ESSAYS ON THE ECONOMICS OF CLIMATE CHANGE AND GEOENGINEERING

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ESSAYS ON THE ECONOMICS OF CLIMATE CHANGE AND GEOENGINEERING

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For my parents. I could not be where I am today without their never-ending support.

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SUMMARY

In this dissertation, I examine the relationship between climate and economic activity. In particular, I analyze methods for the measurement of climate change impacts on macroeconomic outcomes and the role of solar geoengineering in reducing these impacts. Solar geoengineering is different from traditional mitigation in at least three ways; it is inexpensive, quick, and imperfect. These characteristics place the technology as an imperfect but arguably inevitable insurance policy against the extreme effects of climate change. As such, it is important to understand effect of the solar geoengineering option on aggregate and distributional economic outcomes. To examine the economic impacts of solar geoengineering, this study applies an empirically estimated causal relationship between country-level economic growth and climate to illustrative future climate scenarios with and without solar geoengineering. Solar geoengineering is found to have an uncertain, model dependent impact on global economic outcomes but is consistently found to reduce inter-country income inequality by averting the worst economic impacts of climate change in poorer countries. The final study of this dissertation examines the methodology for estimating macroeconomic impacts of climate change to analyze contrasting results between microeconomic and macroeconomic empirical studies of the US. This study develops a general equilibrium theoretical framework with weather shocks that demonstrates how local, micro-level weather shocks impact macroeconomic growth. Using the theoretical findings, I construct macroeconomic impacts of weather shocks across the spatial distribution and industrial composition of economic activity in the US. Weather shocks are found to have a significant impact at the microeconomic level, but as impacts are aggregated, the significance becomes masked by the aggregation. This suggests that macroeconomic impact estimates may obscure important underlying heterogeneity in weather impacts.

CHAPTER 1
INTRODUCTION

Driven by persistent growth in anthropogenic greenhouse gas emissions stemming from economic activity since the industrial revolution, climate change poses an ever-growing risk to many facets of our society. Pertinent to determining the appropriate actions to lessen these risks is an accurate understanding of the relationship between the climate and socioeconomic outcomes and the impact of available policy options. Three distinct options to reduce the impacts and risks associated with climate change have been identified: mitigation of greenhouse gas emissions, adaption, and geoengineering. Each has distinctive characteristics. While an optimal policy prescription is likely to use some of each option in combination, the appropriate mixture remains an open question.

In this dissertation, I write three chapters that apply tools within the economic framework that contribute to this question. These essays extend the boundaries of our comprehension of both the relationship between climate and human society as well as the impact of solar geoengineering as a policy option. I take particular aim at improving our understanding of the distribution and heterogeneity of climate and solar geoengineering impacts across both space and industrial composition of economic activity. This an area critical for informing discussions around climate justice, ethics, and international politics.

I focus on solar geoengineering because it has only been recognized as a credible climate policy option in recent decades. Consequentially, it is the least understood of the three climate policy options. In Chapter 2, "Solar geoengineering economics: from incredible to inevitable and half-way back," written in collaboration with Dr. Juan Moreno-Cruz, I document the evolution of economic thinking around the solar geoengineering option. In this essay, I highlight the importance of its distinguishing characteristics – that it is cheap, fast, but imperfect – on its evaluated role and impact on existing climate policy.

I document that economists were initially intrigued by the *incredible* economics of solar geoengineering due to its low cost and rapid effect. In comparison to mitigation, engineering cost estimates by researchers found that solar geoengineering could potentially alleviate some of the greatest risks of climate change in a fraction of the time and at a fraction of the cost. However, this intrigue quickly transformed into concerns of the *inevitability* of solar geoengineering.

Economists began to construct models of incentives and strategic decision-making around the solar geoengineering option. Using both theory and empirics, economists recognized that the same low-cast characteristic that made the solar geoengineering *incredible* could also make it *inevitable*. This gave rise to concerns of the potential for a "free-driver" problem in which an individual actor or small group of actors unilaterally implement solar geoengineering to their benefit and the potential detriment of others. Further, the presence of the solar geoengineering option can create a moral hazard problem in which countries reduce their mitigation efforts because of an expectation of solar geoengineering implementation in the future.

Consequently, economists have taken a *step half-way back* as they delve deeper into the potential risks and international political concerns of solar geoengineering implementation. Here, I conclude by outlining important avenues for future work where economists can contribute to the discourse around solar geoengineering in the road ahead. Equipped with a framework centered on incentives, economists are well-poised to analyze how to effectively construct a governance structure that permits a coordinated and ethical implementation, or ban, of solar geoengineering. Essential to this are the uncertainties and risks of solar geoengineering implementation as well as its distributional impacts. While economists have recognized these factors, a more careful and detailed analysis needs to be put forward.

In Chapter 3, "Climate econometric models indicate solar geoengineering would reduce inter-country income inequality," written in collaboration with Dr. Katharine Ricke, Dr. Juan Moreno-Cruz, Dr. Douglas MacMartin, and Dr. Daniel Heyen, I address the distributional impacts of solar geoengineering by empirically estimating its impact on country-level economic growth. To facilitate comparison with existing analyses of climate change impacts, I apply existing climate econometric methods. In particular, I apply established econometric methods to estimate a historical relationship between country-level climate and economic growth. I then apply this historical relationship to evaluate projections of socioeconomic outcomes across a range of stylized climate scenarios both with and without solar geoengineering.

Evaluating country-level economic growth over the 21st century across stylized climate scenarios and econometric models, I consistently find that scenarios with solar geoengineering have lower inter-country income inequality. Implementing solar geoengineering to offset the warming of mean global temperatures from climate change reverts the impacts of climate change, but not exactly due to the imperfections of solar geoengineering. Since the poorest countries are consistently found to be the most negatively impacted by climate change, they conversely have the most to gain from solar geoengineering. Implementing solar geoengineering to over-cool mean global temperatures is found to further decrease inter-country income inequality by further benefiting the poorest countries. This accelerates convergence in country-level incomes. Solar geoengineering is also found to improve aggregate global economic outcomes, but this result is dependent on the econometric specification.

Following the findings of Chapter 2, the findings of Chapter 3 provide important and informative insights for the discourse around geoengineering ethics and governance. The finding that solar geoengineering reduces inter-country income inequality by benefiting the economic growth of poorer, developing economies stands in contrast to prevailing concerns that solar geoengineering favors developed countries. Important caveats from this research also highlight important areas for future work. These findings come from the evaluation of stylized climate scenarios, which may be inconsistent with future solar geoengineering. This suggests the need for further evaluation in a strategic decision-making framework as well as further work on the global governance of solar geoengineering. Additionally, these findings rely on the assumption that historically trained climate econometric models are valid for future projections and the application of solar geoengineering. This is a possible concern that warrants greater consideration for both climate change and solar geoengineering projection analyses.

Taking a step back, in Chapter 4, “From Micro-level Weather Shocks to Macroeconomic Impacts,” I examine empirical estimation of the impacts of climate on economic outcomes, such as the climate econometric method implemented in Chapter 3. Specifically, I provide an explanation for a seeming paradox between empirical studies analyzing the relationship between the climate and economic outcomes at the microeconomic and macroeconomic scales. Recent macroeconomic empirical analyses have found the economic growth of developed economies, like the US, to be insensitive to changes in weather or climate. However, at a more resolute scale, microeconomic empirical studies have found a variety of economic factors, such as labor productivity, agricultural productivity, and mortality to be sensitive in these same countries.

I first develop a theoretical framework founded on microeconomic principles to describe the relationship between local weather shocks and macroeconomic outcomes. Using the model, I examine the equilibrium impact of a supply-side shock to the labor productivity of a representative producer for an industry-region from an idiosyncratic weather shock in that region on the Gross Domestic Product (GDP) of the economy. I find that the aggregate economic impact can be captured by the impact of the weather shock on the labor productivity times the economic size of the producer, measured by their value-added share as a fraction of GDP. This provides a theoretical foundation for constructing the macroeconomic impacts of weather shocks.

Applying the theoretical findings, I construct empirical estimates of the macroeconomic impacts of weather shocks across the continental United States (US). I focus on the US because it is exemplary of the contradictory microeconomic and macroeconomic empirical findings I seek to explain. Constructing macroeconomic impact estimates requires information on the sensitivity of labor productivity to weather shocks across region-industry producers and the economic size of these producers. The second I get directly from data from the Bureau of Economic Analysis (BEA), but the first is not observed and must be empirically estimated. I empirically estimate this relationship using panel data fixed effects methods to capture a heterogeneous and non-linear relationship between labor productivity growth and changes in temperature and precipitation across industries. I construct empirical estimates of the annual impact of weather shocks across the US on GDP. Consistent with previous empirical analyses, I find no statistically significant evidence of an aggregate economic impact of weather shocks in the US.

