1: Results for Japan

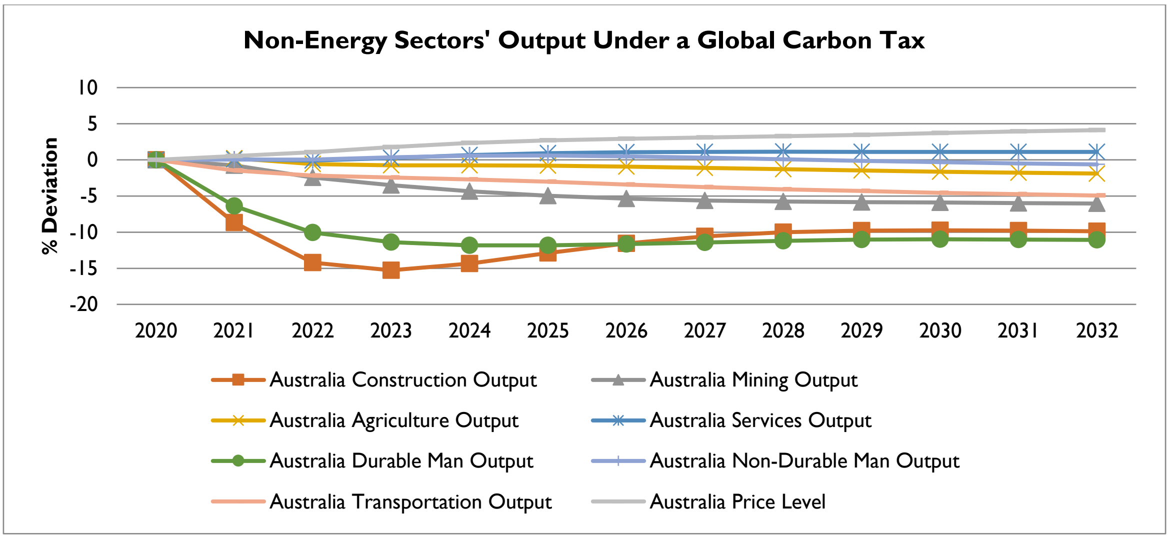


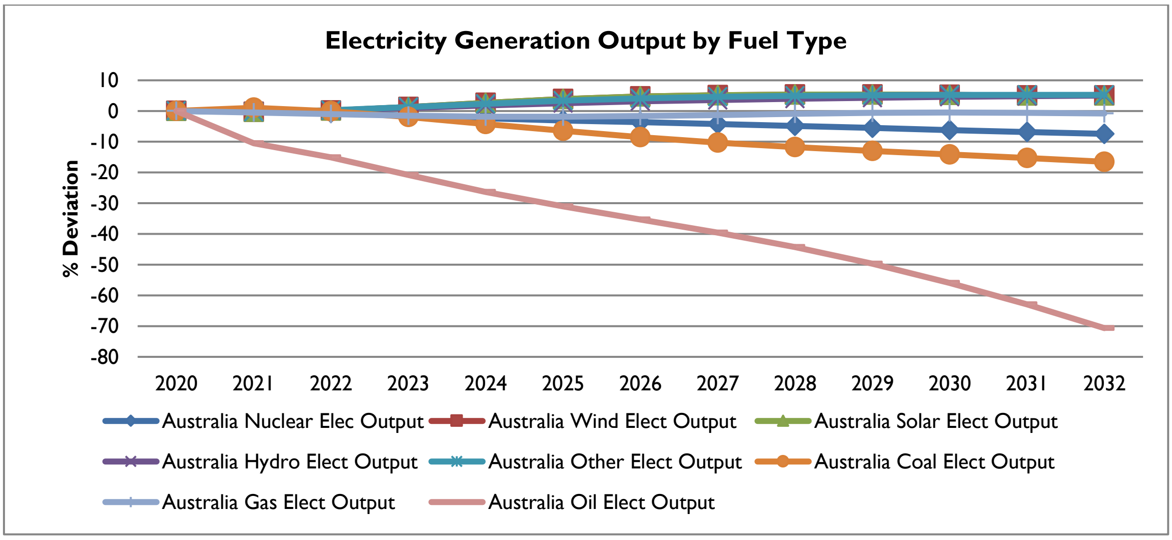




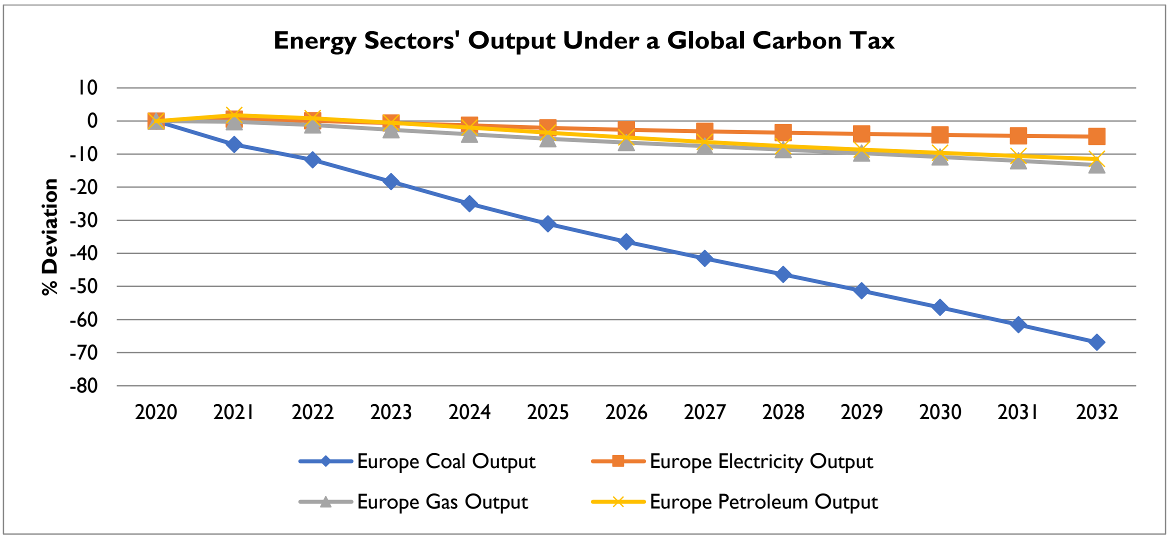
E2: Results for Australia

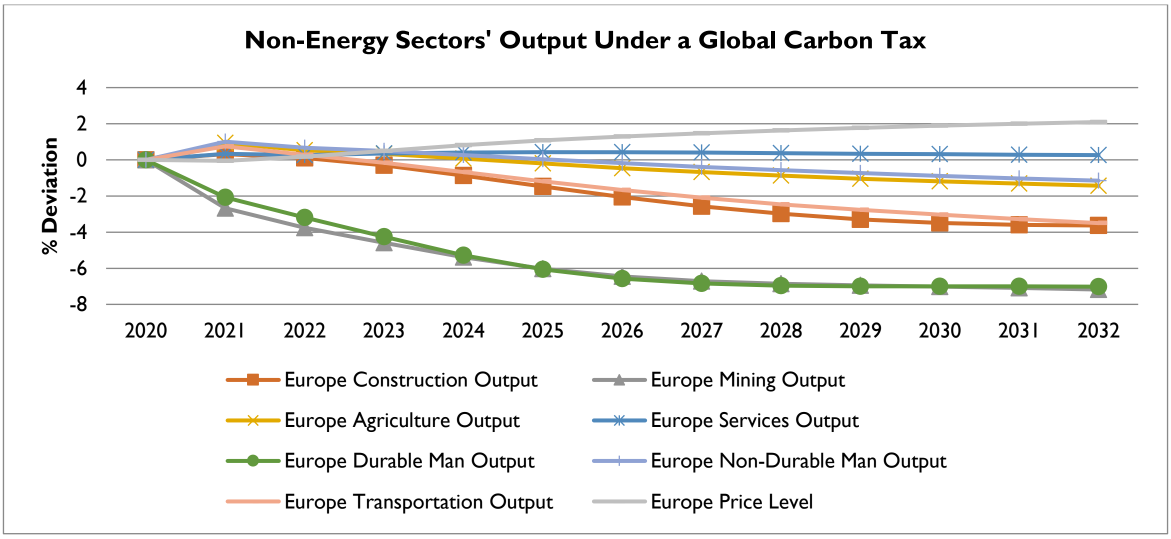


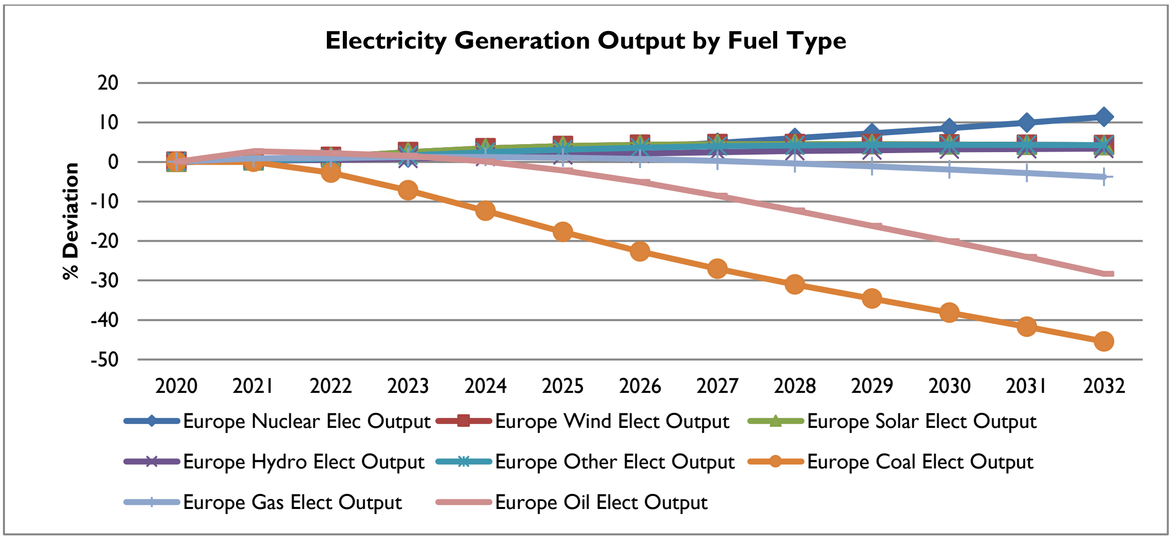




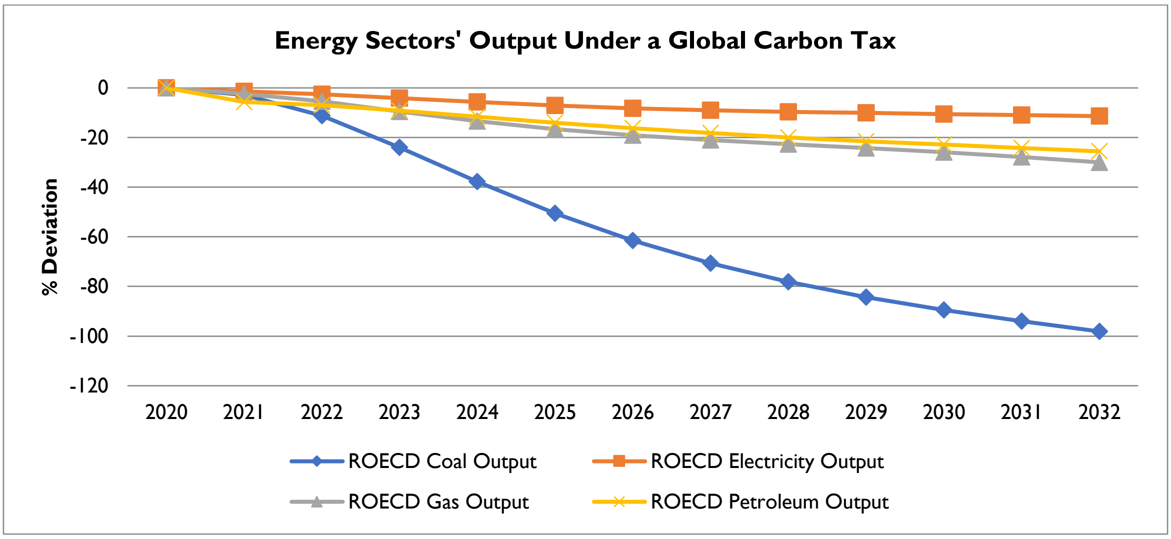
E3: Results for Europe

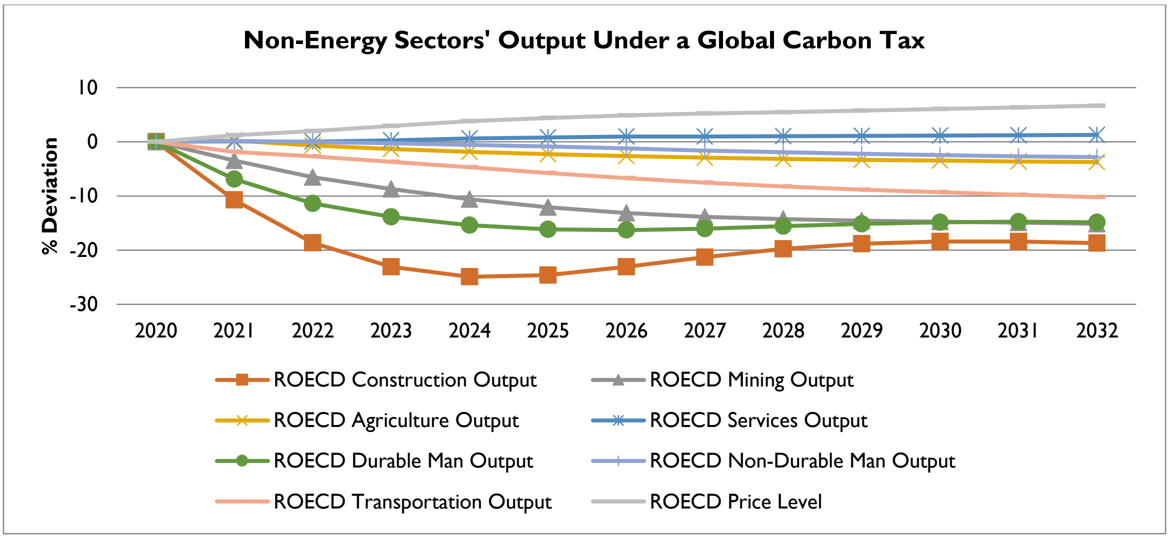


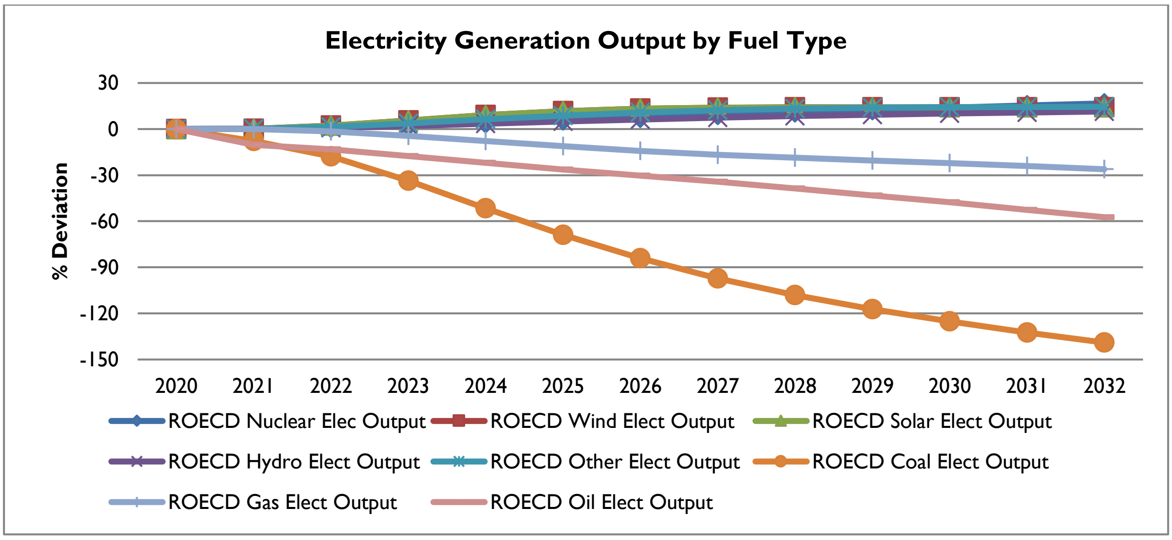




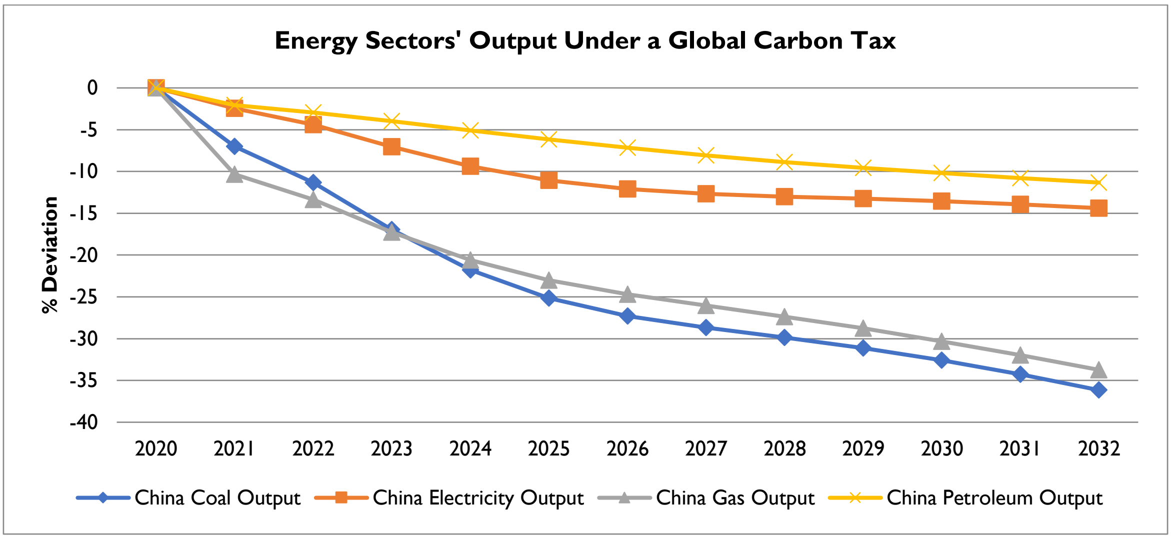
E4: Results for ROECD

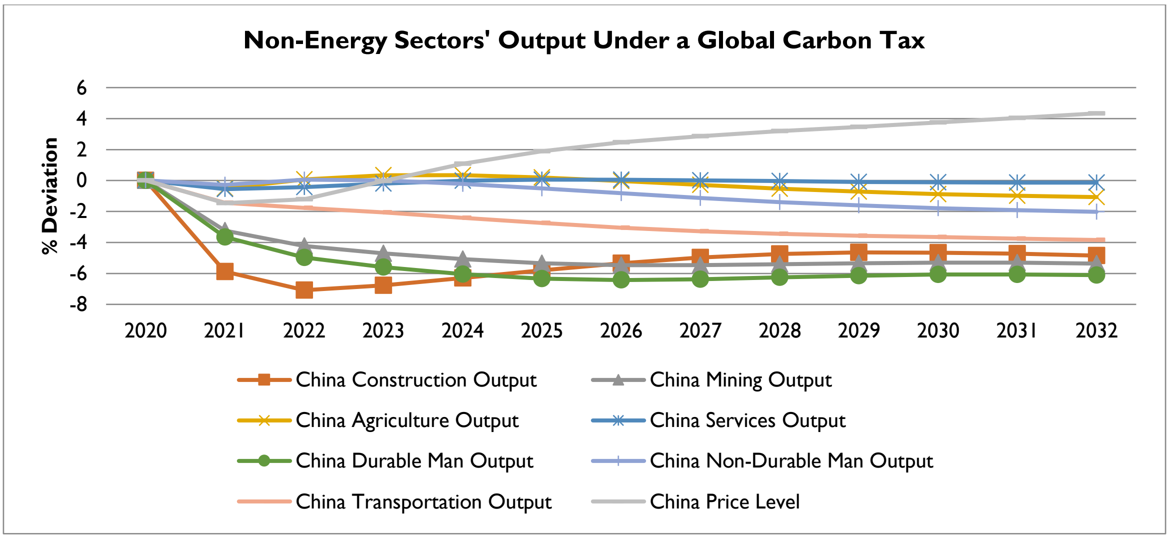