Without a theoretical foundation, interpretation of empirical findings can lead to misleading conclusions and misguided inference. No statistically significant evidence of an aggregate economic impact of weather shocks in the US could lead to the inference that climate change will have little to no effect on the US economy. However, the theoretical framework on which these estimates are based permits an analysis of weather shock impacts on GDP at different resolutions. I examine how weather shocks across the country contribute to economic growth at the county, industry, and county-industry levels. I find that, at higher levels of resolution, weather shocks have statistically significant impacts on GDP in the US. However, these impacts are heterogeneous both across the spatial distribution and industrial composition of the US in any given year. This provides evidence that the aggregation of weather shock impacts can mask considerable underlying heterogeneity and that inference from macroeconomic estimates can be misleading.

The historical insensitivity of macroeconomic US outcomes to weather shocks appears to be a mechanical consequence of how economic impacts aggregate within an economy. However, exploring whether economics can explain this outcome is an interesting possibility. For example, this could be the result of location sorting by producers or the exit of firms following productivity shocks from the weather. The theoretical model analyzed in this chapter does not allow for this type of exploration, but it could be extended. This is left for future research. Another interesting question left to future consideration is whether this macroeconomic insensitivity, a result of considerable underlying heterogeneity, will persist into the future.

CHAPTER 2
SOLAR GEOENGINEERING ECONOMICS: FROM INCREDIBLE TO INEVITABLE AND HALF-WAY BACK.

The following chapter is a reprint of a published paper:

Harding, A. and J.B. Moreno-Cruz (2016), Solar geoengineering economics: from incredible to inevitable and half-way back. *Earth's Future*, 4, 569–577, doi:10.1002/2016EF000462

Solar geoengineering technologies are unique in many ways, and the economic incentives they could unleash are just as interesting. Since their introduction as a potential alternative, economists have been intrigued by the potential of these technologies to dramatically alter the way we think about climate policy. As our scientific understanding of the technologies evolve, so does the way economists think about them. In this paper, we document the evolution of economic thinking around these technologies since before Crutzen (2006) until today and provide some fruitful areas for further research.

2.1 Introduction

The economics and politics of climate change have so far focused, among other things, on creating incentives for individuals and nations to incorporate the environmental costs associated with climate change into their actions and policies. A persisting problem in this field is that of free-riding on mitigation. Free-riding occurs because the climate is shared by everyone, in that any one country cannot exclude others from its use, so there is little incentive for countries to cooperate with others by paying the high costs of mitigation as they expect others to pay for it. Because climate change impacts are heterogeneous across nations and economies, this lack of action also creates differential impacts with poorer, equatorial countries carrying the heaviest burden of these climate impacts [1].

In 2006, Paul Crutzen wrote an article that reintroduced the possibility of solar geoengineering as a technology that could reduce the costs of dealing with climate change [2]. Barrett [3] then asserted that this "incredible" economics of solar geoengineering would fundamentally alter climate change economics. However, solar geoengineering is more than cheap. As identified by Moreno-Cruz and Keith [4] and Keith et al. [5], solar geoengineering is different from traditional mitigation in at least three ways; it is inexpensive, quick, and imperfect. Since it has low costs of deployment relative to mitigation, it has the potential to reduce the free-riding problem to a simpler one of cost-sharing, but it can also introduce new problems. Though there may be political consequences, due to its low deployment costs relative to mitigation costs, individual countries or small coalitions of countries could unilaterally implement solar geoengineering without regard to the damages to others, a problem Weitzman [6] calls a "free-driver" problem. Moreover, it can be implemented and have an effect quickly, almost completely eliminating the inertia of the carbon-climate system. This could allow society to better respond to the uncertainties and threats of climate change. However, solar geoengineering is imperfect in three ways. First, it cannot compensate for changes in the climate that are not directly tied to temperature, for example, ocean acidification. Second, it can create side effects that are unique to the technology, heterogeneous across regions, and worse in a world with high carbon concentrations in the atmosphere. Third, sudden suspension of solar geoengineering can cause climate change to resume at a faster pace than before solar geoengineering deployment. These characteristics imply that, while there is a role for solar geoengineering to play in the climate policy agenda, this role is limited and needs to be understood in the context of other alternative ways to manage climate change.

Building on reviews of the economic literature on solar geoengineering by Klepper and Rickels [7, 8] and Heutel et al. [9], this paper introduces the different ways the literature in economics has introduced solar geoengineering into the economics of climate change to noneconomists in the hope of spurring more interdisciplinary work in this field. As exhibited in the rest of the paper, much of work done by economists has been to add an economic framework to the work of researchers in other fields, providing further insights into the climate change discussion. We hope this paper will inform researchers about the areas of the literature that economists have begun to establish a foothold and the importance of their contribution as well as show the areas of research that need the most contribution by economists and non-economists alike moving forward.

Specifically, in the rest of the paper, we show different ways the literature in economics have introduced solar geoengineering into the economics of climate change in three separate, but related, sections. We first introduce the simplest economic tool to deal with the design and evaluation of climate policy, engineering cost analyses, and show how this tool has been applied to the study of solar geoengineering. Second, we introduce tools used to analyze optimal climate policy and show how allowing for uncertainty and risk in the analysis of climate policy changes the policy prescriptions derived under engineering cost analyses. Third, we discuss the literature on international politics of climate policy and the need for governance of geoengineering. For this, we first present economic analyses of strategic decision making using a game theoretical approach and then we present proposed governance structures. In the final section of the paper, we highlight the areas of research that are promising and where more work needs to be done both in economics and together with the support of interdisciplinary research.

2.2 Engineering Cost Analyses

As solar geoengineering becomes a realistic option to combat the effects of climate change, many researchers and governments have begun to evaluate its feasibility and role in the climate change conversation. The simplest and most frequently used tool to initiate discussions about feasibility is the engineering cost analysis. The goal of an engineering cost analysis is to quantify the accounting or engineering costs of implementing a policy like solar geoengineering. As exhibited in this section, ongoing scientific and economic advances in solar geoengineering research have continually advanced the estimates of engineering cost analyses, but there is always room for improvement in their accuracy.

One of the earliest engineering cost analyses of solar geoengineering, which was cited by Crutzen [2], was conducted by the U.S. National Academy of Sciences' Panel on Policy Implications of Greenhouse Warming in 1992 as part of a larger study of climate change. The panel quantifies the costs of the capital and engineering requirements for implementation using market prices for comparable capital and materials at the time. For an effect equivalent to mitigating the amount of the 1989 U.S. emissions, the panel provides what they consider a conservative estimate for the cost of implementation by naval rifles in the range \$0.25-\$0.5 billion and even less by aircraft [10]. This leads the panel to conclude by expressing their surprise at the nominal cost of geoengineering options. This extremely low cost, especially compared to previously estimated costs for mitigation, opened the door for solar geoengineering as an alternative to mitigation, warranting further research and more in-depth analysis.

Inspired by the National Academy of Sciences' foundational analysis, other researchers have examined different implementation methods in more detail and with greater accuracy as solar geoengineering research has progressed. Robock et al. [11] quantify the costs of commonly discussed solar geoengineering techniques such as the use of airplanes, artillery shells, and balloons. By repurposing existing capital to reduce costs even further, they estimate the costs of injecting 1 TgS of a sulfur gas per year into the stratosphere varies between \$0.225-30 billion depending on the implementation method. Royal Society [12] produce a report similar to the U.S. National Academy of Sciences, examining different geoengineering techniques. In the section on solar geoengineering, the authors, in agreement with existing research, note the high affordability of this technique with estimates in the order of \$10 billion to deliver between 1 and 5 million tons of stratospheric aerosols per year [12]. McClellan et al. [13], the most detailed study to date, examine the costs of delivering 1-5 million metric tons of albedo modification material into the stratosphere using different airship based delivery systems. The authors conclude that the costs would be in the range of $1-8 billion depending on the delivery system and the quantity delivered [13].

The consistency of results in engineering cost analyses provides evidence that, in terms of engineering deployment costs, solar geoengineering could be significantly cheaper than previously estimated costs of global emission control [14]. With these results, Barrett [3] argues that the costs of implementation are far outweighed by the potential benefits of reducing damages from climate change. Barrett [3], Schelling [15], and Blackstock and Long [16] additionally argue that the estimated costs are so low compared to the benefits, just a fraction of some countries' gross national product, that nations may be able to act alone, unilaterally implementing solar geoengineering. This has redirected the climate change conversation from the issue of free-riding on mitigation to one of free-driving on solar geoengineering, in which implementation seems inevitable. We explore this more in section 2.4.

2.3 Optimal Climate Policy

Engineering cost analyses serve an important purpose in providing an initial, simple evaluation of solar geoengineering and its financial plausibility through the use of a cost benefit analysis. However, they do not capture the whole picture from an economists' viewpoint. As discussed by MacKerron [17], the true economic cost of solar geoengineering must incorporate any externalities or social costs in addition to just engineering costs. This includes costs as abstract as the changes in agricultural productivity due to impacts on precipitation to the change in peoples' utility due to the predicted effect of the sky turning from blue to white [18]. Additionally, the use of engineering cost analyses lack information in terms of the "best way" to use these technologies because they can only determine whether a single policy path is beneficial. "Best way" here has a very precise meaning of "optimal" in an economic sense of maximizing the well-being of society. As a qualitative approach to incorporate potentially missing costs, Moreno-Cruz and Smulders [19] use a simple, generalized model to examine climate change policy in the presence of solar geoengineering. They find that the optimal use of geoengineering depends on the potential harmful side effects as well as how well solar geoengineering can counteract all the different sources of climate change impacts. This reinforces the need for a better quantitative analysis of solar geoengineering.

To perform a quantitative analysis of the optimal use of solar geoengineering, researchers have turned to numerical techniques. The most frequently used technique adopted by researchers in this section of the literature is dynamic analysis of integrated assessment models (IAM). The most widely used IAM among the solar geoengineering literature is the dynamic integrated climate-economy model (DICE) developed by Nordhaus [20]. While there are a variety of IAMs used in the literature, the main objective of each is to simulate the economic impacts of climate change over different policy scenarios by integrating economic growth models with Earth system models. Using IAMs, researchers are able to simulate the economic outcomes of different policy choices in prespecified time horizons and then recursively develop an optimal policy path. It should be noted that the validity of the conclusions of these models depend to a significant extent on the calibration of both the economic growth models and the Earth system models. Most IAMs were designed for mitigation policy analysis, however, researchers have extended the models to examine optimal climate policy in the presence of solar geoengineering as well as mitigation. Wigley [21] uses the model for the assessment of greenhouse gas-induced climate change (MAGICC) to examine the impact of varying degrees of solar geoengineering combined with various levels of mitigation. Wigley [21] argues that a combination of solar geoengineering and mitigation is better than either alternative alone or that solar geoengineering can limit the impacts of climate change while mitigation is implemented. For a recent review of IAMs and economic applications see Metcalf and Stock [22]. For a critique of IAMs see Pindyck [23].

The papers discussed above are a step in the right direction regarding the optimal role of geoengineering in climate policy, but there are important factors of both geoengineering and climate change that are not considered [19]. Specifically, there are many unknowns and risks in the impacts of both climate change and solar geoengineering that persist due to the complexity of Earth's climate systems. Weitzman [24] and Pindyck [25] make an argument that climate change may follow a fat-tailed probability distribution, meaning that there may be a higher chance of extreme outcomes than most consider. As a result, they argue that uncertainties should play a larger role in optimal climate policy. Researchers have built dynamic stochastic programming into existing IAMs to incorporate different sources of uncertainty and determine their impacts on optimal climate policy. Emmerling and Tavoni [26] and Heutel et al. [27] use the World Induced Technical Change Hybrid model (WITCH) and DICE IAMs, respectively, to analyze the optimal mitigation and solar geoengineering levels in the presence of uncertainty. (For more information on the basics of dynamic stochastic analysis see Bellman and Dreyfus [28] and Ross [29]. For economic applications of dynamic stochastic analysis see Miranda and Fackler [30].) Emmerling and Tavoni [26] consider uncertainty in the success of solar geoengineering, while Heutel et al. [27] considers uncertainty in climate change and solar geoengineering. The results of both studies indicate that at low levels of uncertainty solar geoengineering is preferred to mitigation. This result is consistent with most engineering cost analyses, which come to the same conclusion under the assumption of no uncertainty. However, as uncertainty increases, they find that solar geoengineering becomes less preferred. Moreno-Cruz and Keith [4] also find this strong relationship between uncertainty and optimal policy in a theoretical analysis of mitigation in the presence of solar geoengineering and uncertainty. These results suggest that most engineering cost analyses underestimate the costs of solar geoengineering by not considering potential risks and uncertainties.

Weitzman [24] critiques the way uncertainty is introduced to IAMs in general by arguing that the compounding of uncertainties is still underestimated, especially for extreme scenarios. In response to this criticism, some researchers have extended IAMs also to include the possibility of major adverse events in the climate change timeline, such as climate tipping points or the sudden suspension of solar geoengineering. Climate tipping points are distinct points of global climate change in which drastic changes occur that may be irreversible, such as the collapse of the West Antarctic Ice Sheet [31]. These tipping points are predicted in growing strength by researchers in the existing climate change literature [32]. However, as the likelihood of experiencing one of these catastrophic events grows, it is still uncertain where they will be experienced and the extent of economic damages if a tipping point is crossed.

Bickel [33] and Heutel et al. [34] extend the DICE model to analyze the effects of climate tipping points and solar geoengineering on optimal climate policy. These studies indicate that the presence of these climate tipping points actually leads to lower peak temperatures and greenhouse gases in the optimal policy decisions than previous analyses. In effect, because these tipping points may exist and are potentially nontrivial in their economic damages, agents will increase mitigation levels earlier to try to prevent climate change from reaching any of these tipping points, while solar geoengineering serves as an insurance policy in case a tipping point is reached.

By not dealing with the root cause of climate change, the accumulation of greenhouse gases in the atmosphere, researchers have predicted that a sudden suspension in the implementation of solar geoengineering could cause climate change to resume at a much quicker pace than prior to the implementation of solar geoengineering [35]. This gives rise to two additional sources of uncertainty to consider in the optimal choice of policy. The first is the probability of a sudden suspension of solar geoengineering occurring. The other is the extent of damages due to climate change resuming at an increased pace.

Similar to the climate tipping points literature, Goes et al. [36] extend Nordhaus' DICE model with the possibility of the sudden suspension of solar geoengineering to better understand its impact on policy decisions. To simplify the analysis Goes et al. [36] assume that either mitigation or solar geoengineering can be used, but not a combination of both. Under the assumptions made, the authors found that the presence of potential damages from these uncertainties cause solar geoengineering to fail as a substitute for abatement over a wide range of model specifications. Responding to Goes et al. [36], Bickel and Agrawal [37] relax some of the assumptions made by Goes et al. [36]. Most importantly, they allow for society to respond to a sudden suspension in solar radiation management through the use of mitigation. Under this reframed model, the authors show that solar geoengineering can pass a cost-benefit analysis more often than predicted by Goes et al. [36], but still less often than suggested by previous studies that do not consider major adverse events like the possibility of the sudden suspension of solar geoengineering.

By considering these major events, economists are able to inform the optimal policy conversation. They suggest that existing studies, even those that try to broadly include uncertainties, underestimate costs, and that by decreasing these uncertainties, solar geoengineering is more likely to play a more important role in optimal climate policy than it should. The flip-side of the coin is that the best way to deal with geoengineering uncertainties is by increasing the use of mitigation as a way to reduce the reliance on geoengineering. In this way, later studies have shown that geoengineering and mitigation are complimentary in dealing with climate uncertainties. The relationship of geoengineering and mitigation is discussed further in section 2.5.

2.4 International Coordination and Cooperation

While it is important for researchers to improve the accuracy of optimal climate change policy analyses to evaluate the role of solar geoengineering in the climate change discussion, it is also important to analyze the international politics by relaxing the assumption of a central, benevolent social planner. That is, researchers must examine strategic choices of different actors rather than examining the optimal choice for a singular omniscient decision-maker who acts to maximize the combined well-being of everyone. As evidenced by current international environmental agreements and climate treaties, such as the Kyoto Protocol, an understanding of optimal climate policy does not always translate into successful implementation of those policies. One of the main shortfalls that has led to the low ambitions and underwhelming results of existing climate treaties and environmental agreements like the Kyoto Protocol has been the free-riding problem of mitigation [38]. However, as further research and discussions of solar geoengineering make it a credible alternative or supplement to mitigation, the possibility of solar geoengineering implementation has the potential to transform the political problem of climate change implementation from one of cooperation among countries to a simpler one of coordination and cost-sharing [3]. However, this potential for solar geoengineering implementation also introduces the problem of free-driving, where any country has the ability to unilaterally implement geoengineering to the benefit or detriment of others because of the low deployment costs [6]. This has spurred economists to reanalyze the international politics and negotiations in the presence of solar geoengineering.