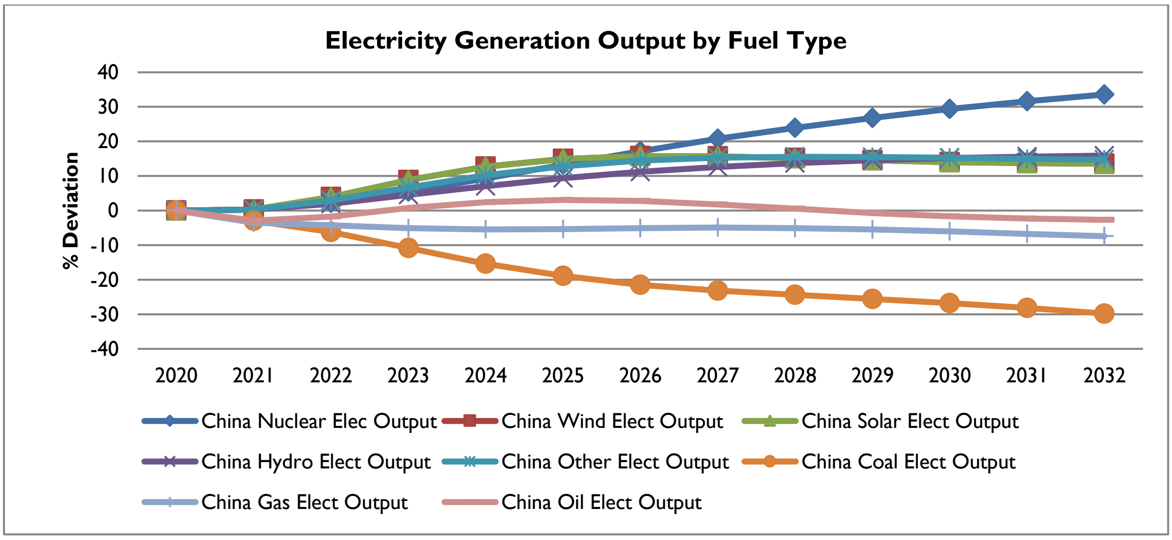




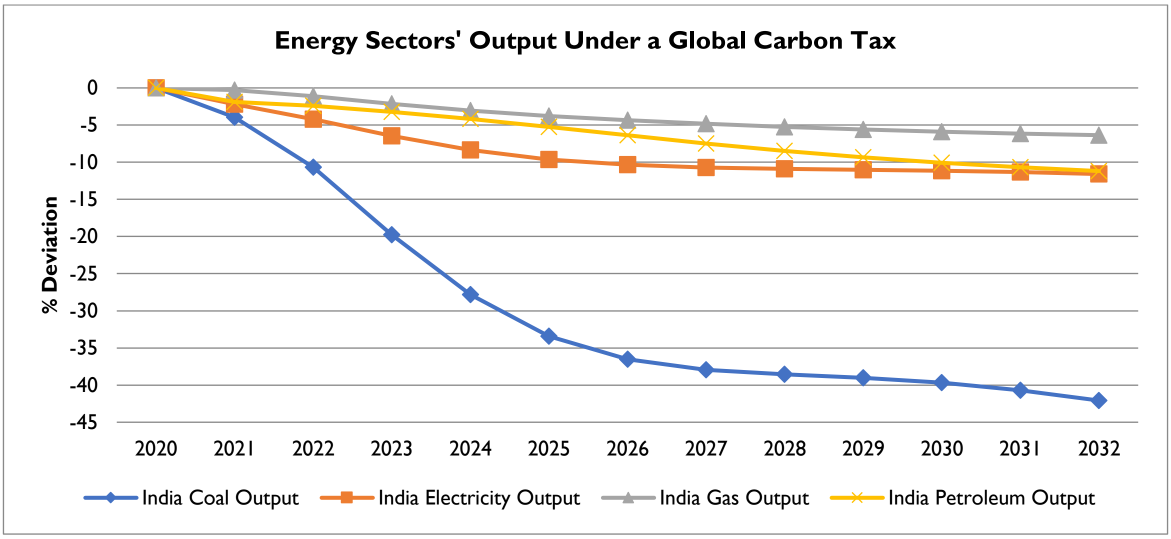
E5: Results for China

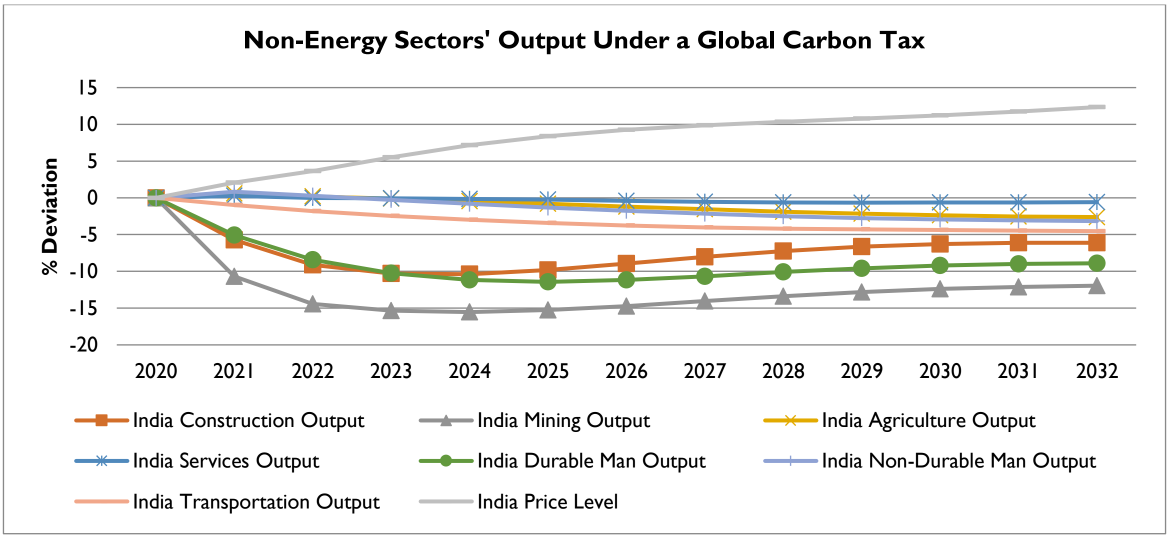


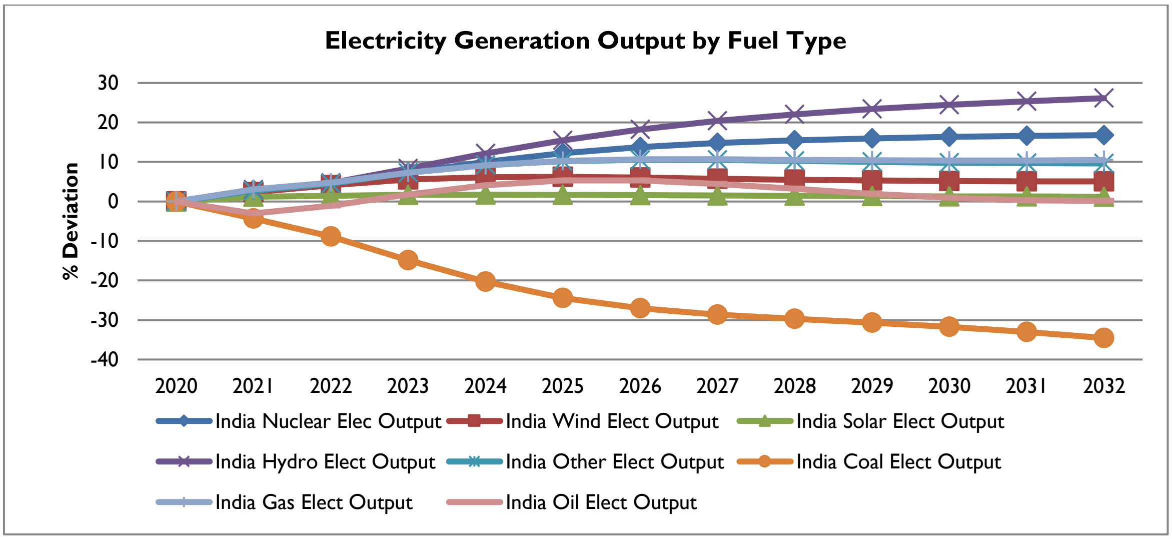




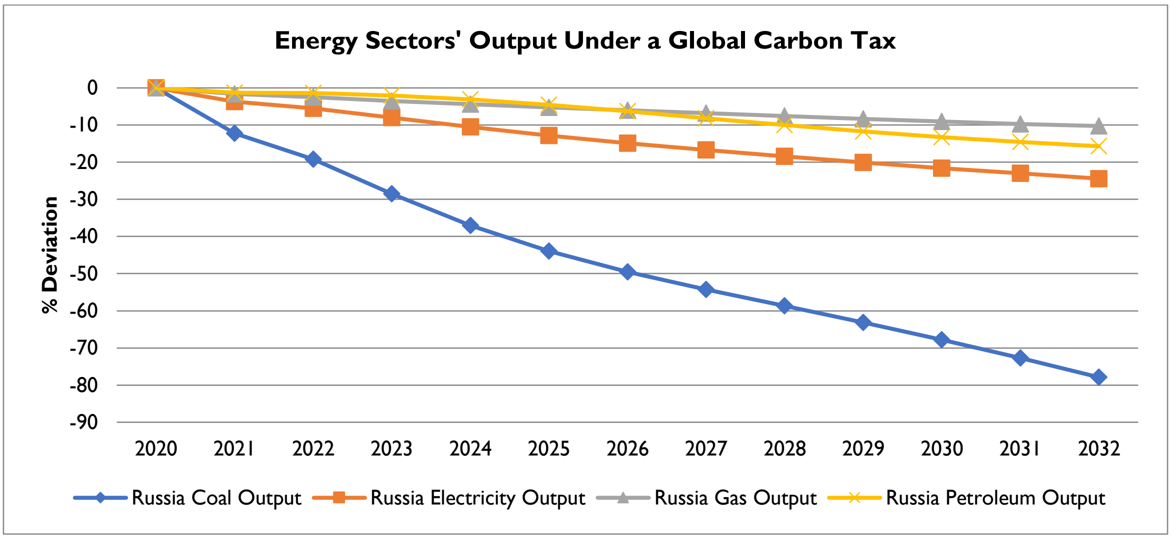
E6: Results for India

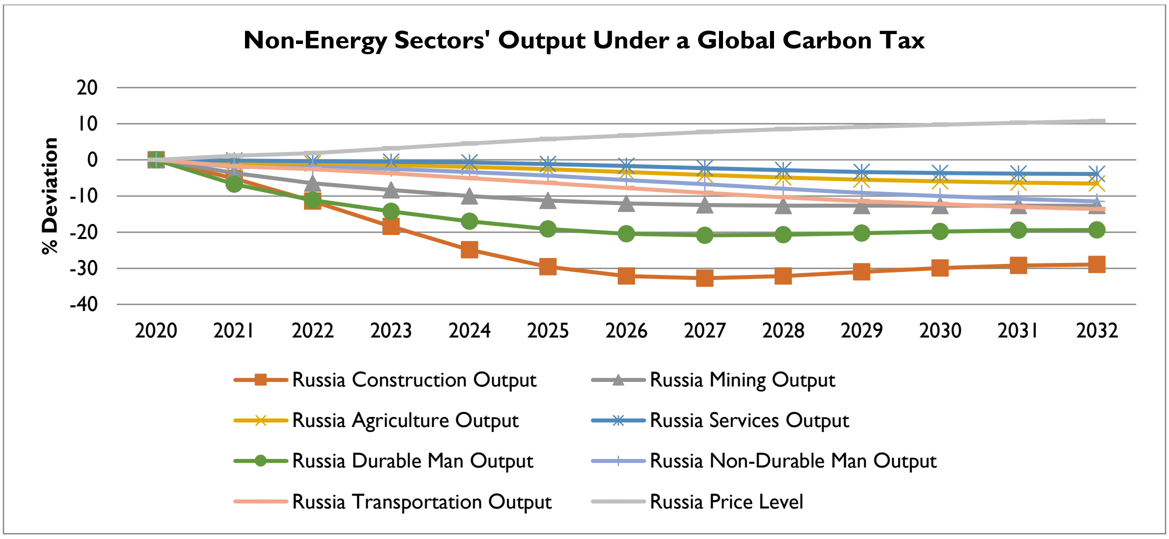


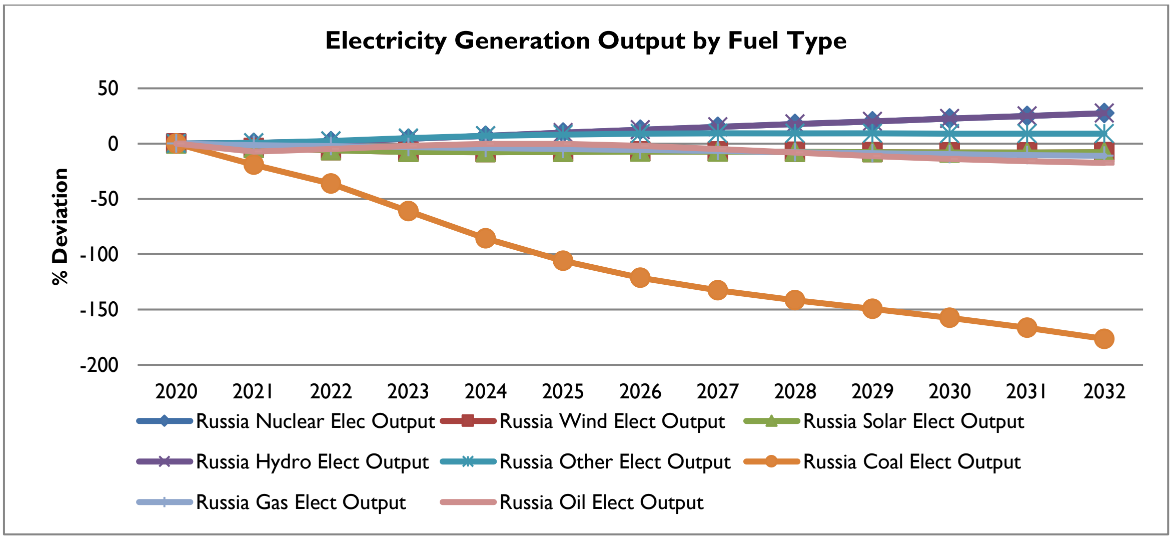




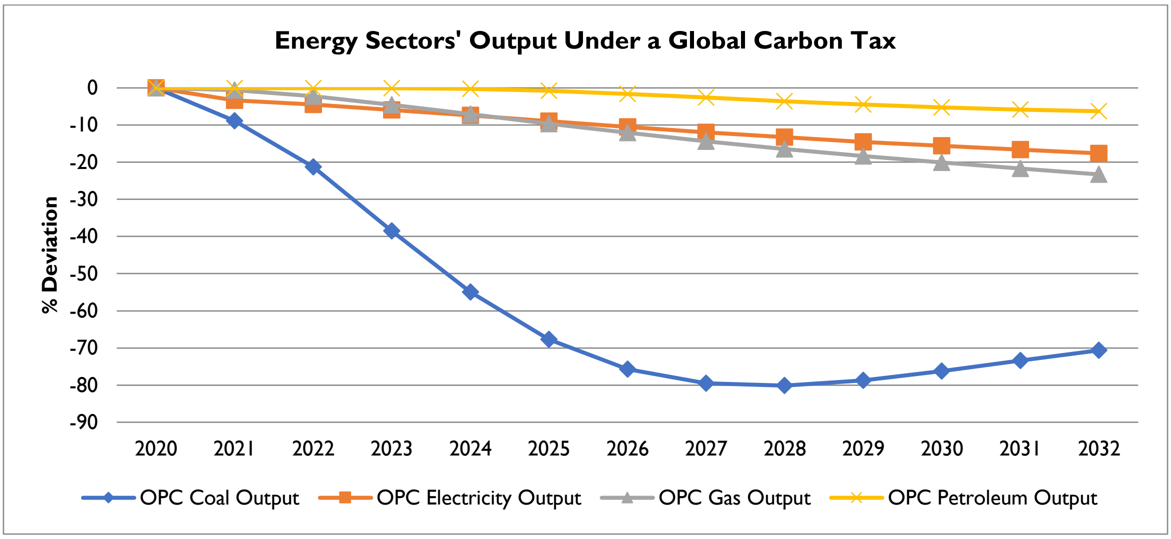
E7: Results for Russia

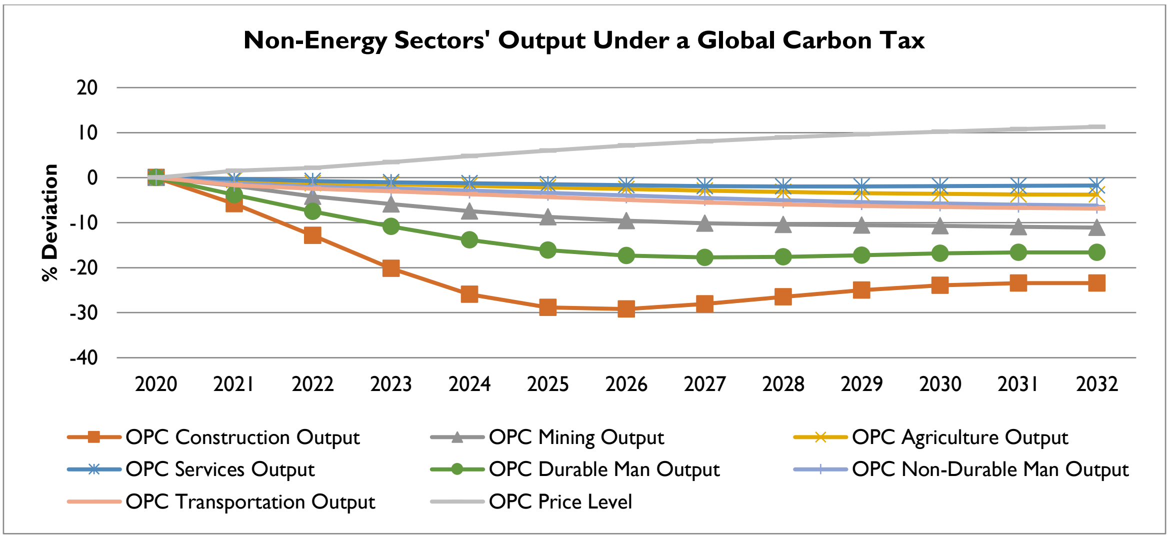


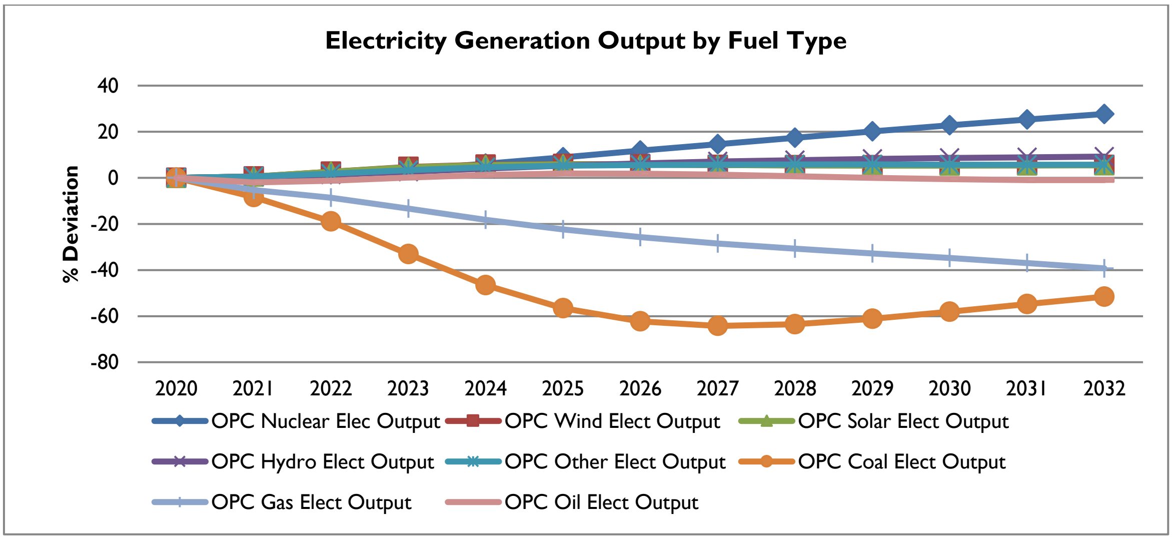