Compounding with the problems of free-riding on mitigation and free-driving on solar geoengineering and further complicating the international politics of climate change is the heterogeneity in preferences across regions. Since it does not directly impact the accumulation of greenhouse gasses in the atmosphere, the source of climate change damages, solar geoengineering would differentially cool the planet. This gives rise to different regions favoring different levels of solar geoengineering, wanting to "set the global thermostat" to their preferred temperature. Additionally, solar geoengineering does nothing to counter other damages from climate change such as ocean acidification. This leads to heterogeneity in the persisting damages experienced by regions based on their geographical characteristics [39]. In an evaluation of solar geoengineering, using a computable general equilibrium model, Aaheim et al. [40] emphasize the importance of regional heterogeneity in their estimates of economic impact. The authors argue that this regional heterogeneity stems from the economic impacts from solar geoengineering based on regional location as well as their primary economic activities. In optimal climate policy analysis, this heterogeneity can be underestimated. While shifts toward a global optimal may be beneficial to society as a whole, they may not be beneficial to each individual country. In economic terms, changes toward the optimal climate policy need not be Pareto improvements. Countries may then stand against the successful implementation of what is considered the optimal climate policy from a societal framework. Heterogeneous impacts, then, are central to the analysis of the strategic interactions across countries.

To better understand the impact of solar geoengineering on international politics through a framework of strategic decision making, Moreno-Cruz [41], Manoussi and Xepapadeas [42], Urpelainen [43], and Millard-Ball [44] use game theoretical techniques (For more information on the basics of game theory analysis in economics see Gibbons [45]). This has allowed them to relax the assumption of a central, benevolent social planner and allow for different actors to negotiate and interact in a strategic environment. Moreno-Cruz [41] uses a simple two-country model in which the countries strategically choose their level of mitigation, then their level of geoengineering, and finally experience damages based on the mitigation and geoengineering choices of both countries. Under the model used, Moreno-Cruz [41] finds that the levels of mitigation and geoengineering chosen depend on the degree of symmetry between the countries. If countries are highly symmetric in their costs of geoengineering and mitigation as well as their sensitivity to damages from temperature and geoengineering, countries will mitigate suboptimal levels. However, if countries are highly asymmetric in their damages, such that one country has a very low cost of geoengineering and the other has a high sensitivity to geoengineering damages, the latter country may mitigate at inefficiently high levels relative to the level that maximizes the countries combined well-being in order to reduce geoengineering by the former country. Manoussi and Xepapadeas [42] performs a similar analysis by examining a dynamic, calibrated two-country model, and again demonstrates the importance of the degree of symmetry in the strategically chosen mitigation and geoengineering levels. Urpelainen [43] analyzes a two-country model in which both countries are strategically choosing mitigation and geoengineering levels. He implies that the presence of geoengineering and the detriment it may cause in the future can incentivize countries to increase emissions reductions in the present, similarly to the asymmetric case of Moreno-Cruz [41]. Millard-Ball [44] considers more countries and the possibility of an international environmental agreement. Millard-Ball [44] argues that the credible threat of a country unilaterally implementing geoengineering may incentivize countries to agree to higher mitigation levels than in current international environmental agreements.

While Urpelainen [43] and Millard-Ball [44] concentrate on the threat of unilateral implementation of solar geoengineering by individual countries incentivizing higher mitigation levels, Ricke et al. [46] considers the role of potential political consequences of implementing solar geoengineering by requiring a majority coalition for implementation. Ricke et al. [46] define a majority coalition as a coalition that has the majority share of power, as represented by a variety of economic and political measures such as gross domestic product. Using the heterogeneous preferences across 22 regions of the world, Ricke et al. [46] simulate strategic coalition formation in which regions seek to form the strongest, smallest coalition possible among regions with similar preferences. Comparing this exclusive collation formation to an inclusive top-down approach, Ricke et al. [46] finds the benefits of exclusivity to be small.

Following concurring engineering cost estimates exhibiting how low the deployment costs of solar geoengineering could be, Victor [47]. Victor et al. [48], Barrett [3], Betz [49], and Blackstock and Long [16] argue the importance of developing a governance structure before any country or coalition acts unilaterally in their own interest to the detriment of others by either implementing solar geoengineering, or in the case of Betz [49] by even researching it as a future option. Betz [49] compares the free-rider problem on geoengineering to the building of the Large Hadron Collider in Europe and the remaining stocks of smallpox virus to emphasize that, unlike with mitigation, the governance problem is no longer one of getting countries to participate, but who should decide to implement geoengineering and how it should be implemented. Building on his previous paper, Barrett [50] provides a review of governance analyses, arguing that more work is needed. Virgoe [51] examines three approaches to geoengineering governance: "through the United Nations, by one state unilaterally, and through a consortium of states." Virgoe [51] presents the pros and cons of the different approaches and when they may arise. Importantly, Virgoe [51] also notes that no existing international legal instruments "would pose an insuperable barrier to geoengineering," furthering the importance of quickly developing a governance structure prior to implementation. Weitzman [6] proposes a potential voting architecture for the governance of geoengineering in which a qualified majority among countries is required to increase or decrease the level of geoengineering. In addition to arguing the importance of governance, Victor [47] argues that the existing top-down approach of encouraging broad participation among countries used for current climate treaties and international agreements will likely not be successful in the presence of solar geoengineering. Because countries or small groups of countries could act unilaterally implement solar geoengineering, they may have little incentive to join a large coalition. For this reason, Victor [47] argues researchers need to investigate bottom-up coalition formation in which smaller groups of country coordinate their decision to better understand coordination and governance, which is reflected by the game theoretic analyses discussed above.

2.5 Road Ahead

In this paper, so far, we summarize the still nascent literature on the economics of solar geoengineering to inform noneconomists in the field of the development and importance of current economic thinking. As we show, economists were initially intrigued by the *incredible* economics of geoengineering following Crutzen [2]. Achieving any temperature target at such low costs could change the game, making the free-driving problem irrelevant. However, the same low costs introduce the possibility of a free-driver choosing a temperature goal without consideration of others, making solar geoengineering implementation almost *inevitable*. However, economists have taken a *step half-way back* as they begin to delve deeper and discover the various risks, uncertainties, and problems with international politics of implementation. While economists have built on the work of other researchers to provide insight and make important contributions to the areas of the solar geoengineering literature discussed above, there is still more research to do. In this final section, we emphasize the importance of interdisciplinary research in the different directions of research moving forward. We discuss areas of the literature that economists have just begun to explore, but need more contribution by economists and noneconomists alike moving forward as well as areas that economists have identified as needing more from noneconomists to continue.

An important aspect of the game theoretic analyses of international strategic decision making by Moreno-Cruz [41], Manoussi and Xepapadeas [52]. Urpelainen [43], and Millard-Ball [44] as well as the generalized analyses by Moreno-Cruz and Smulders [19] and Moreno-Cruz and Keith [4] is the trade-off between mitigation and geoengineering when countries strategically choose their implementation levels. Each of these papers show that this trade-off can have a large impact on the results of their analyses. In economics, this trade-off is known as substitutability. Two products, like mitigation and geoengineering, are considered perfect substitutes if they can be used for the same purpose and perfect complements if they must be used together. There are varying degrees of substitutability in-between.

Some researchers have expressed concern about this trade-off through a moral hazard framework. Lin [53], Morrow [54], Reynolds [55], and Preston [56] critically analyze this potential moral hazard problem. Lin [53] argues that the geoengineering may undermine mitigation efforts, creating a moral hazard problem. Morrow [54] address the question of why the undermining of mitigation would be a bad by using three ethical approaches to show conditions under which a moral hazard problem could arise. On the other side of the debate, Reynolds [55] and Preston [56] argue that empirical evidence suggests that society may be better off reducing mitigation and implementing geoengineering. However, both admit that the empirical evidence is not necessarily accurate due to uncertainties about the impacts and risks of solar geoengineering. As discussed by Reynolds [55], the answer to this debate depends heavily on the substitutability of solar geoengineering and mitigation as well as a better understanding of the potential risks of solar geoengineering and climate change. While Moreno-Cruz and Smulders [19] make an argument that geoengineering can never be a perfect substitute for mitigation because it only deals with the temperature-related impacts of climate change, further work closely examining and quantitatively estimating the substitutability of mitigation and solar geoengineering could be a major contribution toward applying the results of these types of analyses.

In a similar vein of the ethics of geoengineering, some researchers have taken a step further by questioning the intergenerational ethics of continuing research on solar geoengineering. This branch of the literature has built off of what Gardiner [57] has called "arming the future" in which by deciding whether or not to research geoengineering the current generation is deciding whether or not to "arm" future generations with the technology. This section of the literature has been undecided in its conclusions. Burns [58] argues that the potential risks of solar geoengineering as well as the potential limitation of future generations options by continuing to pursue this line of research causes further research into geoengineering to fail in the framework of intergenerational equity. Robock [59] argues that the "indoor," theoretical and empirical modeling research of solar geoengineering research is ethical, while the "outdoor" research of field tests is not. Betz [49] examines both sides of the intergenerational ethics problem and argues that a reframing of the question and applications of the research could reduce objections of further research. Against this backdrop of possible futures, Goeschl et al. [60] analyzes this problem through an economic framework. Goeschl et al. [60] model generations' choices of whether to pursue and implement solar geoengineering as a function of mitigation and solar geoengineering costs as well as potential resulting climate damages to strategically examine generations choices. They find that the strategic decisions depend on the relative size of the parameters, but importantly note that if solar geoengineering research is relatively cheap, the current generation may decide not to research solar geoengineering and increase mitigation. As shown by the results of Goeschl et al. [60], research furthering our understanding of the risks and costs of solar geoengineering research and implementation could help clarify this ethical debate.

While the areas of growing research discussed above could benefit from future work by economists and researchers in other fields alike, we appeal for interdisciplinary research in areas that could benefit the literature that has been more developed by economists. First, as with Keith et al. [5] we call for researchers to develop a better understanding of potential uncertainties in solar geoengineering and climate change impacts alike. As discussed in section 2.3, reducing the uncertainty of these impacts could greatly inform economic analysis of optimal climate policy. Second, we, along with Heyen et al. [39], Moreno-Cruz et al. [4], and Manoussi and Xepapadeas [42], call for researchers to develop a better understanding of the heterogeneity of solar geoengineering and climate change impacts. This can greatly benefit evaluations of solar geoengineering as well as our understanding of the international politics of climate change. Finally, specific questions about liability, legitimacy, and international cooperation need further study. Concurring with Victor [47], Victor et al. [48], Barrett [3], Betz [49], and Blackstock and Long [16], we call for research analyzing the governance and international politics of solar geoengineering and climate change. As these authors indicate, solar geoengineering as a free-driver in the climate change discussion has altered the dynamics of the problem, and progress is needed in understanding this new state of the climate change conversation. As our understanding of the downsides of solar geoengineering and climate change grows, we also need more work akin to Reynolds [61] analyzing the role of liability or compensation for harm in international policy.

Economists have been at the forefront of the research in solar geoengineering, but a more careful and detailed analysis needs to be put forward. The best way to achieve this is for economists to embrace this area and go play in the sandbox with other researchers across all the disciplines currently involved in solar geoengineering research, and for other disciplines to play along.

CHAPTER 3

CLIMATE ECONOMETRIC MODELS INDICATE SOLAR GEOENGINEERING WOULD REDUCE INTER-COUNTRY INCOME INEQUALITY

The following chapter is a reprint of a published paper:

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Exploring heterogeneity in the economic impacts of solar geoengineering is a fundamental step towards understanding the risk tradeoff associated with a geoengineering option. To evaluate impacts of solar geoengineering and greenhouse gas-driven climate change on equal terms, we apply macroeconomic impact models that have been widely applied to climate change impacts assessment. Combining historical evidence with climate simulations of mean annual temperature and precipitation, we project socio-economic outcomes under high anthropogenic emissions for stylized climate scenarios in which global temperatures are stabilized or over-cooled by blocking solar radiation. We find impacts of climate changes on global GDP-per-capita by the end of the century are temperature-driven, highly dispersed, and model dependent. Across all model specifications, however, income inequality between countries is lower with solar geoengineering. Consistent reduction in inter-country inequality can inform discussions of the distribution of impacts of solar geoengineering, a topic of concern in geoengineering ethics and governance debates.

3.1 Introduction

Climate change poses many risks to society and natural ecosystems, and action will be required to reduce its harms [62]. While the most straightforward and certain way to reduce these harms is by reducing, and eventually reversing, emissions of greenhouse gases, such mitigation is expensive and subject to free-rider incentives. The consequent inaction has led to consideration of intentional intervention in the climate system through solar geoengineering [63], but many are reluctant to pursue one global climate intervention to correct for another [64, 65]. It is of paramount importance to understand, to the best of our abilities, the relative global and distributional socio-economic impacts of all climate change options.

Solar geoengineering is the intentional reflection of solar radiation to reduce the temperature effects of climate change. Until recently, understanding of the consequences of blocking sunlight to cool the planet was limited in comparison to our understanding of the effects of rising greenhouse gases. A decade of research has greatly increased our knowledge of what the climate effects of solar geoengineering might look like [66, 67], but solar geoengineering impacts assessment still lags behind evaluations of other types of climate change [9]. This is for two reasons: first, the field is still relatively immature, and hence the type of physical climate modeling results required to drive impacts models did not exist until recently [68]. Second, the broader field of climate change impacts assessment has evolved in a way that does not easily accommodate application to solar geoengineering. For the sake of setting straightforward but meaningful climate policy targets, global or regional temperature anomalies are often used as proxies for the level of impact or damage [69], but with solar geoengineering, the correlations between temperature and other impact-relevant variables such as precipitation and ocean pH may differ substantially from the correlations between these variables under greenhouse gas-driven change [70]. This has made it difficult to translate projected climate effects of solar geoengineering into impacts on society using the standard frameworks used to compare, for example, a high and low carbon dioxide emissions scenario.

In this paper, we examine the global and distributional impacts of solar geoengineering on socio-economic outcomes using a state-of-the-art macroeconomic climate impacts assessment approach. This methodology, as developed by Dell et al. [71], Burke et al.

[72], and Burke et al. [73], estimates the historical relationship between mean annual temperature and precipitation and country-level growth in economic production measured as gross domestic production (GDP) per capita. The empirically estimated climate-economy relationship is then applied to stylized climate scenarios constructed from projections of mean annual temperature and precipitation derived from multi-model ensembles of climate change and solar geoengineering model simulations [74, 75, 76]. We then evaluate how solar geoengineering may affect global economic growth and inter-country income inequality by comparing global and country-level economic outcomes across scenarios.

The empirically estimated climate impact models we apply use mean annual temperature and precipitation to measure the relationship between the climate and the economy, as measured by GDP. Factors such as climate variability and extremes are only captured by this model to the extent that they are related to the climate indicators used in these models. We cannot partition these effects from the aggregate effects using the empirical impacts estimation models we apply, and as such, considering the impact of these is outside the scope of our analysis. However, recent work using a high-resolution forecast-oriented model found that the type of solar geoengineering simulated in the GeoMIP simulation ensemble (which we apply here as well) mediates precipitation extremes over 99.6% of grid cells and reduces tropical cyclone intensity, not just mean climate response, supporting the assumption that there is a strong relationship between reduction of mean anomalies and mitigation of extremes [77]. Side-effects of solar geoengineering such as changes in ground-level UV [78] as well as impacts of elevated atmospheric CO_2 concentrations on ocean acidification [79, 80] are similarly not incorporated.

Empirical economic climate impacts estimation methods are an area of active research and the extent to which projections applying such models can be reliably interpreted is a matter of some dispute in the climate change economics community [81]. We remain agnostic to this debate by applying a well-established methodology for climate change impacts estimation [72, 73] to solar geoengineering in order to compare several illustrative future climate change scenarios with different levels of solar geoengineering on equal terms. We conduct a broad sensitivity analysis using competing econometric model specifications to illustrate which of our findings are contingent upon assumptions across various state-of-the-art impacts models.

The econometric models we estimate capture a mixture of linear and non-linear effects, different country trends, different climate variables, and growth and level effects. To allow for the influence of different climate variables on economic production, we estimate models with temperature and precipitation. As shown in Table A.1, temperature is the only climate variable found to be statistically significant across all the models. Economic outcomes may be delayed in their response to climate, so we estimate models with only contemporaneous climate variables as well as models that include lagged climate variables up to 5 years. Since it is unclear whether climate change impacts are on the level or growth of economic output, we estimate both types of models. Microeconomic evidence suggests the impact of temperature on outcomes follows a non-linear structure, so we estimate models both linear and non-linear in climate variables [82, 83]. Finally, since countries may be following different economic trends, we estimate models using country-level trends. Results for all models can be found in the Supplementary Materials (Table A.1). In the text, we present results for the model used in the text of Burke et al. [72], but comparable results for other model specifications can be found in the Supplementary Materials (Table A).