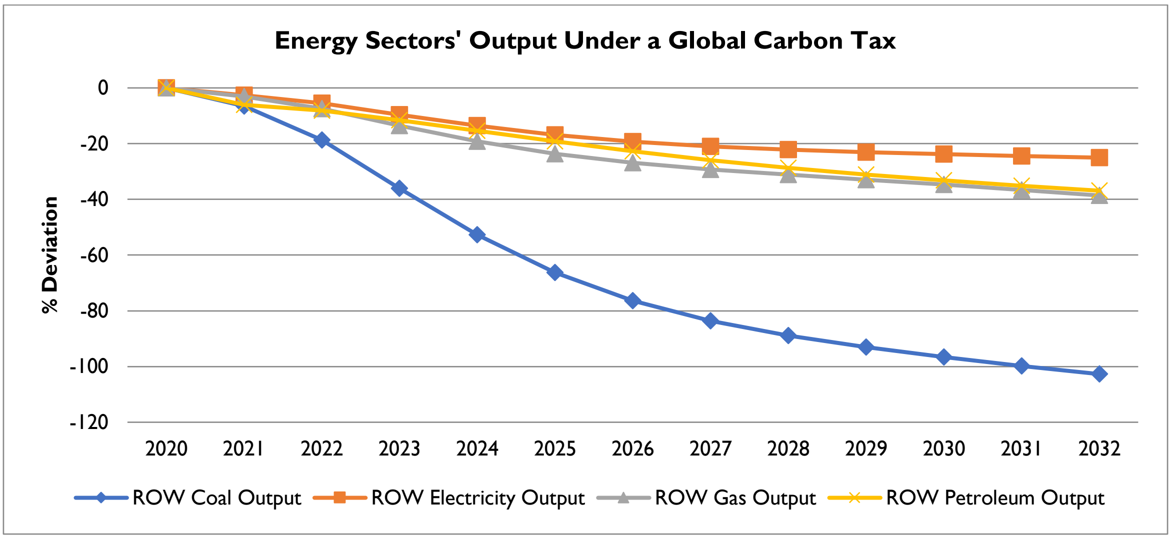
E8: Results for OPC

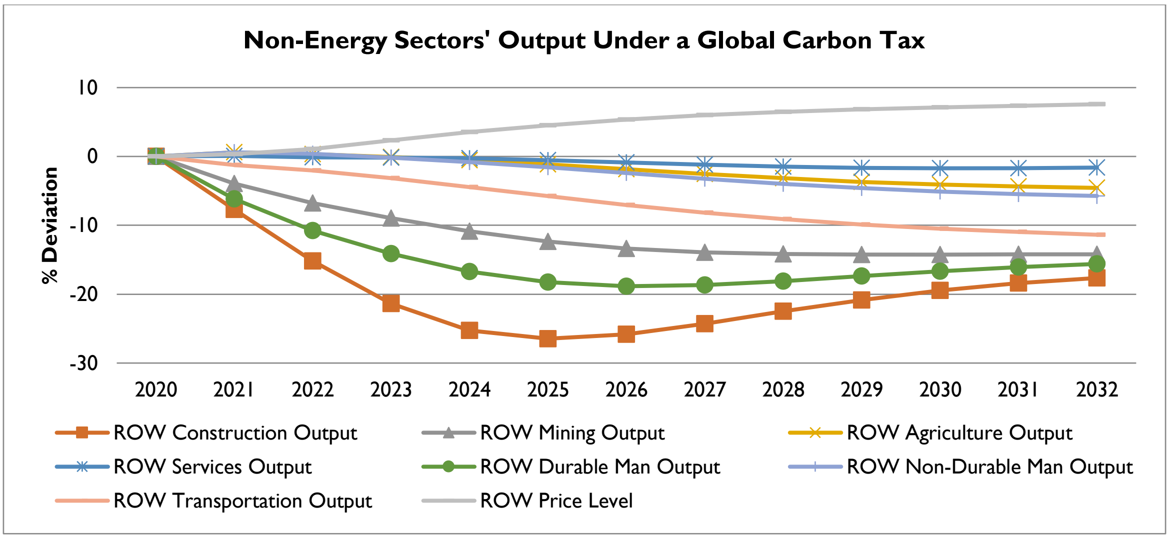


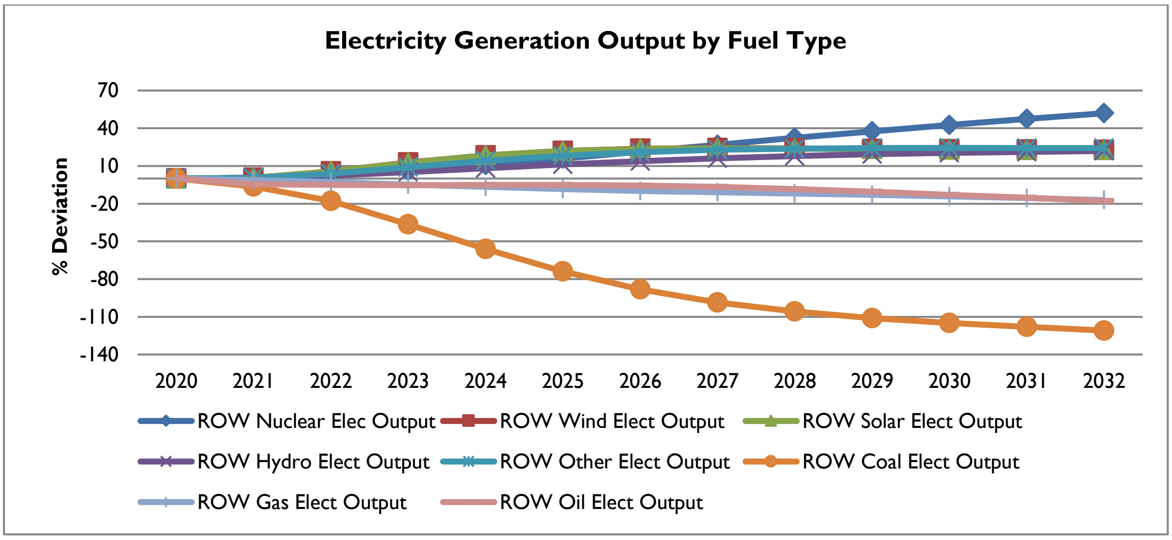




E9: Results for ROW

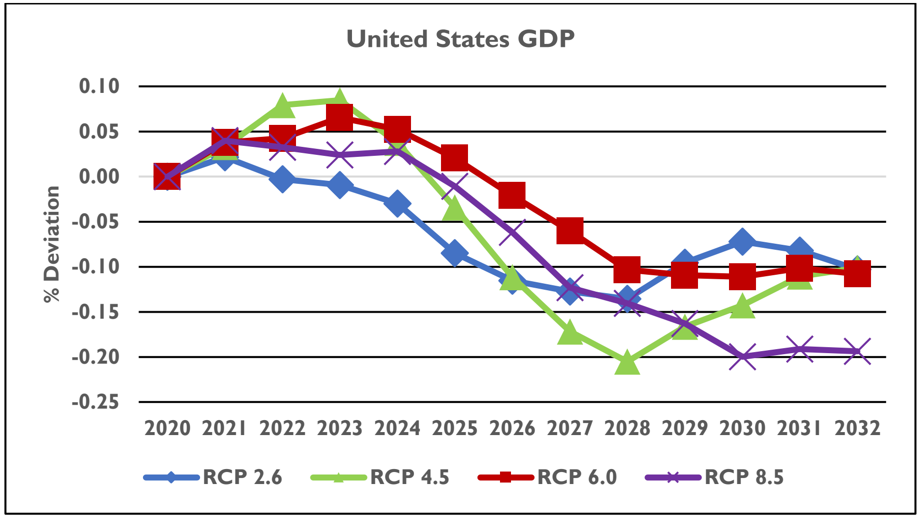


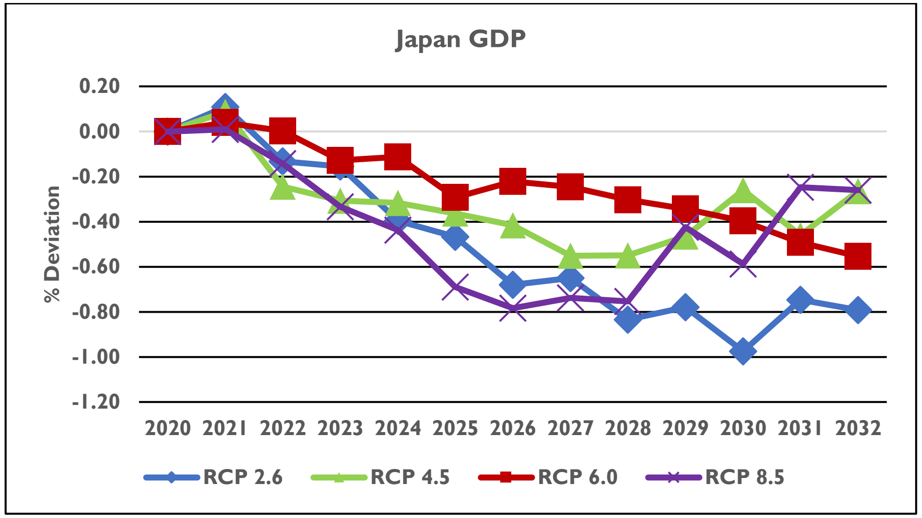


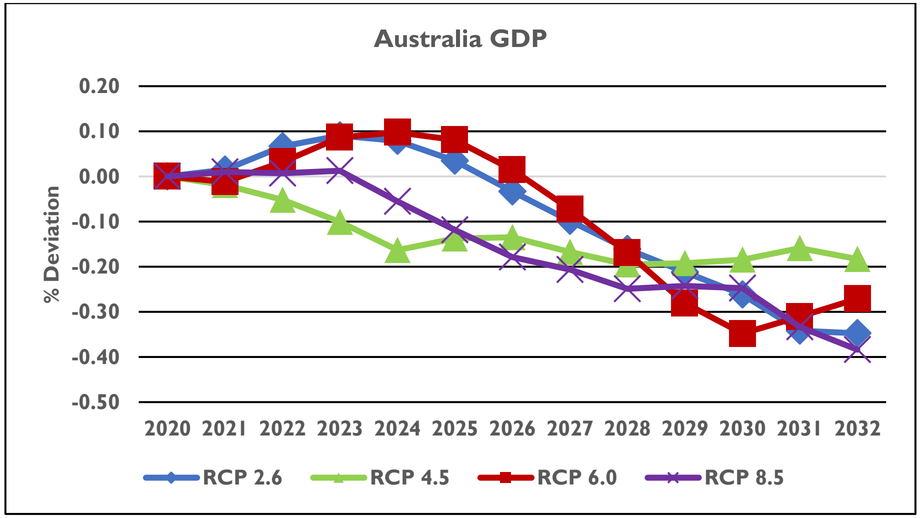


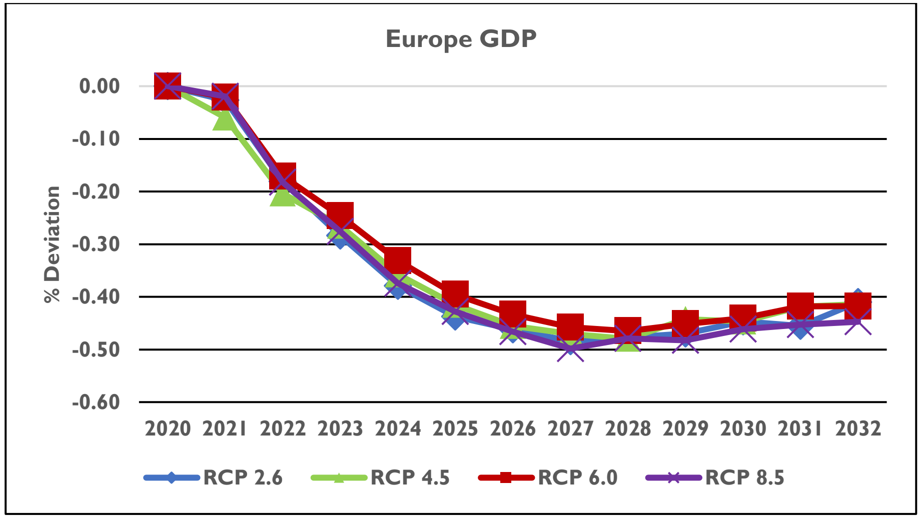
APPENDIX F: DYNAMIC RESULTS FROM CHANGES IN RISK ASSESSMENT

Appendix F1: Changes in GDP by country

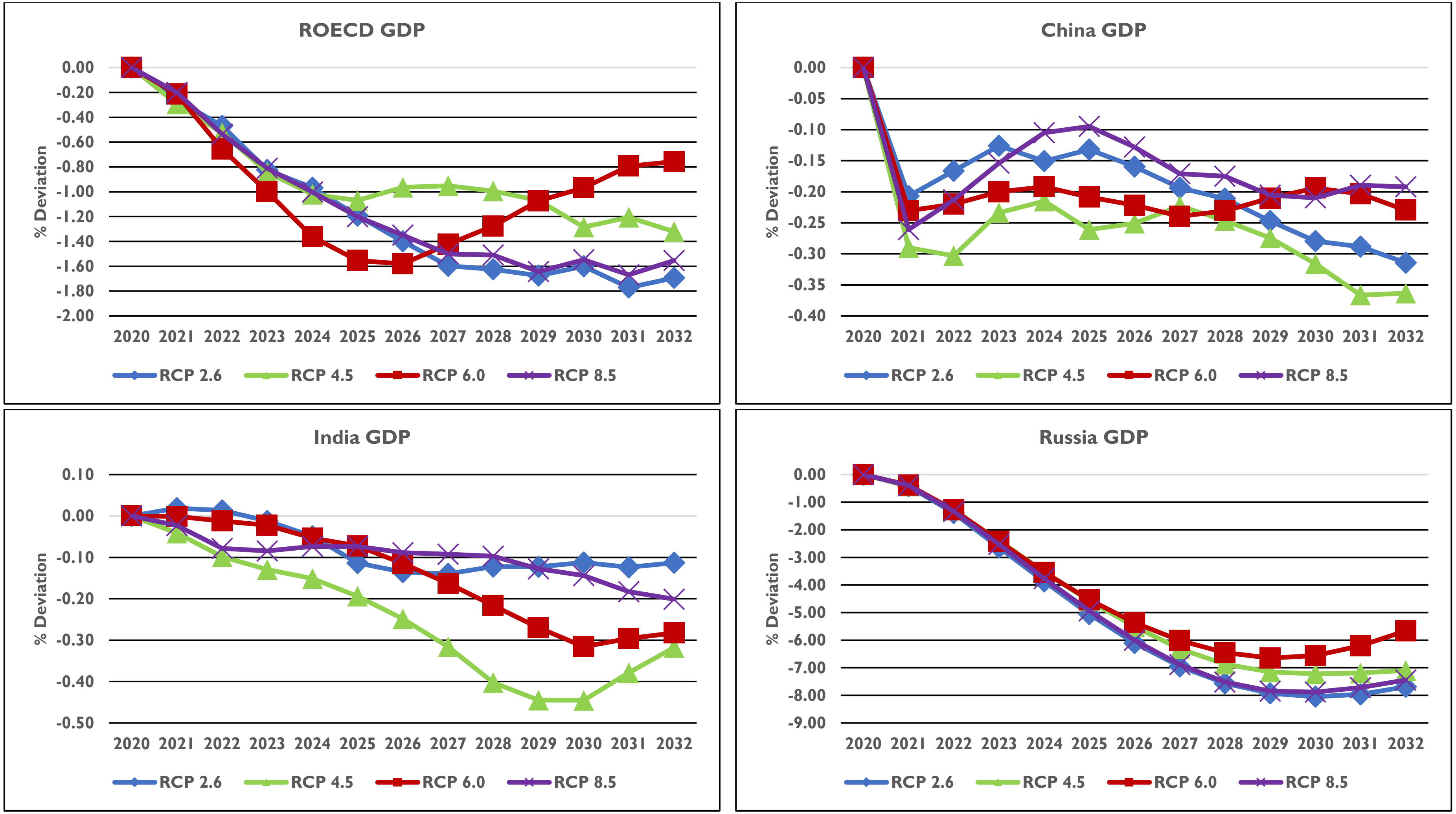