Through this analysis, we find that the harms of warming and benefits of cooling both accrue disproportionately to warmer, poor, more populous countries. As such, climate-econometric models indicate that solar geoengineering would reduce inter-country income inequality. While the magnitudes of the economic impact of greenhouse gas-driven warming and solar geoengineering-driven cooling are highly model dependent, their influences on inter-country inequality are consistent.

3.2 Results

3.2.1 Four illustrative future climate scenarios

To comparatively evaluate the impacts solar geoengineering with climate change impacts, we construct stylized climate scenarios from climate change and solar geoengineering projections widely used in impacts assessment. For projections of climate change without solar geoengineering, we utilize grid-cell level projections of temperature and precipitation by 2100 from the representative concentration pathway (RCP) 8.5, an emissions intensive scenario and the highest warming pathway among RCPs [84]. Temperature and precipitation responses for RCP8.5 are constructed from an ensemble mean of the climate models participating in CMIP5. Projections of grid-cell temperature and precipitation responses to solar geoengineering are constructed from climate model responses to the GeoMIP G1 experiment in which a solar reduction was used to offset CO_2 forcing [85] (See the section 3.4). Temperature and precipitation responses for solar geoengineering are constructed from an ensemble mean of 12 climate models in the GeoMIP G1 experiment (Table A.2). We also analyze climate impacts for each of the 12 climate models individually to examine sensitivity to uncertainty in solar geoengineering climate response.

We integrate the RCP8.5 and solar geoengineering projections to simulate economic growth under four illustrative future climate scenarios (Fig. 1). These four scenarios are: no climate change, where a present-day climate is held constant, and the only simulated changes are the socioeconomic projections; RCP8.5, the highest warming scenario simulated in the CMIP5 ensemble; geoengineering-stabilized RCP8.5, in which solar geoengineering is used to stabilize global mean temperature at its present-day level despite the increased greenhouse gas concentrations associated with RCP8.5; and geoengineering-mirrored RCP8.5, a scenario in which solar geoengineering is deployed to cool the global mean temperature at the same rate of warming under RCP8.5 also despite the increased greenhouse gas concentrations associated with RCP8.5. These stylized scenarios were designed to illustrate the comparison of solar geoengineering with RCP8.5, a climate change scenario commonly utilized in climate change impact assessment.

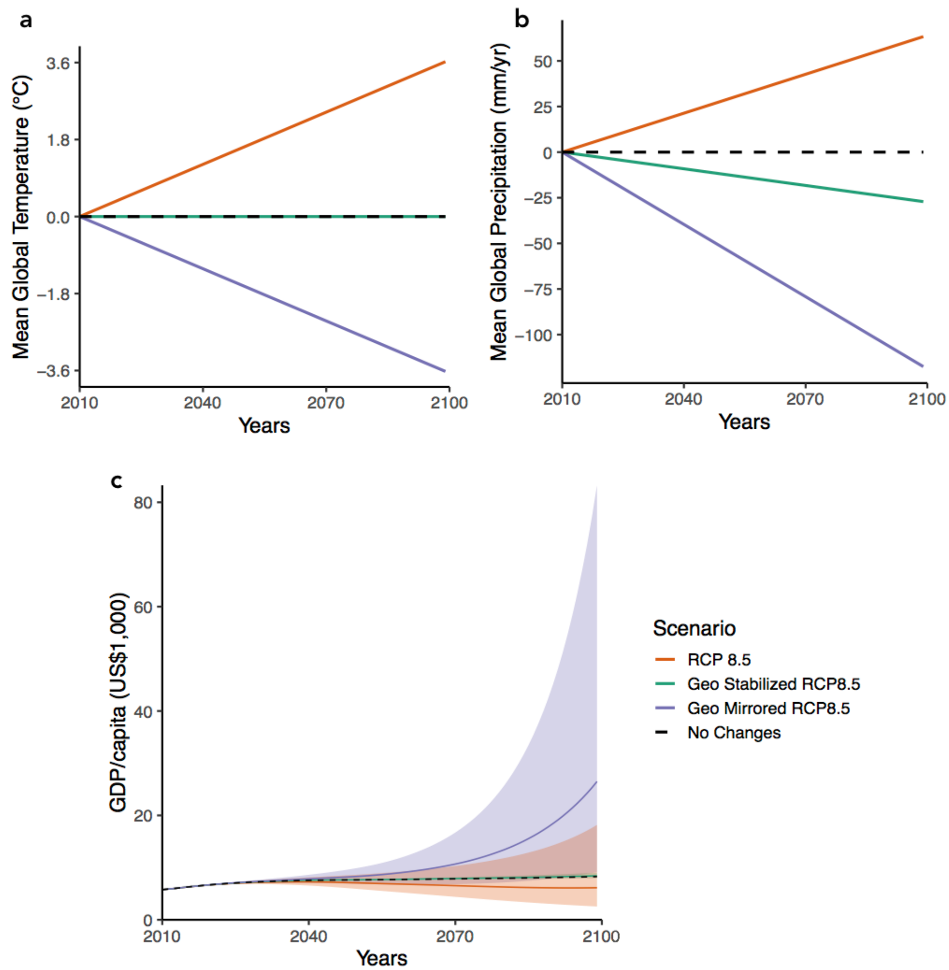


Figure 3.1: **Simulated changes in climate and projected GDP/capita over the 21st century.** Curves are estimated using the model in column (1) of Table A.1 for Shared Socioeconomic Pathway (SSP) 3. **a** Change in global mean temperature and **b** change in global mean precipitation under the four illustrative climate scenarios. **c** Projected GDP/capita for the four illustrative climate scenarios where lines represent median projections and shaded area represents 95% confidence (See the section 3.4). See Table A for other SSPs, climate-economy model specifications (Figure A.12).

A baseline economic growth scenario is required to apply the empirical climate impact function in projections. We use the shared socio-economic pathways (SSPs) that project key socio-economic factors such as population and economic development contingent upon challenges to adaptation and mitigation of climate change [86]. In the text, we present the results for outcomes under SSP3, the pathway associated with high challenges to both mitigation and adaptation—the conditions under which solar geoengineering seems most likely to be needed. Results for all four illustrative climate scenarios and all five SSPs can be found in the Supplementary Materials.

Changes in global temperature and precipitation for the four climate scenarios are displayed in Fig. 1a, b. The relative effects on temperature and precipitation as well as the spatial heterogeneity of impacts from solar geoengineering do not match those of anthropogenic climate change (see Figure A.1). Solar geoengineering reduces global precipitation more per degree of cooling than CO_2 and other greenhouse gases increase it per degree of warming. Uniformly applied solar geoengineering also overcools equatorial regions relative to the poles.

3.2.2 Macroeconomic impacts of solar geoengineering

When the economic impacts of solar geoengineering are estimated using the same historical evidence used to project harms from greenhouse gas-driven warming, we observe impact model-dependent results. Following the approach of Burke et al. [72, 73], we find that solar geoengineering to stabilize global temperature mitigates the economic harms of warming-associated climate change and even provides a modest increase in global GDP (Fig. 1c). This increase is the result of the more zonally uniform global temperatures associated with canceling CO_2 radiative forcing with solar forcing. If anthropogenic warming is not just eliminated but solar geoengineering is used to cool the planet at a rate equal to the RCP8.5 warming rate, global GDP increases substantially due to rapid economic growth in warmer developing nations (Fig. 2b). This increase in global GDP is the result of cooling the areas of the world with high population densities that are currently warmer-than-optimal. However, these results are sensitive to econometric model specification. Figure A.12 shows that global economic growth varies across econometric specifications as well as socioeconomic pathways.

Global results mask considerable heterogeneity in the distribution of economic losses and gains. Projections under the no-climate-change scenario and the geoengineering-stabilized RCP 8.5 scenario are similar in terms of country-level outcomes (Fig. 2c, d); no country is poorer by the end of the century than in 2010 for either scenario (Table A.3). As projected by Burke et al. [72], under RCP8.5 and SSP3, 43% of countries are poorer at the end of the century and 76% of countries are relatively poorer than they would be under SSP3 alone. Using the same impacts model, we find that under the geoengineering-mirrored RCP8.5 scenario, just 11% of countries are poorer at the end of the century and 32% of countries are relatively poorer than they would be under SSP3 alone. As shown by Figures Figure A.23 to Figure A.36 in the Supplementary Materials, the identity of countries that experience economic losses and the magnitude of their absolute or relative losses also varies across models.

3.2.3 Solar geoengineering and inter-country income inequality

From our projections we analyze differences in country-level incomes, as measured by GDP, as a metric of global income inequality. Changes in climate from climate change or solar geoengineering can additionally impact inequality across communities within the boundaries of a country. This is an important consideration for a comprehensive analysis of the impacts on inequality, however, because the models we use are identified on country-level GDP, we cannot analyze the impact on inequalities within a country's borders. The effects of each scenario on country-level economic growth, inequality, and the percentage of countries absolutely or relatively poorer varies across economic impact model specifications (see Tables Table A.3 and Table A.4). However, unlike projections of global economic growth over the next century, projections of global income inequality are qualitatively consistent across models, suggesting that using solar geoengineering to negate or reverse climate change can reduce global income inequality.

Figure 3 shows the cumulative share of global GDP vs. the cumulative share of the global population (known as a Lorenz curve) in 2099 for the baseline SSP3 scenario. Absent consideration of climate change, most long-term economic projections anticipate some degree of country-level income convergence over the coming century, that is, a narrowing of the global income distribution over time. This is illustrated by the black curve. With no climate change, an end-of-century Lorenz curve is less convex than that of the present day (gray dashed line), indicating a decrease in global income inequality. These gains in equality are eliminated under RCP8.5 but are restored in a geoengineering-stabilized climate. Global cooling further increases income convergence, except in the lowest-wealth quartile. (For example, the poorest country in 2100 under the geoengineering-mirrored climate is Mongolia with $316/capita, a decrease from $860/capita in 2010.) Figure A.47 displays the Lorenz curves across different model specifications.

3.2.4 Sensitivity analysis and robustness

In Fig. 4 we display the percentage of countries that gain relative to no climate change and the Gini coefficients for country GDP/capita in 2099 for the different econometric models and illustrative climate scenarios under SSP3. Gini coefficients are a widely used measure of inequality, related to the curvature of the Lorenz curves in Fig. 3, where a lower Gini coefficient indicates lower inequality. Despite significantly disparate models of how climate impacts economic growth, several consistent trends emerge. RCP8.5 (orange) consistently increases inter-country inequality and the percentage of countries with poor economic growth, whereas the geo-mirrored scenario (purple) consistently decreases inequality. For all impact models, the Gini coefficient decreases with the use of solar geoengineering. The coefficient is the lowest for the Geoengineering-Mirrored RCP 8.5 scenario. Under all but one economic impacts model, the Geoengineering-Mirrored RCP 8.5 scenario decreases the percentage of countries with a GDP loss relative to RCP8.5, and under that particular model (Model 5, an income-dependent growth model with no country time trends), geoengineering has a particularly large effect on reducing inequality.

While the effects of climate change and solar geoengineering on convergence varies somewhat depending upon the socioeconomic scenario and economic impact model specification, results indicate that anthropogenic warming consistently hinders or even reverses convergence, whereas solar geoengineering enhances or accelerates it. Solar geoengineering is not perfectly equitable in countering climate change in terms of key climate indicators, but it is more equitable in economic outcomes than under a no climate change scenario [87]. These results display a consistent decrease in global income inequality with solar geoengineering across economic model specification. Likewise, this result is consistent among all SSPs.

The underlying econometric models have very different assumptions that can explain both the wide range of future global production and simultaneously the consistency of solar geoengineering's impact on global income inequality across model specification. In both cases, it is the impact on economic growth in poorer countries that drive faster economic growth under some models and consistently reduce global income inequality across all models. For example, under model specifications that are quadratic in climate variables, poorer countries, which represent a large fraction of the world's population, initially have temperatures several degrees above the estimated optimal temperature. Reducing global temperatures does little to change outcomes for richer countries clustered around the temperature optimum because of relative insensitivity to marginal changes in temperature around the optimum. However, countries far from the optimum can experience large gains due to the non-linear relationship between temperature and the economy. In linear model specifications, it is a similar mechanism where initially poorer countries drive income convergence because estimates find that only poorer countries are sensitive to changes in climate. Additionally, masking CO_2-driven warming with solar reduction reduces the equator-to-pole temperature gradient, bringing all countries' climates slightly closer.

This analysis only captures the projected economic effects of anthropogenic warming and solar geoengineering that are associated with annual-mean temperature and precipitation, two commonly reported climate indicators which were used to calibrate the empirical impacts models applied. Changes to annual mean temperature and precipitation are closely related to changes in extremes, both for GHG-driven warming [88] and solar geoengineering [77]. Impacts unaddressed by solar geoengineering, such as ocean acidification and CO_2 fertilization, and side-effects such as changes in ground-level UV, are potentially important factors in the economic assessment of both solar geoengineering and conventional climate change. Likewise, effects such as variability in extremes and sea level rise that may be addressed by solar geoengineering are outside of the scope of the empirical methodologies applied in this analysis. However, even a conservative interpretation of studies of the economic impacts associated with ocean acidification [79, 80, 89] and elevated ground-level UV [90], seem to indicate such costs would be small compared to the temperature-driven impacts of climate change.

3.2.5 Uncertainty about the significance of precipitation changes

The impacts that solar geoengineering may have on global and regional hydrological change has been a focus of considerable study and concern over the past decade [91, 92, 18, 93]. This study and others have found limited effects of precipitation on economic growth [71, 94, 95], meaning our projected outcomes are mainly driven by temperature. Both greenhouse gas-driven warming and solar geoengineering are expected to decouple the historical regional relationships between temperature and precipitation in a way that is not necessarily well-accommodated by empirical impacts models. While historically, annual precipitation and temperature are negatively correlated most areas over land (Fig. 5a), the sign of the projected relationship between precipitation and temperature changes for nearly half of all countries in the analysis (Fig. 5b, c). Lack of cross-sectional variation in correlations could prove problematic when projections are then made using a model that includes country fixed effects [96, 97] in which the value of a base climate state are aggregated with the value of non-physical properties such as economic and political institutions.

To examine the impacts of uncertainty about precipitation responses to solar geoengineering on economic outcomes, we apply the 12 individual GeoMIP climate ensemble members (Table A.2) to project GDP per capita for each climate model individually. Climate variable output from individual model ensemble members span a broader range of temperature and precipitation responses, which translates into greater uncertainty in global economic impacts (Figure A.50). However, across projections for each of the climate models, our finding that solar geoengineering reduces global income inequality still holds (Table A.5). Further, when we apply the ensemble mean temperature response and only vary precipitation response across solar geoengineering climate models to analyze sensitivity to uncertainty in the hydrological impact of solar geoengineering, we find little variation in economic impacts for the different models (Figure A.53). This suggests that, counter to common conceptions about solar geoengineering impacts, uncertainty about temperature responses is a more important driver of uncertainty about economic impacts than uncertainty about precipitation responses.

3.3 Discussion

Our findings indicate a potentially large global economic gain from solar geoengineering, if implemented. This does not necessarily indicate that a globally governed deployment strategy would resemble our stylized scenarios. Heterogeneous impacts suggest that the scenario with greatest global economic growth may not be politically feasible under a globally governed system. Furthermore, the scenario with the largest global economic gains is associated with relative losses for the lowest wealth quartile (Fig. 3). Using the methodology employed in this analysis to evaluate potential solar geoengineering by different governance structures, or lack thereof, are important topics for future research but beyond the scope of this paper.

For purposes of this analysis we generated stylized geoengineering scenarios based on those that have been widely used by climate modelers because our interest is to explore how extreme geoengineering might affect economic growth and inequality. Among the many additional important questions that are beyond the scope of the analysis is how the exact kinds of geoengineering interventions might affect these same outcomes. Already in the broader literature, some scholars have imagined ideal global geoengineering schemes while others see geoengineering emerging in more haphazard ways—initially with actions by governments that may act unilaterally and then, later, with a wider group that sees systemic responses as better than uncoordinated unilateral actions [48, 51, 98, 99]. Understanding whether and how these different kinds of deployment scenarios impact outcomes an important topic for future research [100].