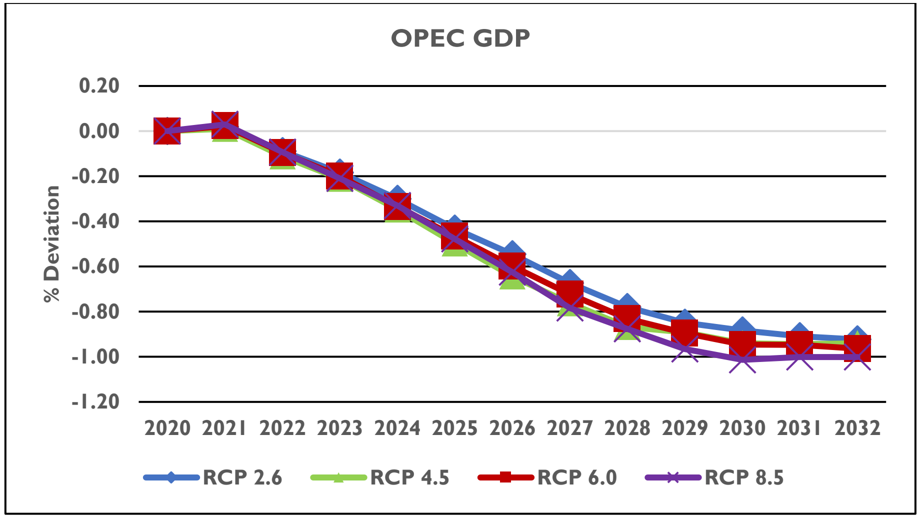


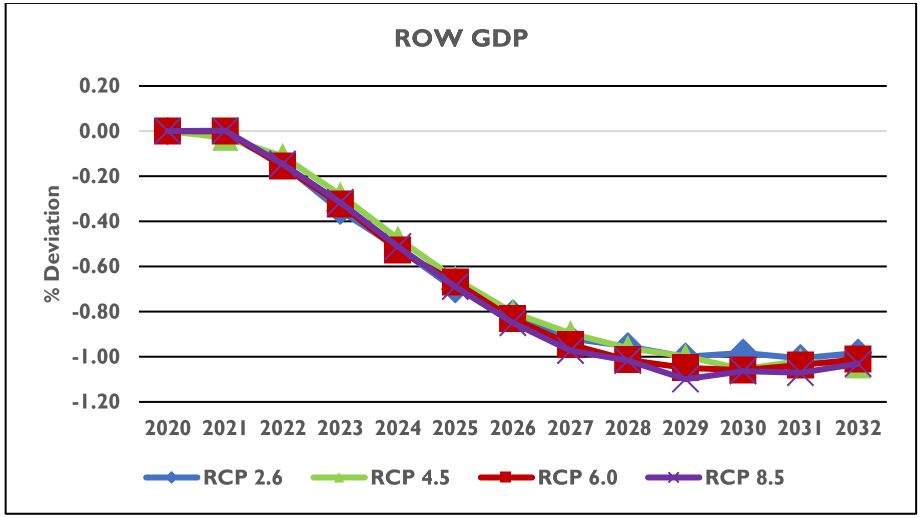


Appendix F1: Changes in GDP by country (Contd.)



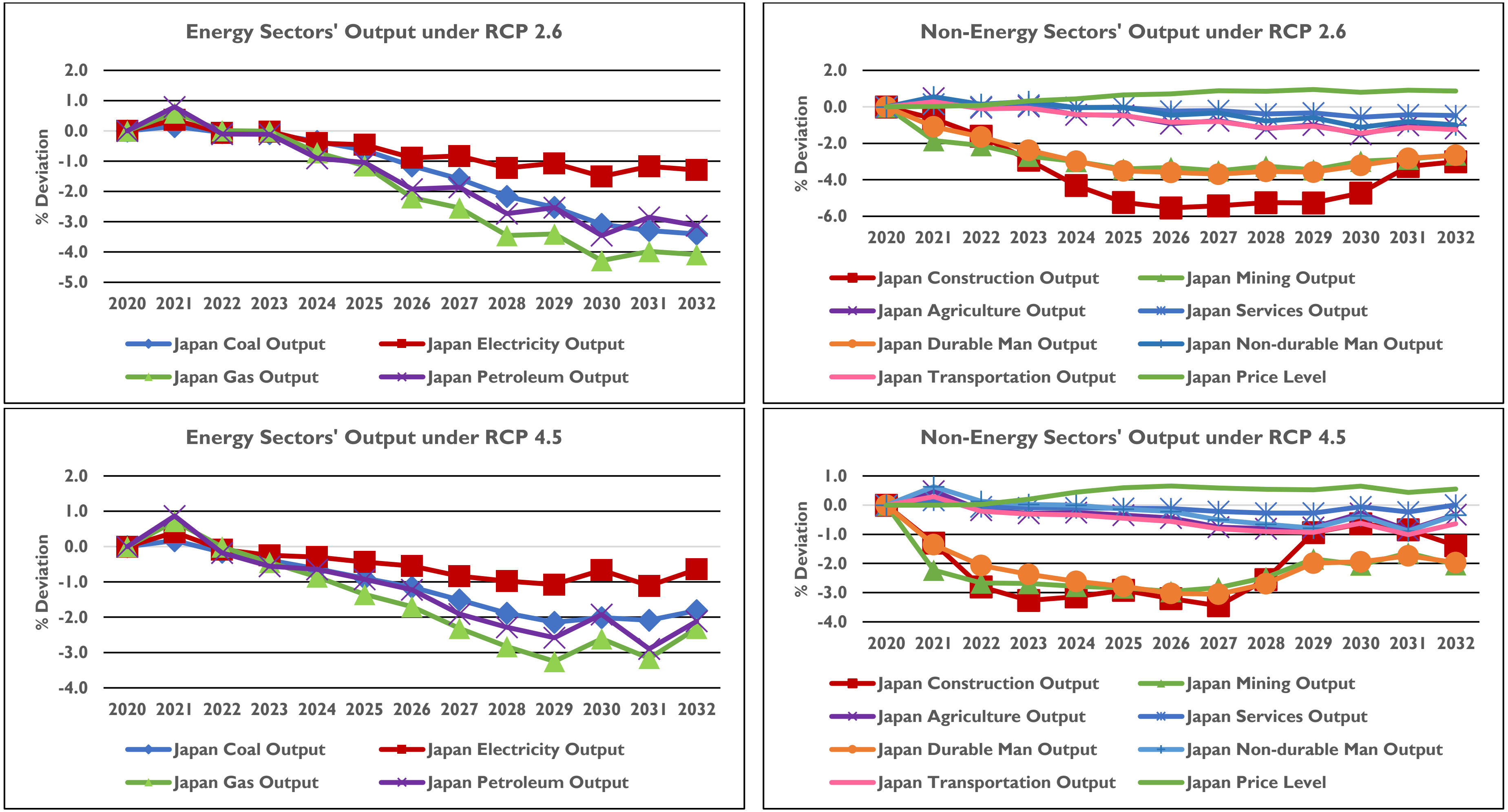
Appendix F1: Changes in GDP by country (Contd.)



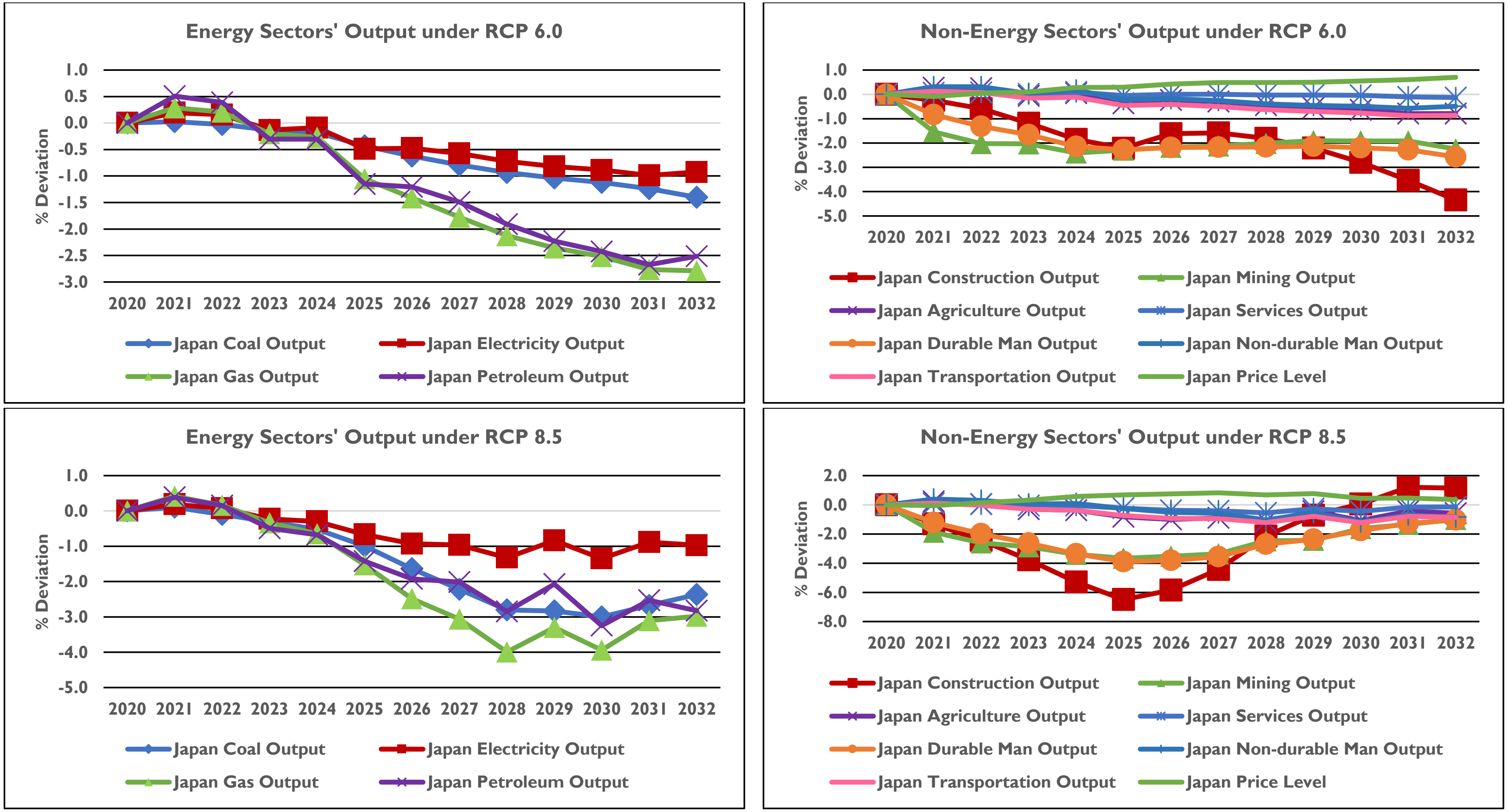


Appendix F2: Changes in Energy and Non-Energy Sector Outputs

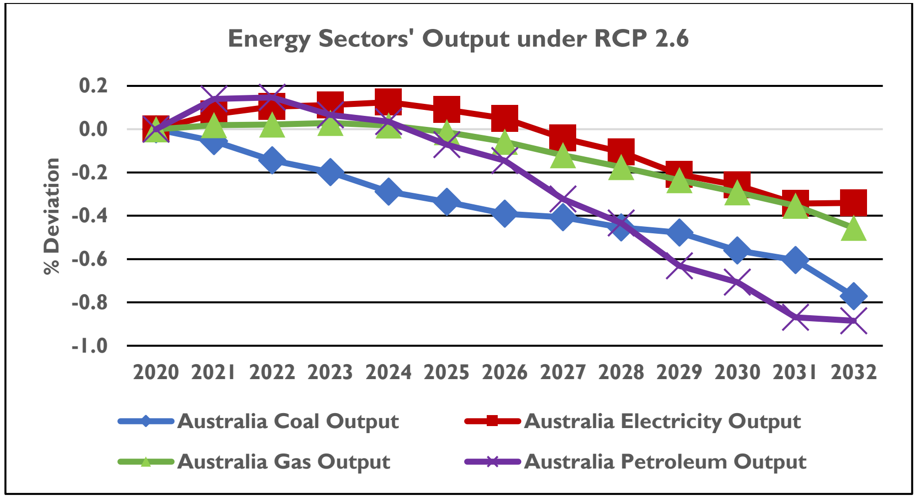
F2.1: Results for Japan

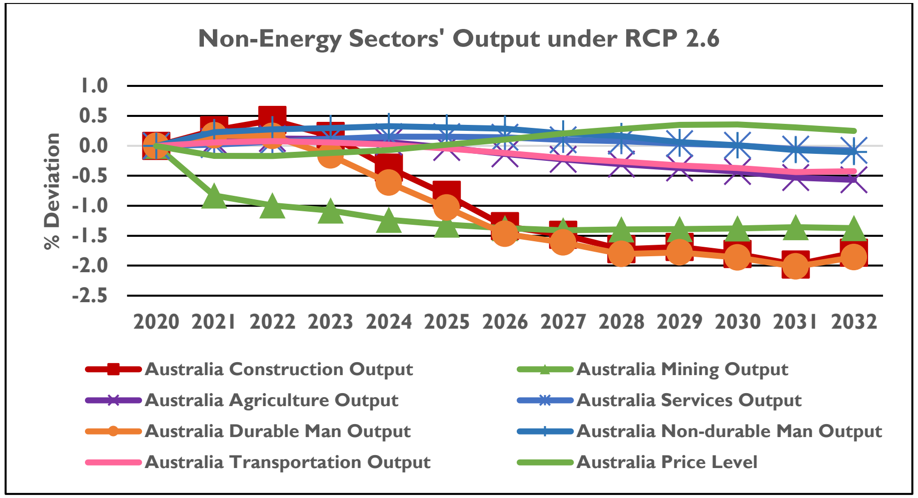


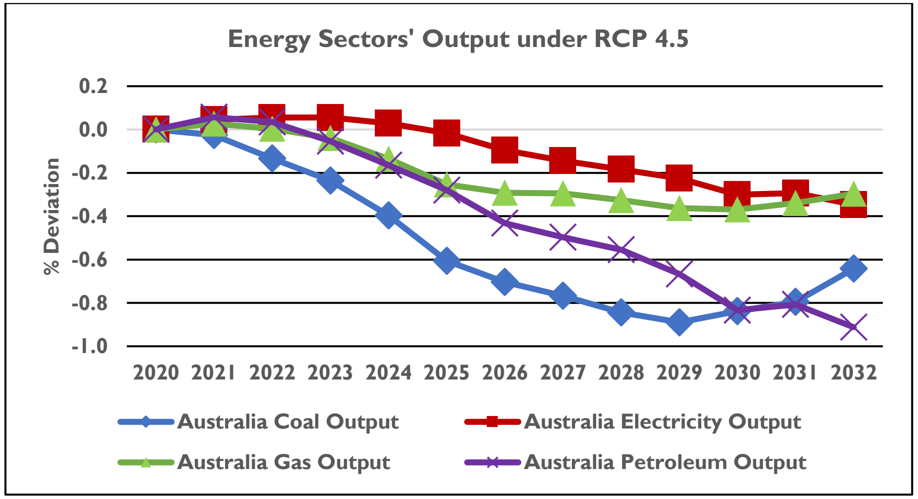
F2.1: Results for Japan (Contd.)

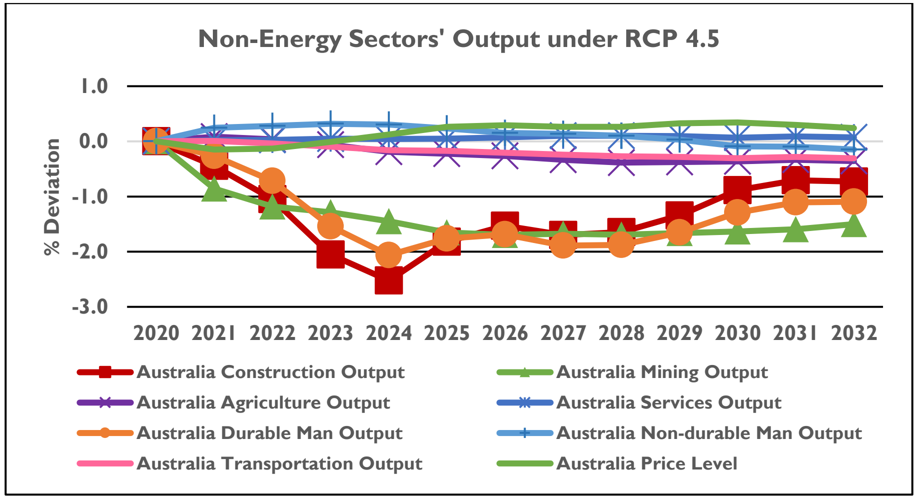


F2.2: Results for Australia

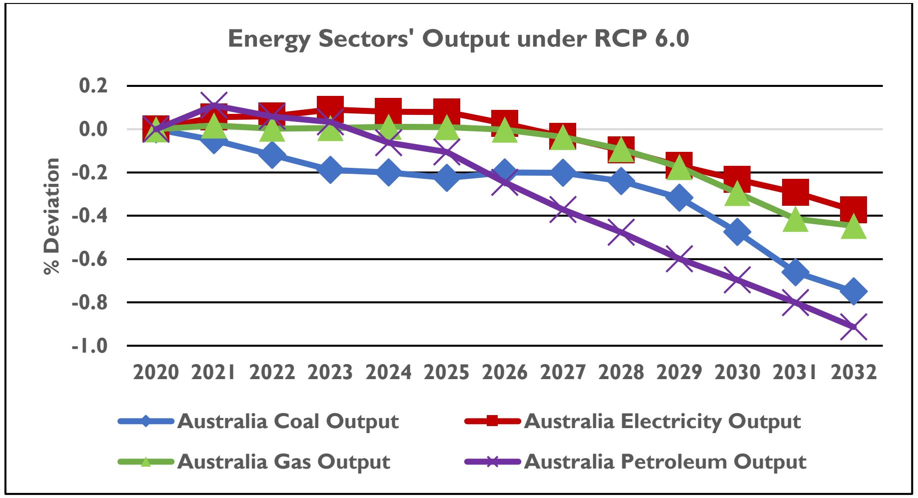


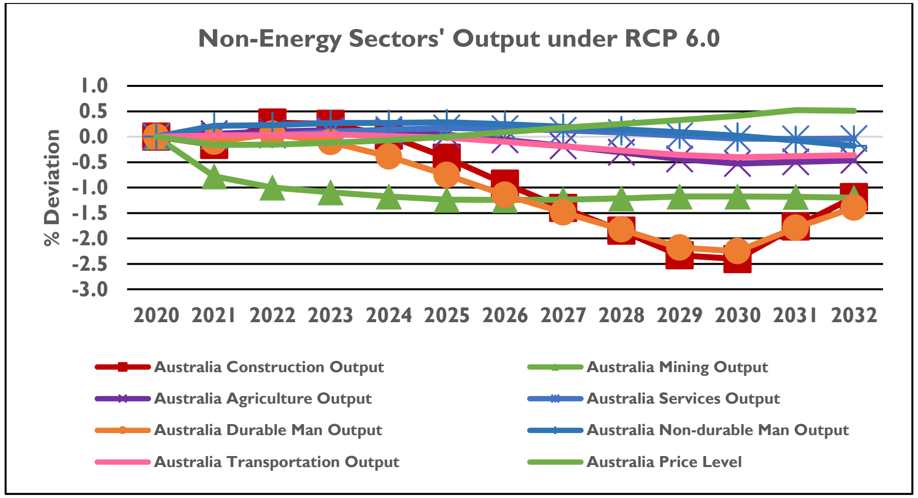


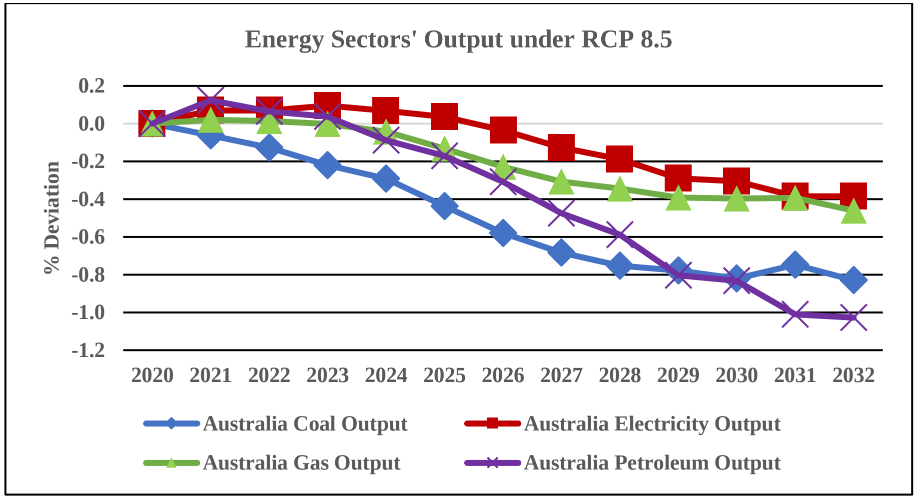


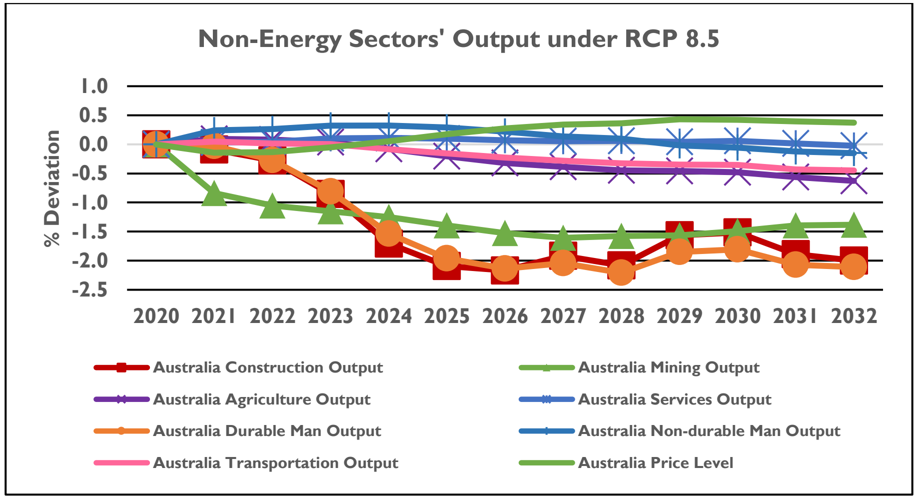


F2.2: Results for Australia (Contd.)

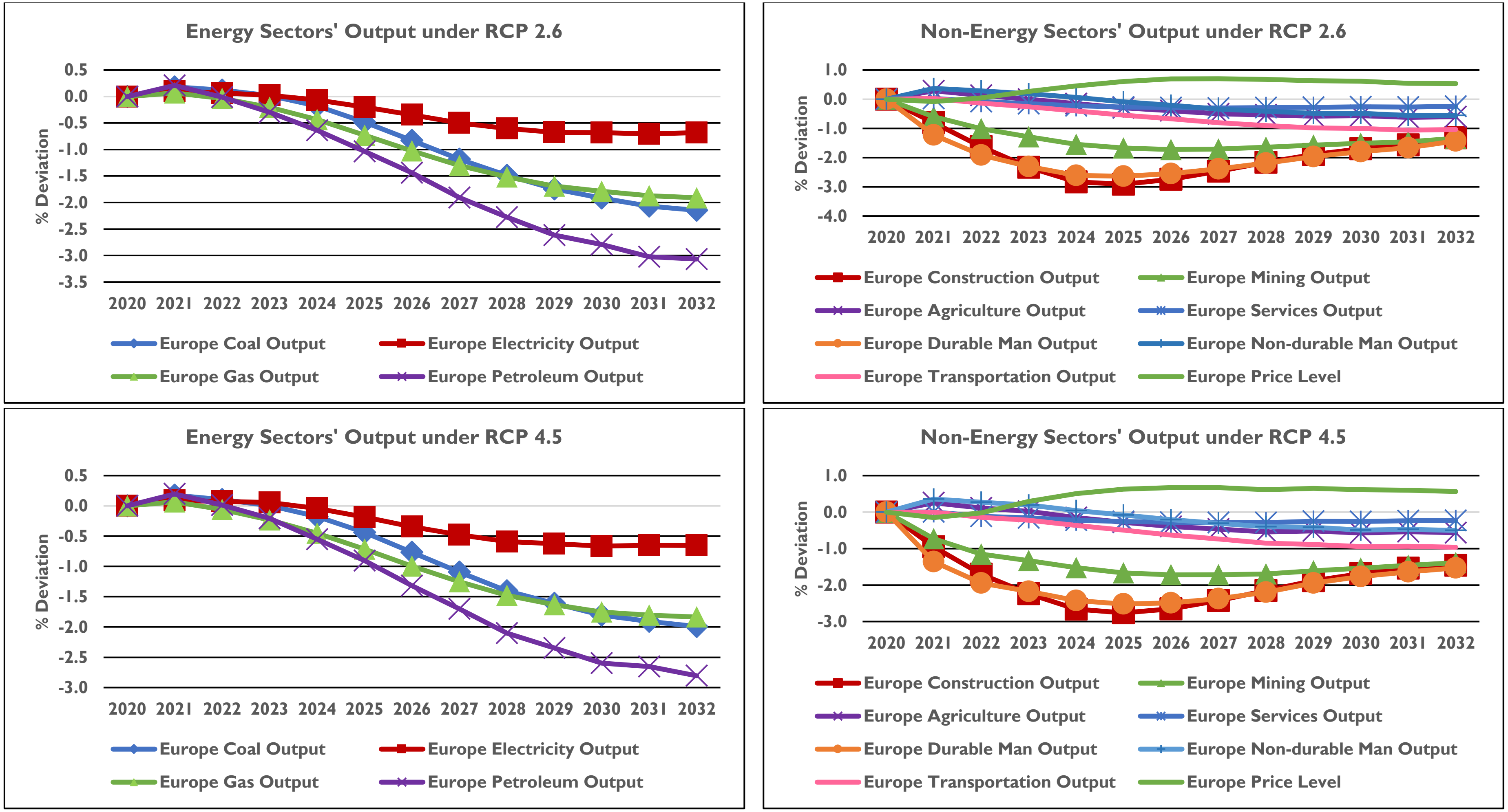




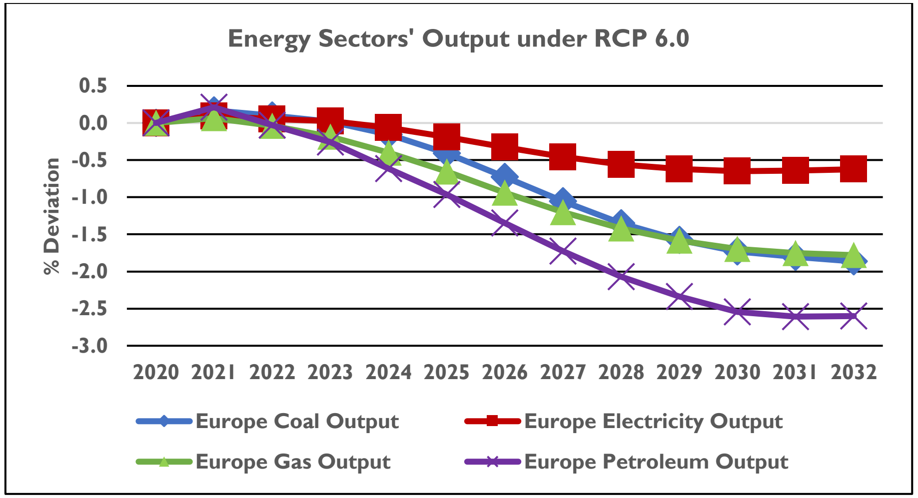


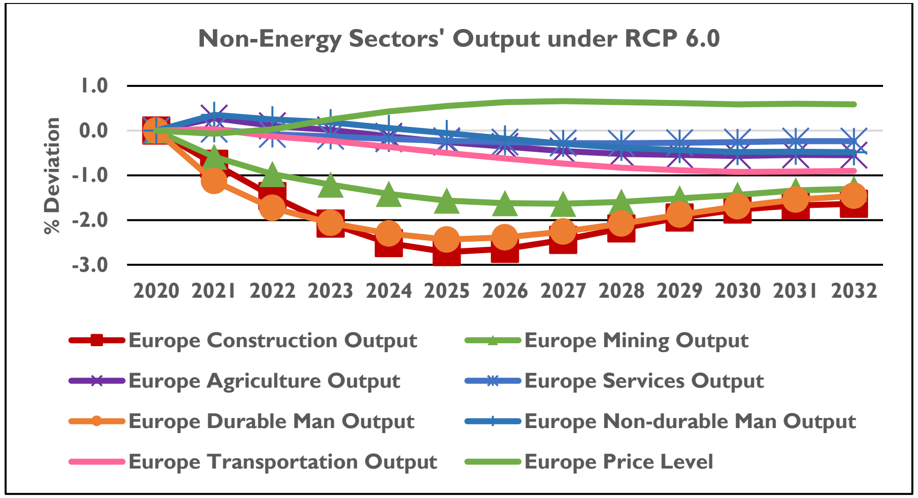


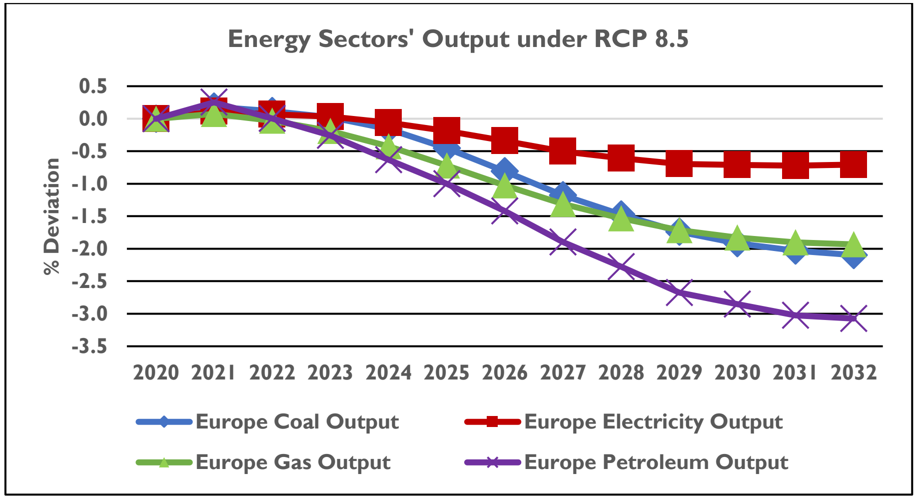
F2.3: Results for Europe

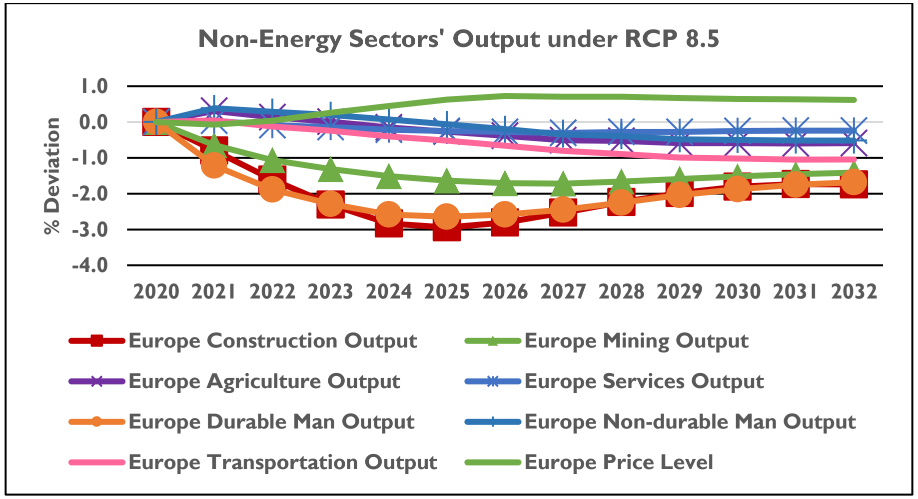


F2.3: Results for Europe (Contd.)

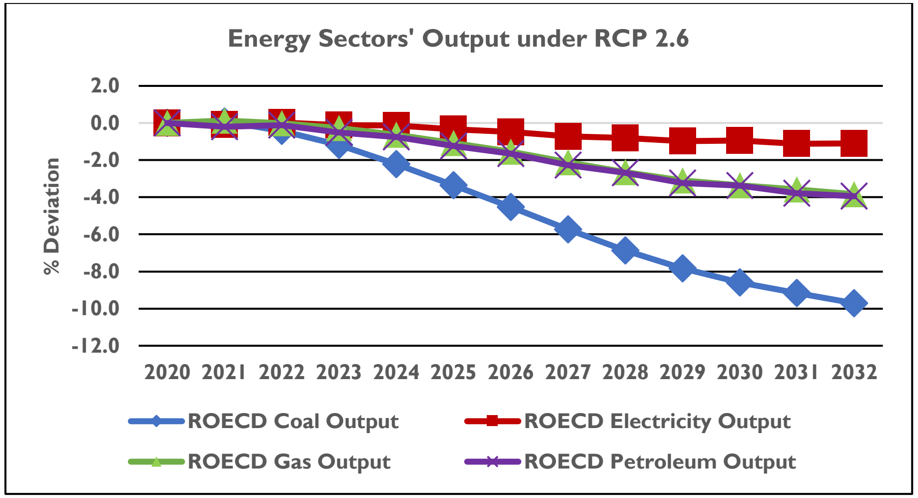


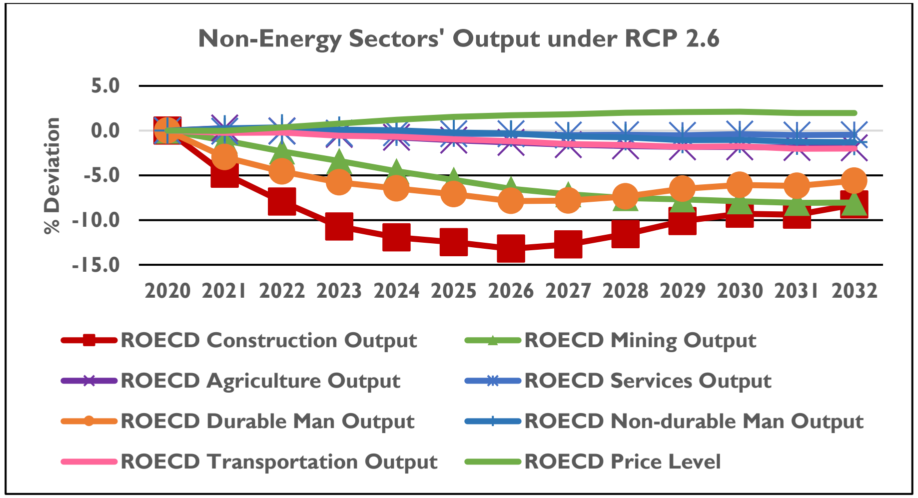


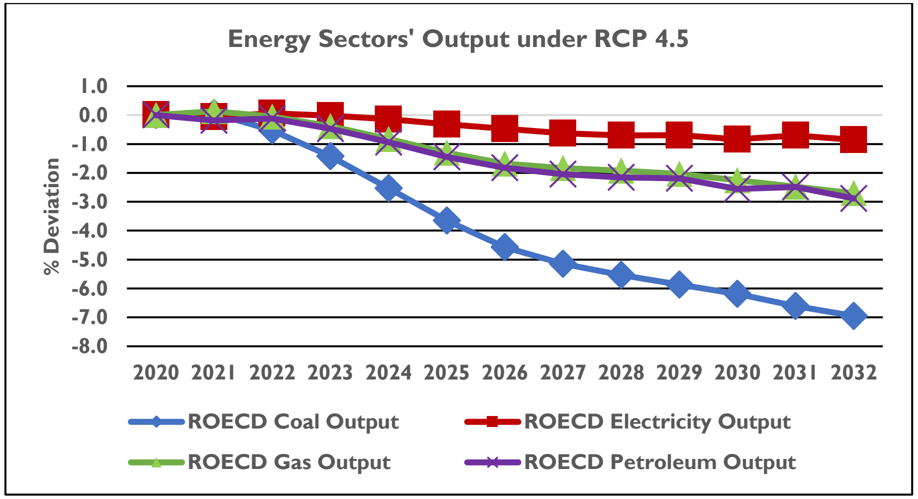


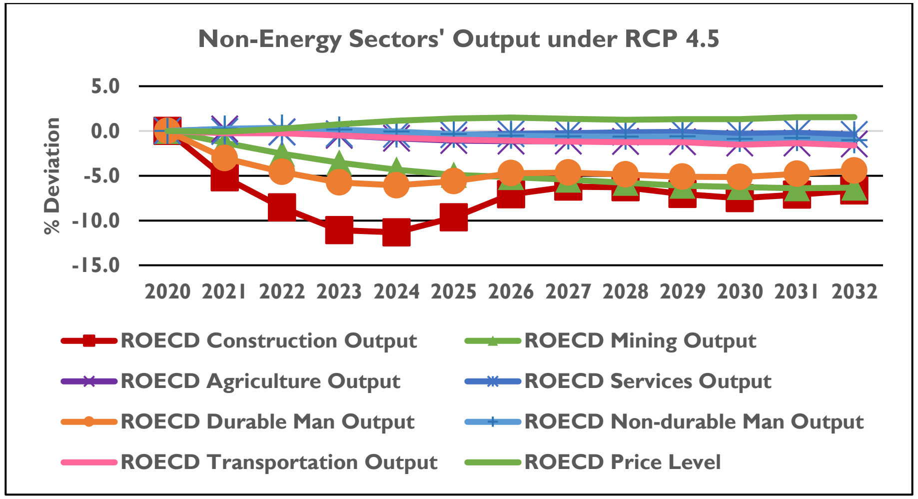


F2.4: Results for ROECD

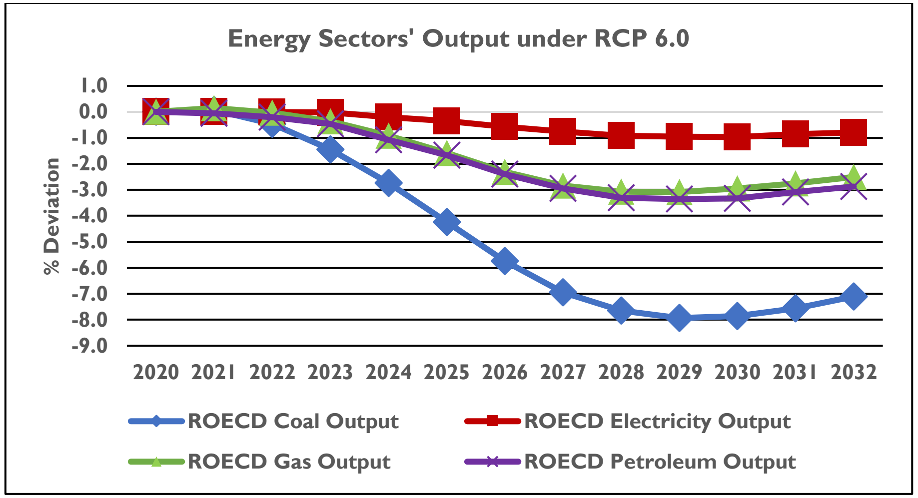


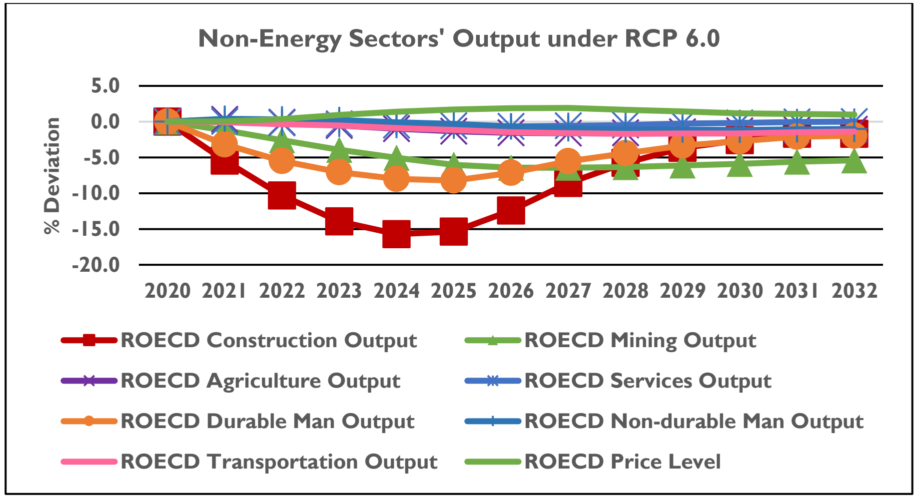


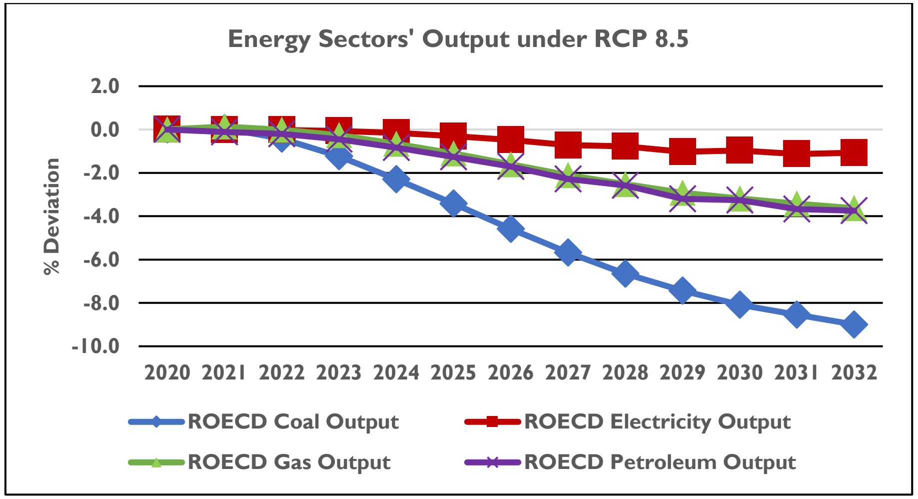


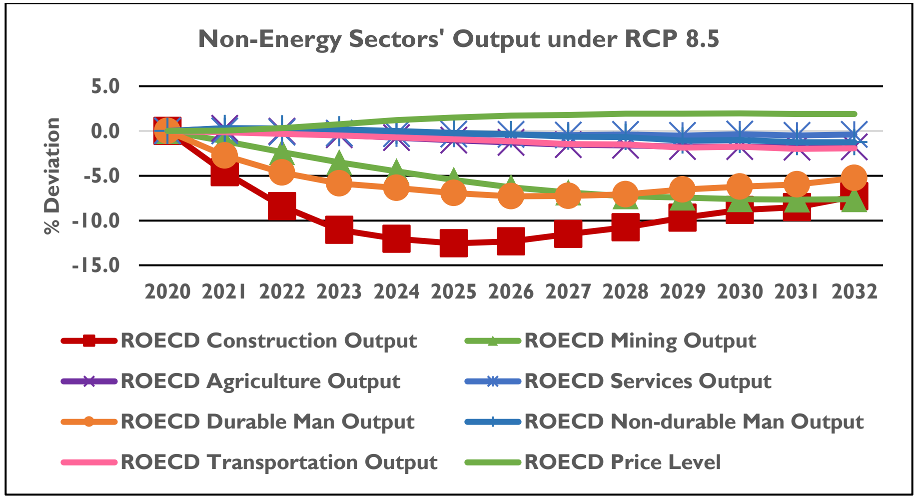


F2.4: Results for ROECD (Contd.)

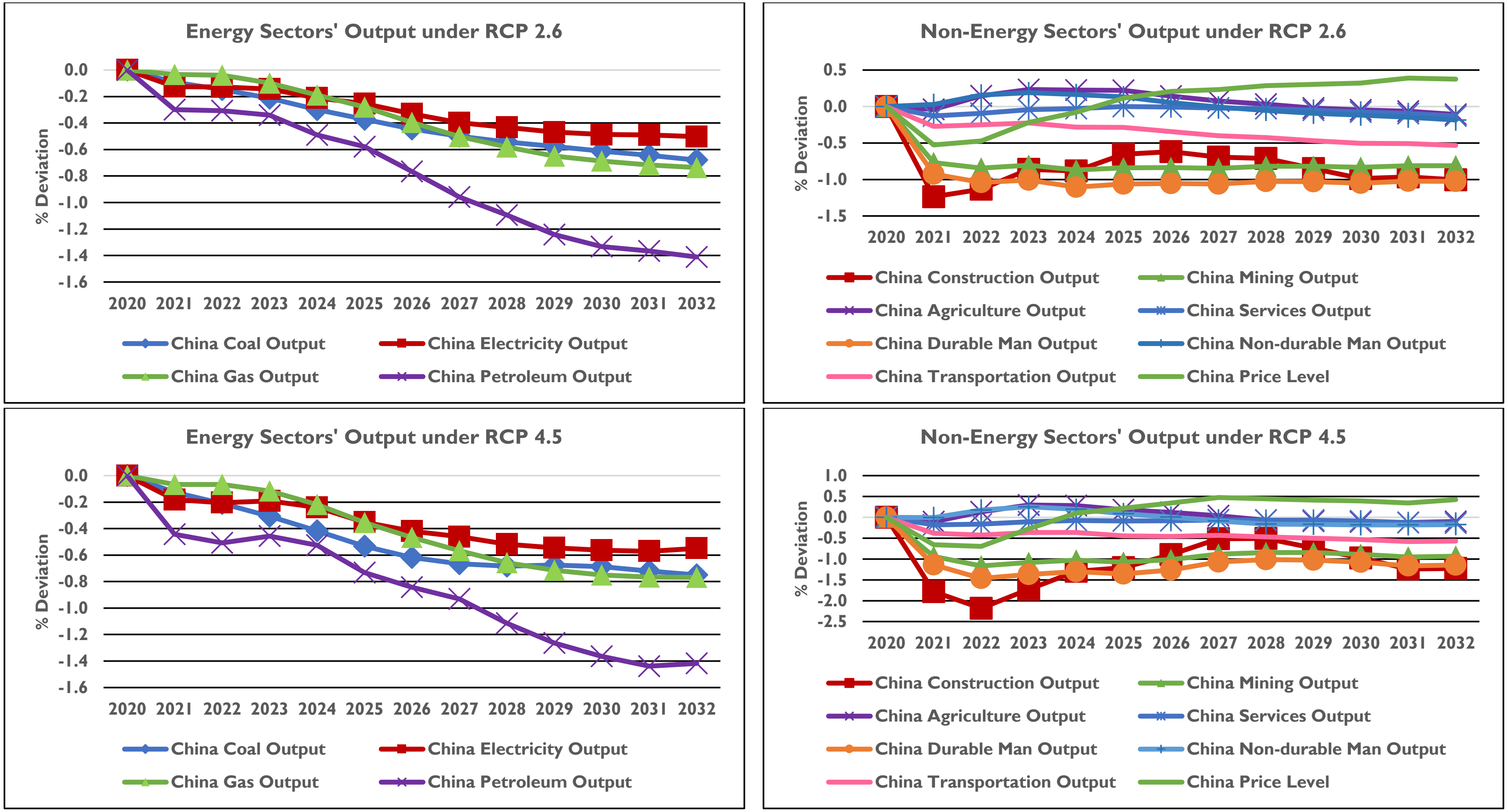




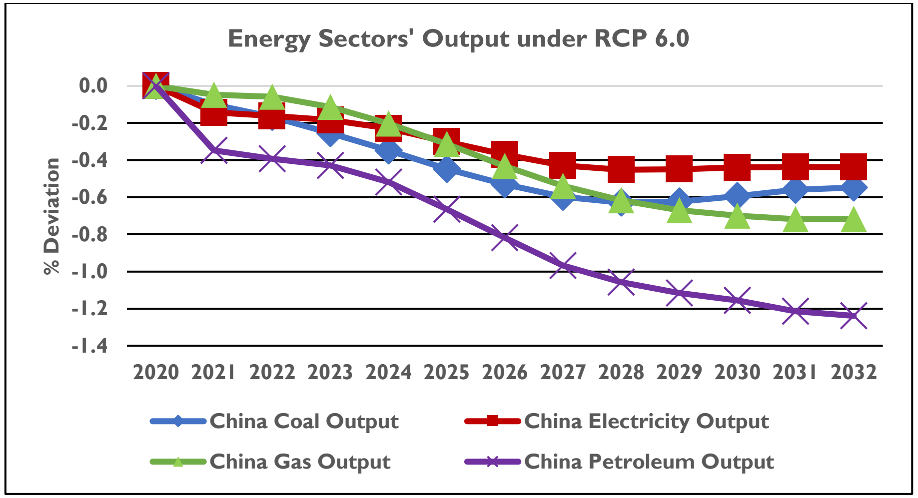


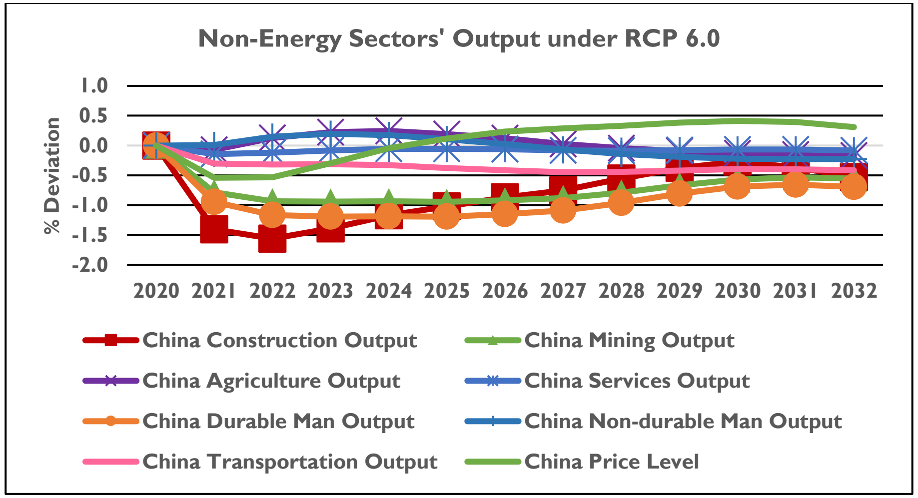


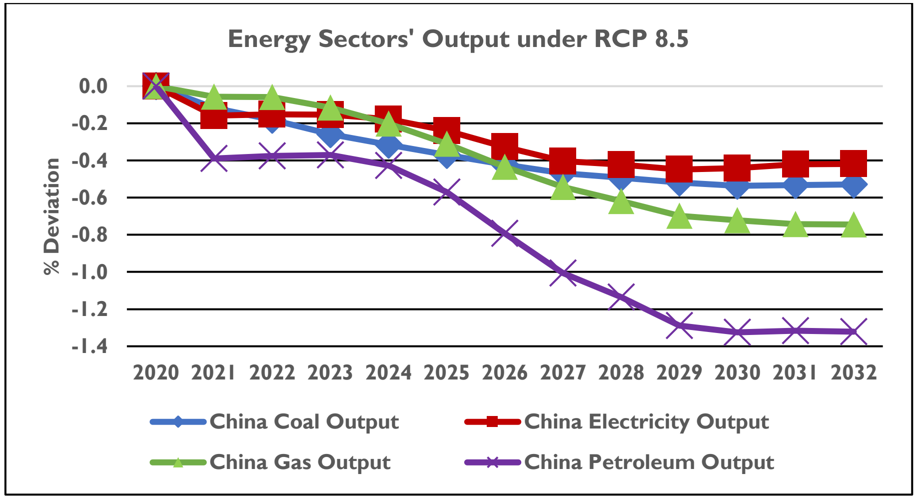
F2.5: Results for China

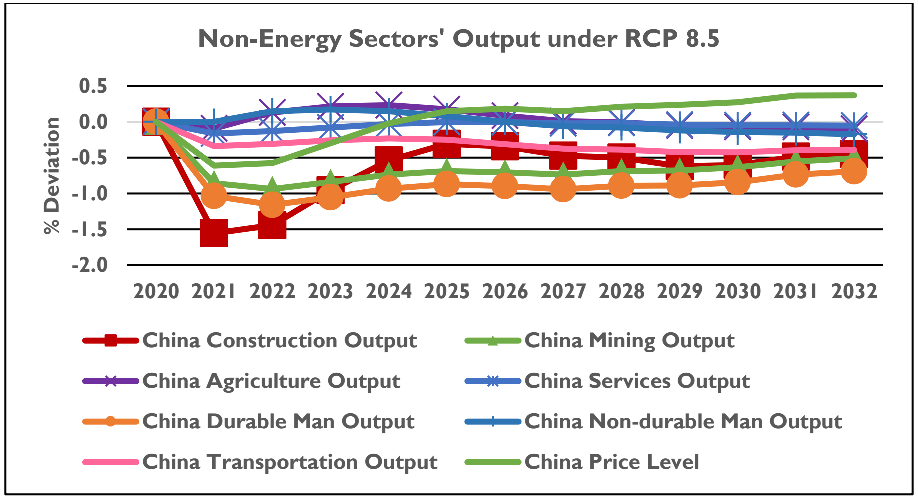


F2.5: Results for China (Contd.)

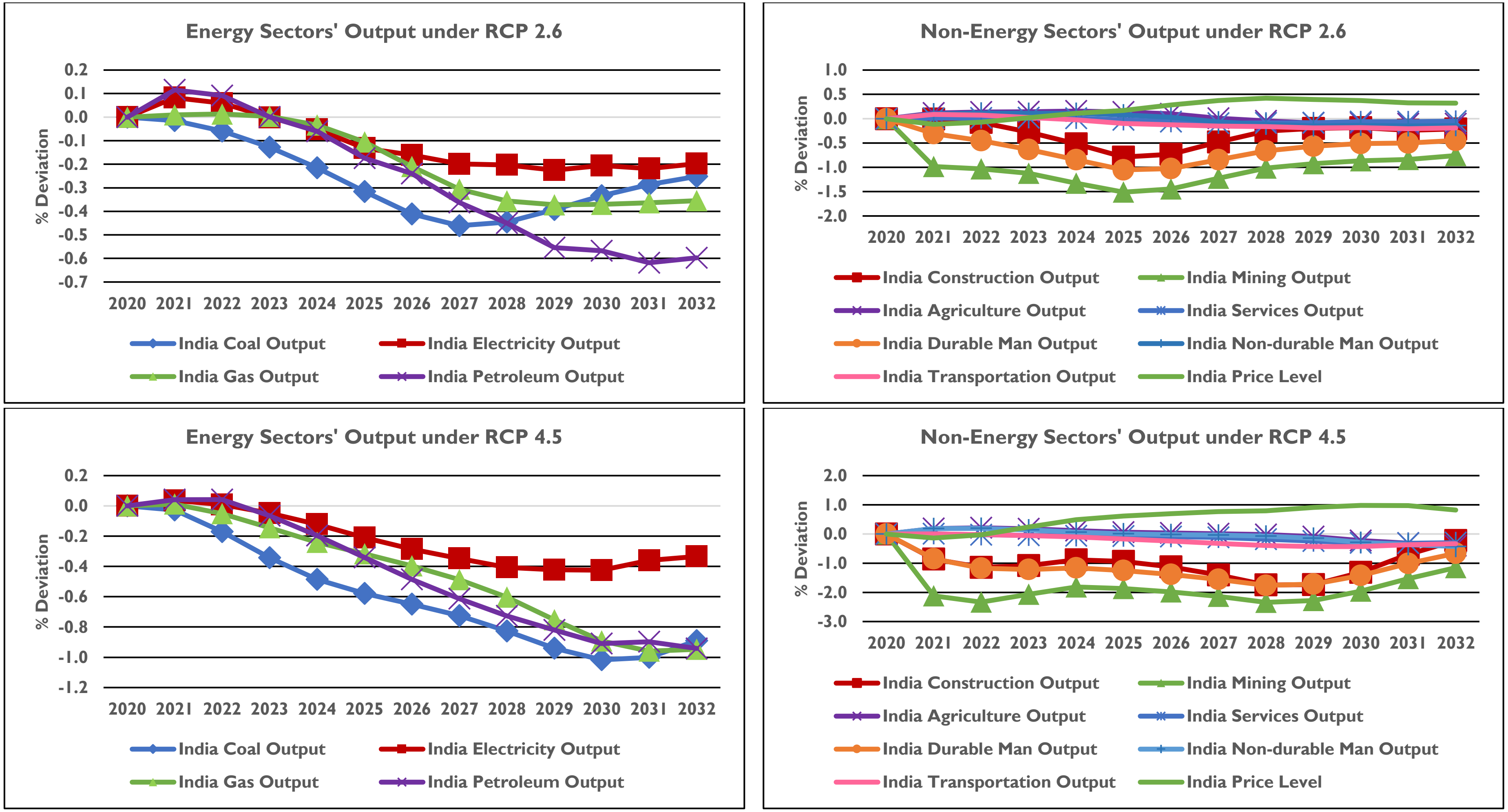




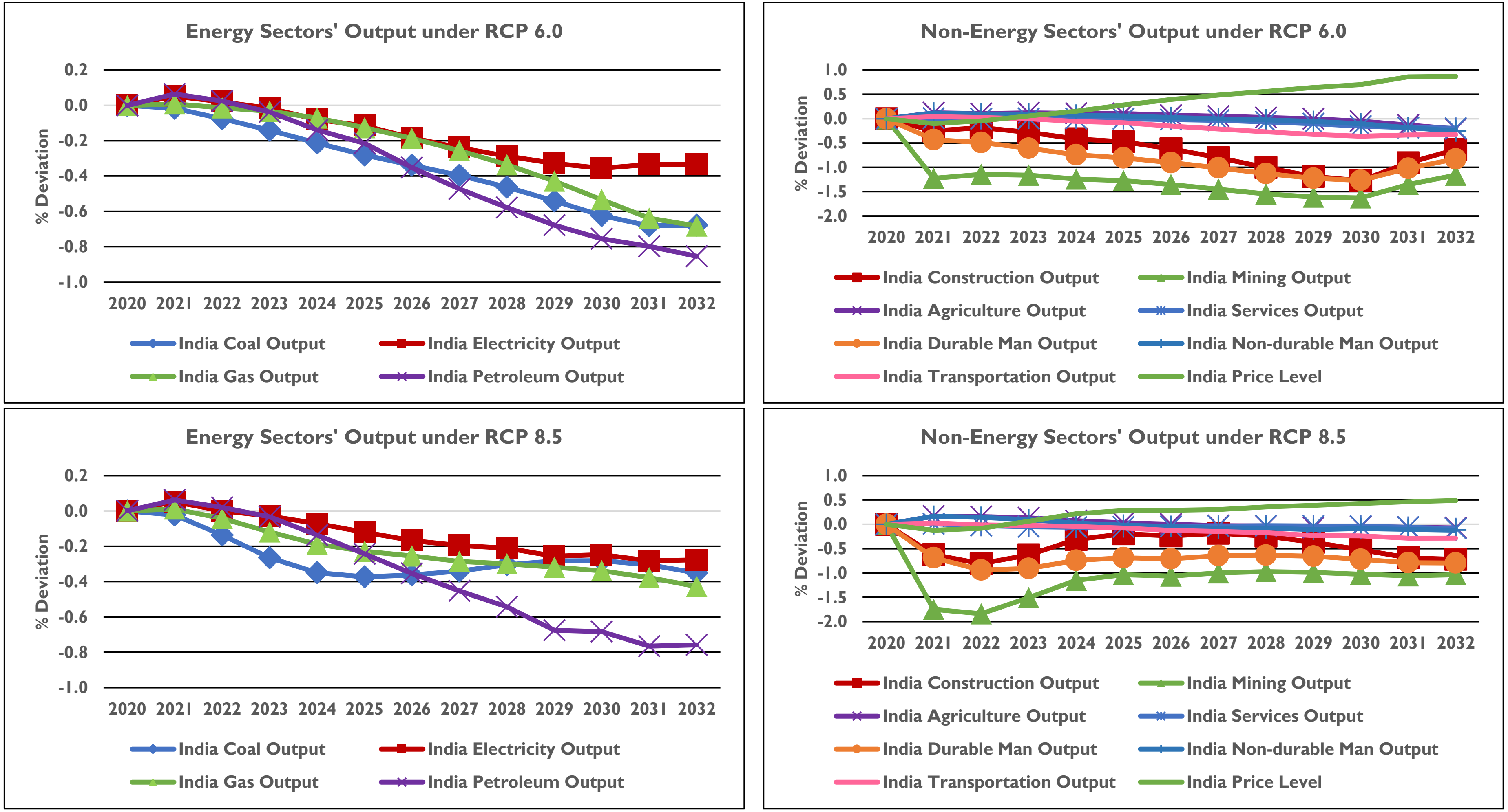




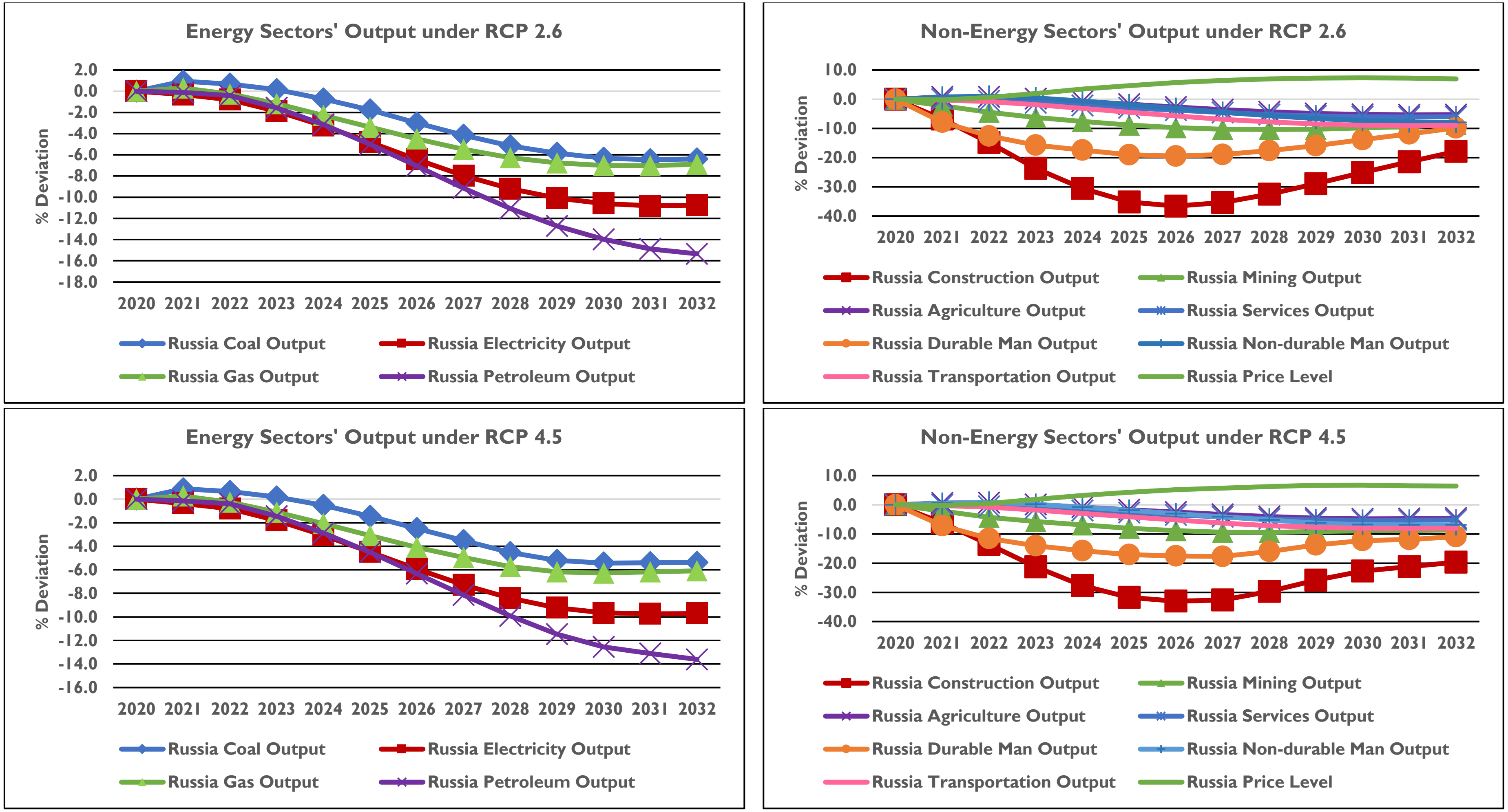
F2.6: Results for India



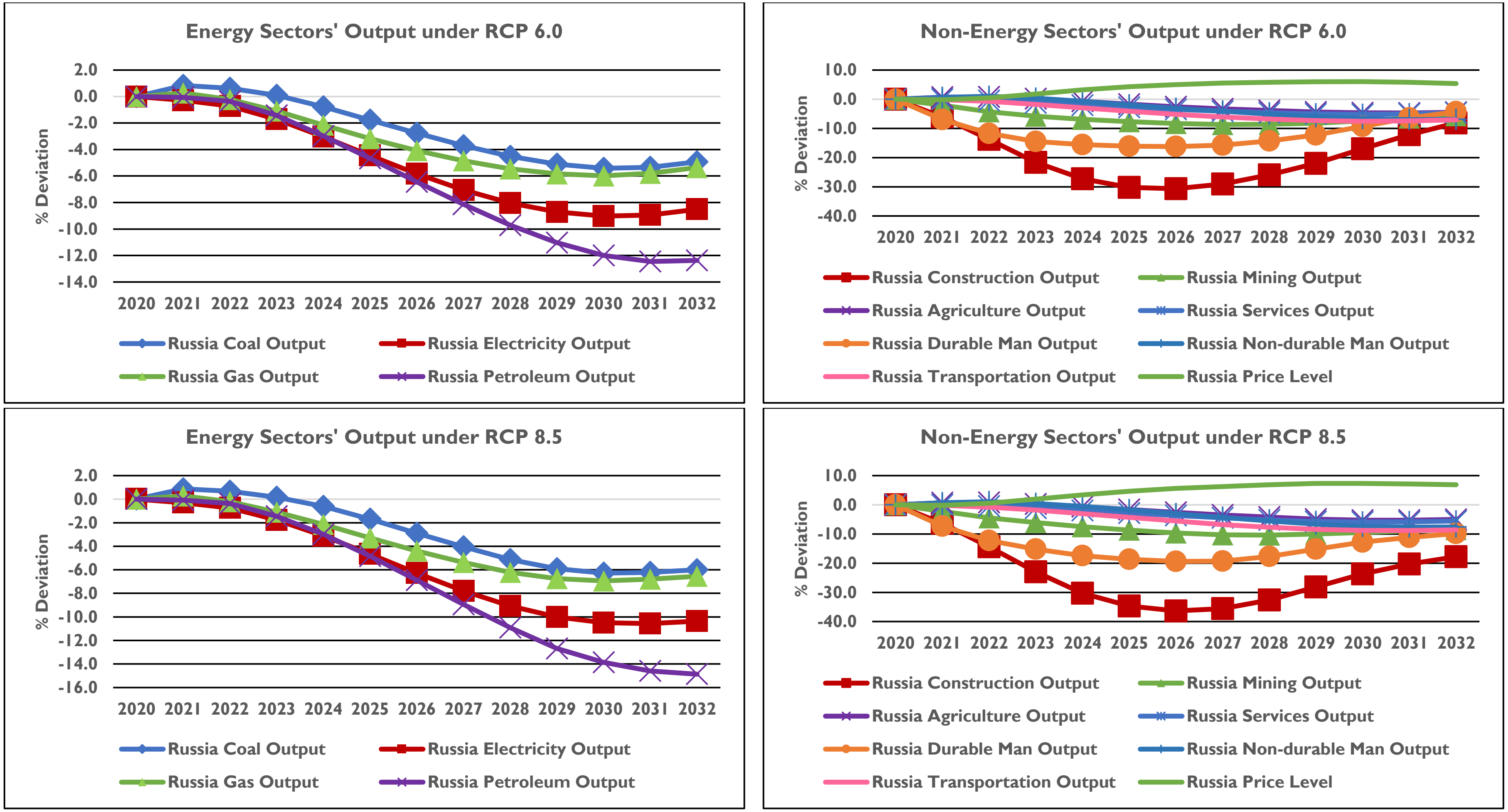
F2.6: Results for India (Contd.)



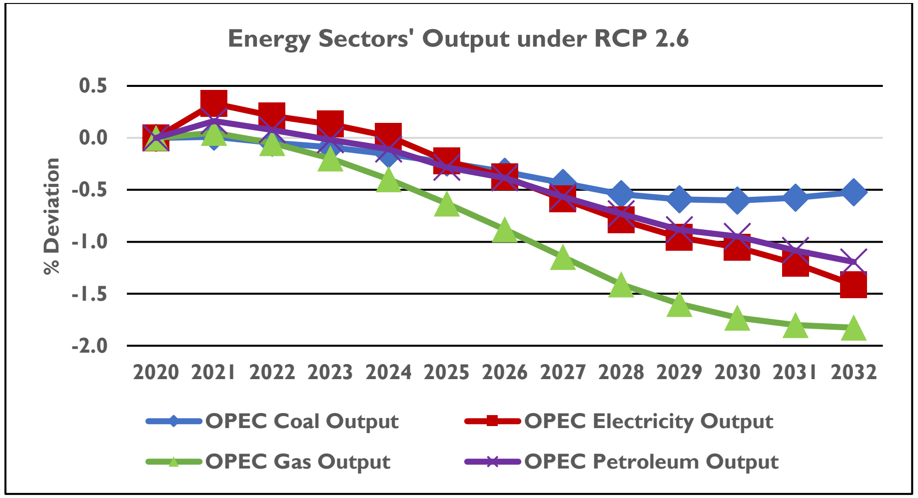
F2.7: Results for Russia

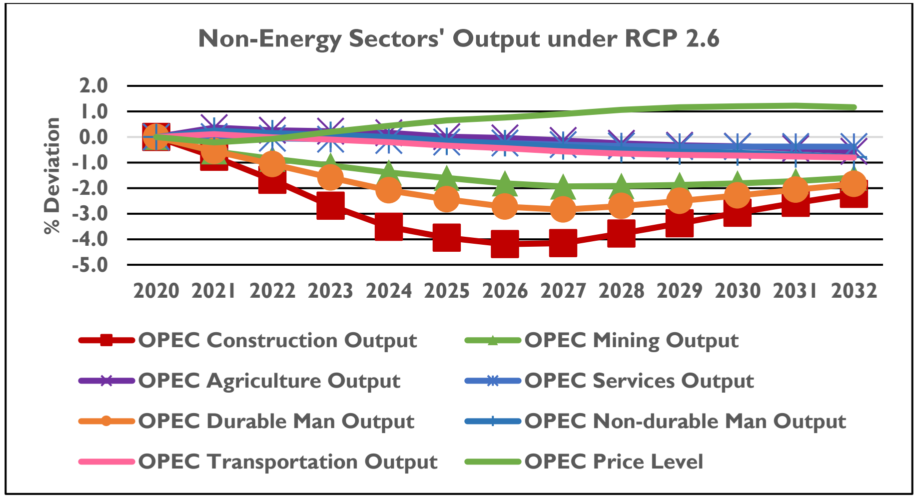


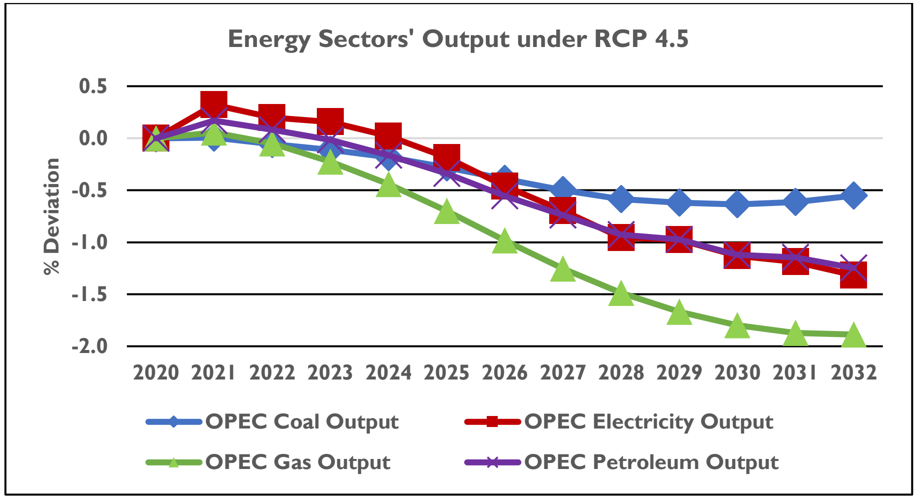
F2.7: Results for Russia (Contd.)

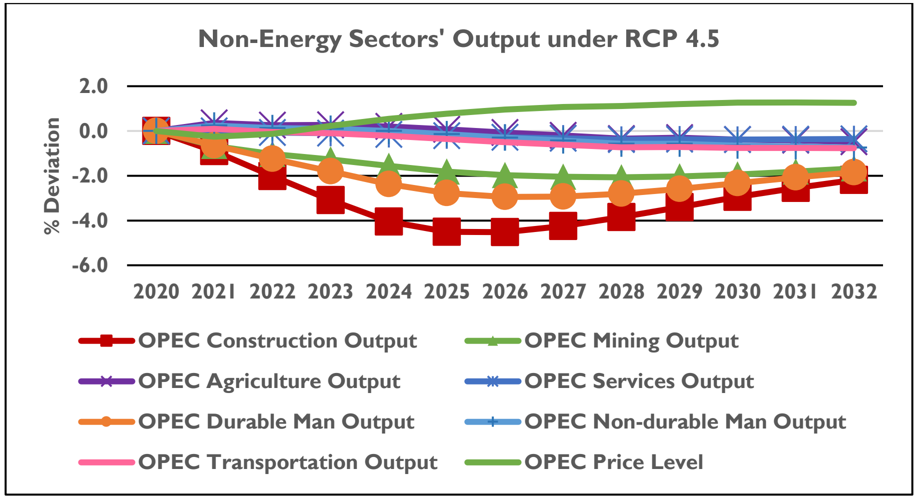


F2.8: Results for OPC

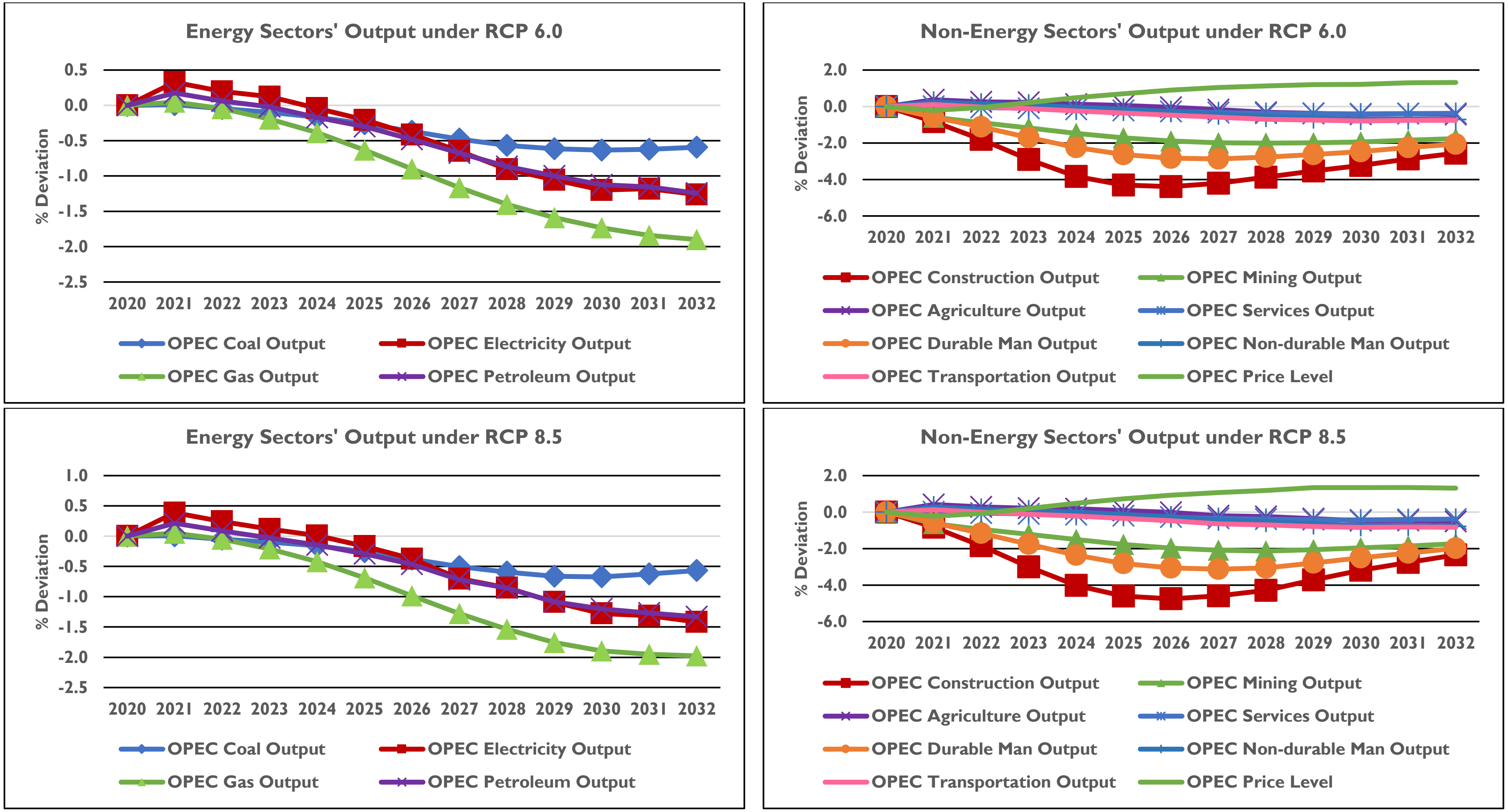




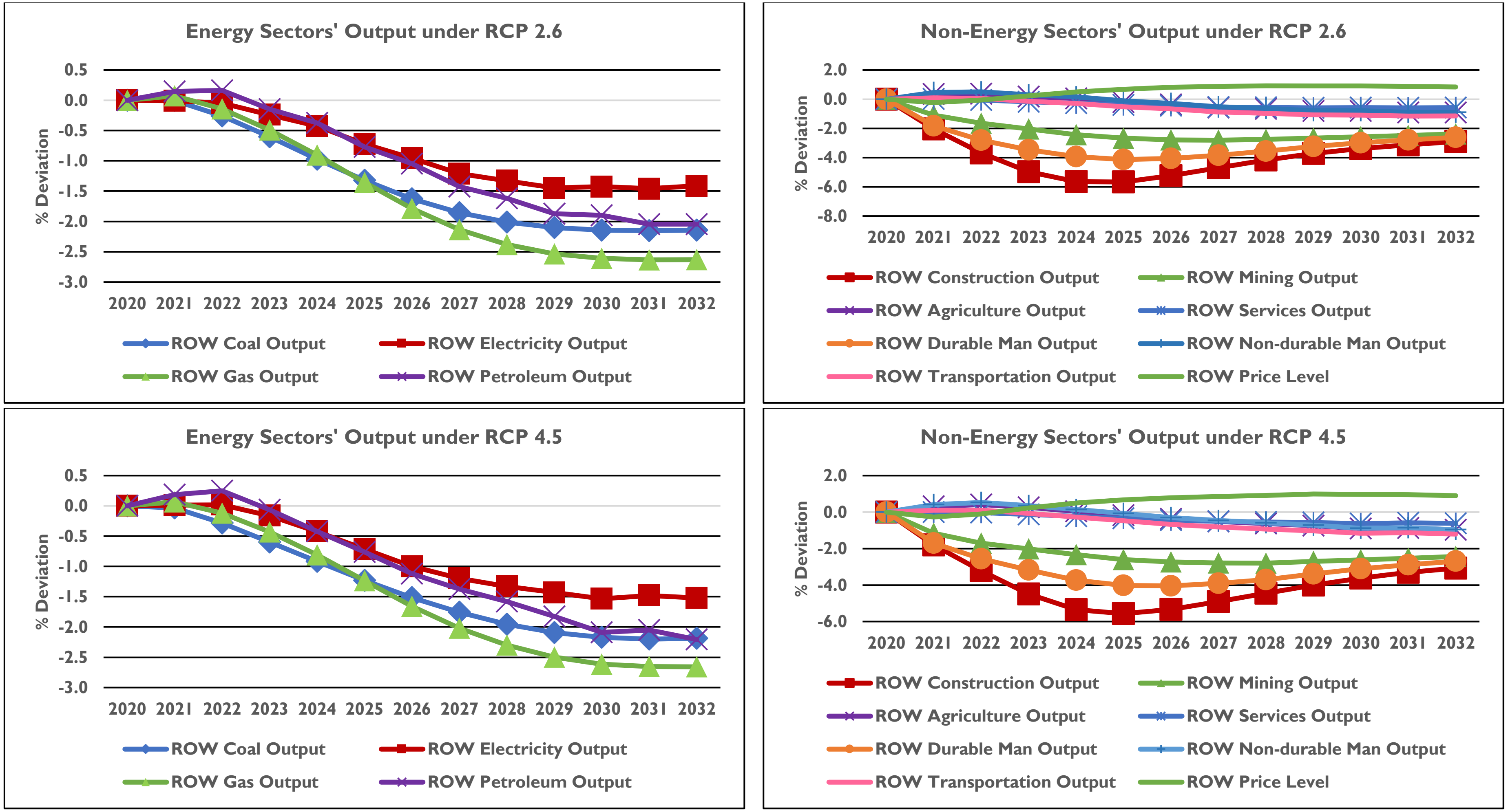




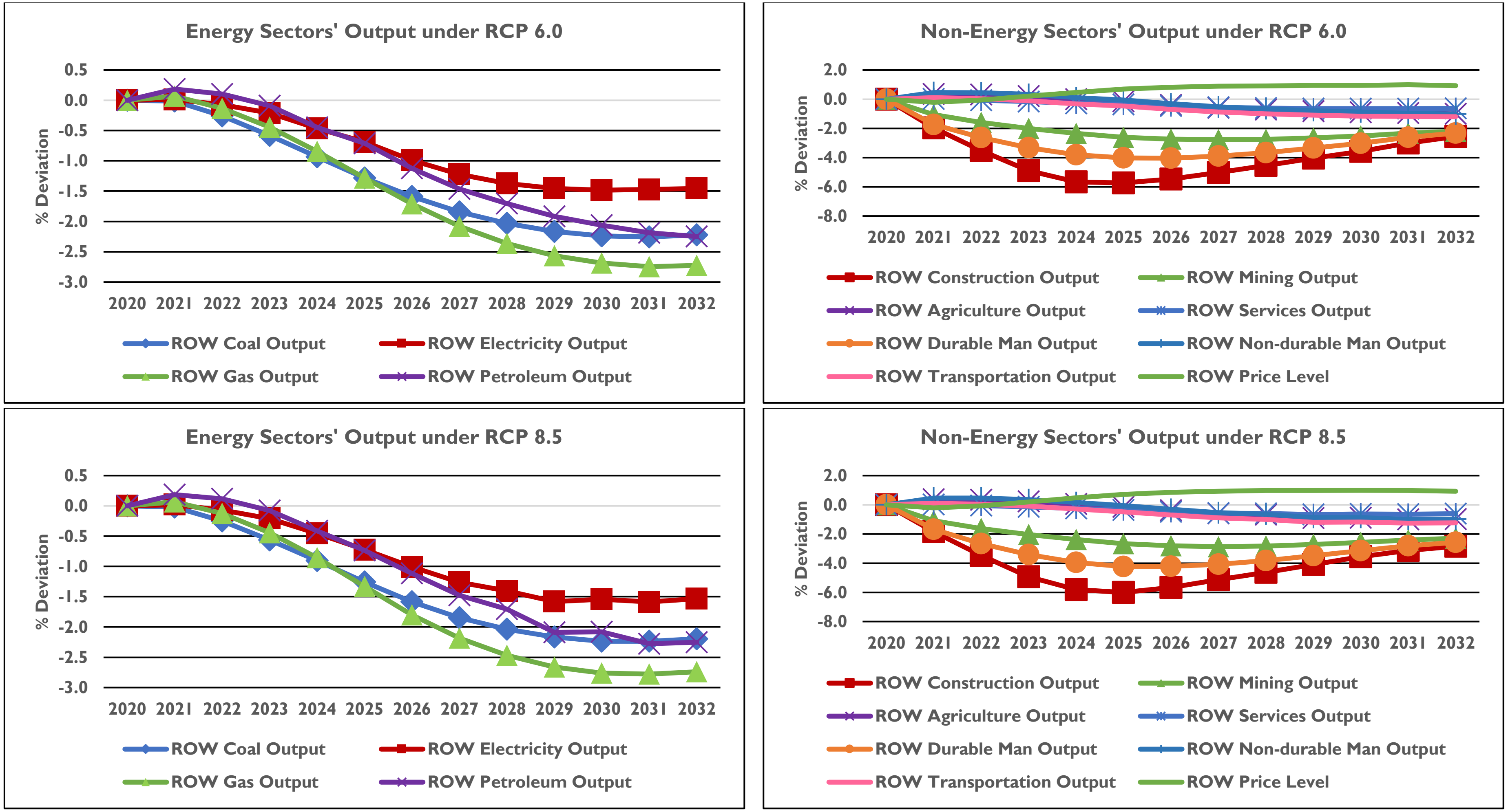
F2.8: Results for OPC (Contd.)



F2.9: Results for ROW



F2.9: Results for ROW (Contd.)



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