Finally, these conclusions are dependent on the historically trained climate-econometric models being valid in predicting future impacts of geoengineering, but if these models are not valid for geoengineering, we should also expect them to also be invalid for GHG-driven climate change. As macroeconomic analyses have become a standard tool for climate change impact [71, 72, 73, 83], it is essential to apply these same tools to evaluate the impacts of solar geoengineering in order to evaluate policy alternatives on equal footing. If our application and results induce skepticism, this may indicate that the empirical macroeconomic impacts assessment approach is inappropriate to apply in projecting future climate damages in general, whether solar geoengineering is a component of that future change or not. If this modeling approach accurately identifies the climate-economy relationship independent of the driving cause of climate variation, then empirical macroeconomic impacts models suggest that, depending on how it is ultimately deployed, if ever, solar geoengineering could potentially ameliorate some of the projected economic impacts of warming. There is no apparent reason that this empirical modeling approach and resulting climate change impact projections would be appropriate to apply in one instance and not the other.

Our results are not consistent with several prevailing concerns about the potential impacts of climate geoengineering: that solar geoengineering favors developed countries over developing ones, that it would have large residual economic impacts, or that maintaining a climate close to present day is clearly preferable [39]. There are substantial uncertainties associated with the models applied in this study, but the reduction of inter-country inequality is consistent across all socioeconomic scenario, climate model and economic model combinations. The insignificance of precipitation that is suggested by empirical impacts models results renders large hydrological changes associated with solar geoengineering unimportant even if intuitively this appears to be a highly consequential side effect. These inconsistencies between solar geoengineering impact assessment and state-of-the-art climate econometrics need to be addressed and resolved in order to provide a sound basis for climate risk mitigation decision-making.

We have presented results based on stylized scenarios that are unlikely to be politically or legally feasible. However, the strategic incentives implied by the results highlights the need for further work on the global governance of solar geoengineering. Following the extensive body of literature on solar geoengineering governance [101], our findings underscore that a robust system of global governance will be necessary to ensure that any future decisions about solar geoengineering deployment are made for collective benefit.

3.4 Methods

3.4.1 Climate projections

The projections of anthropogenic climate change are an ensemble mean of the change in precipitation and near-surface temperature in 2081–2100 relative to 1986–2005 from all global climate models participating in CMIP5 (Figure A.1). The grid-cell level climate projections are aggregated to the country-level population-weighted means by using the grid-cell level distribution of the global population in 2000 (Figure A.1). We interpolate annual climate change for RCP 8.5 under the assumption that temperature and precipitation follow a constant linear trend from 2010 through 2100 [72]. This is consistent with temperature and precipitation trends under RCP 8.5.

The projections of changes in temperature and precipitation from solar geoengineering are constructed from the ensemble mean of 12 models contributing to GeoMIP (Table A.2) [85, 102, 103]. These projections represent the respective change in each climate indicator for a degree Celsius decrease in global temperature from solar geoengineering (Figure A.1; note that the shift in equator-to-pole temperature gradient may be different for different solar geoengineering strategies). Solar geoengineering projections are aggregated to country-level population-weighted means using the population distribution in 2000 [72]. In our illustrative scenarios, we consider two levels of solar geoengineering. The first, Geoengineering-Stabilized RCP 8.5, deploys solar geoengineering to counter increases in the global mean temperature from RCP 8.5 to stabilize the global mean temperature at 2010 levels throughout the 21st century. The second, Geoengineering-Mirrored RCP 8.5, deploys solar geoengineering to decrease the global mean temperature at the same rate it would increase under RCP 8.5 without any solar geoengineering. These two scenarios are illustrated in Fig. 1a, b.

3.4.2 Economic impact function

Our impact function estimations start with direct replications of Dell et al. [71], Burke et al. [72, 73]. For the econometric estimation of the historical climate-economy relationship, we follow the approach of Burke et al. [72]. Using historical data on interannual and inter-country variation in annual average temperature and precipitation from 1960–2010 for 165 countries [104] and GDP per capita [105], they estimate the historical non-linear relationship between key climate indicators and growth in GDP per capita. (See Table A.1 for regression results.)

3.4.3 Economic projections

For the economic projections, we follow the approach of Burke et al. [72] with a small extension. The economic projection consists of three steps. The first step is to select one of the five SSPs. This choice of an SSP determines, for each of the 165 countries, a baseline projection of population and per capita GDP growth for each year between 2010 and 2099 [86]. This baseline projection implicitly assumes that climate indicators do not change over the course of the century and therefore represents the growth profile in the no-climate-change scenario. The second step (for the remaining three scenarios that feature a change in climate conditions) is to iteratively adjust, for each country separately, the growth projection according to changes in climate indicators. The basis for this adjustment is the impact function (see Economic Impact Function above) that describes the historical climate-economy relationship. For a given year, the growth rate is modified upwards or downwards according to a country's position on the climate impact function in that year relative to their climate in 2010. In this way, we obtain a growth profile over time for each country. Finally, the third step of the economic projection is to apply these annual growth rates to the initial GDP/capita of each country in 2010 to evaluate each country's GDP/capita throughout the century.

3.4.4 Uncertainty analysis

To test consistency of our findings across specifications of the climate-economy relationship we estimate multiple impact models. While in the main text we follow the model used in the text of Burke et al. [72], the Supplementary Materials show results for a variety of alternative specifications. While the specification used in the text follows the assumption that growth rates only depend on present climate conditions, we also estimate models where economic impacts depend on climate conditions in the previous five years (lagged). In addition to using uniform impact function (pooled), we allow response functions to vary across countries by estimating models with a separate climate-economy relationship for rich and poor countries. While microeconomic evidence suggests a non-linear response structure to temperature, we estimate both linear and non-linear model specifications. Finally, since it is unclear whether the climate-economy relationship impacts levels or growth of economic output, we estimate both types of model.

To account for uncertainty in the estimated historical response functions, we use a bootstrap estimation of the econometric impact functions (N = 1000) in which countries are sampled with replacement. For median results, we use the 50% quantile projections. To describe 95% confidence intervals, we use 2.5% and 97.5% quantile results.

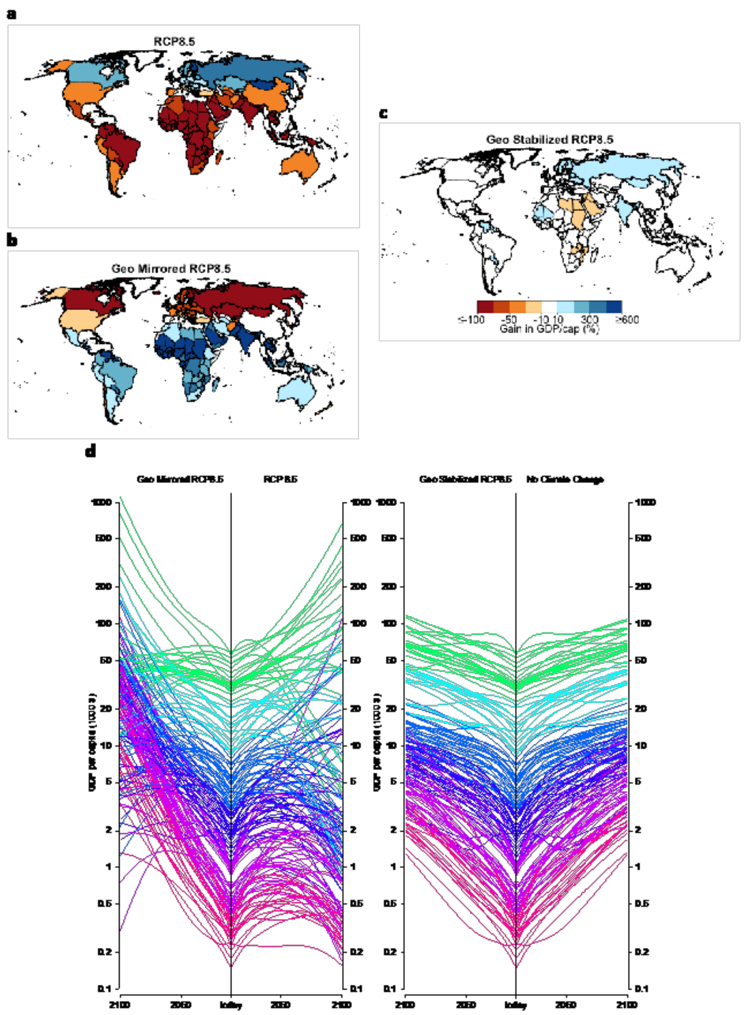


Figure 3.2: **County-level income projections over the 21st century with and without solar geoengineering.** Results are estimated using the model in column (1) of Table A.1 for Shared Socioeconomic Pathway SSP3. Projected percent gain in GDP per capita by 2100 relative to no climate changes for: **a** Geoengineering-mirrored RCP8.5, **b** RCP8.5, and **c** Geoengineering-stabilized RCP8.5 scenario. **d** the transient evolution of GDP per capita for each country over time under geoengineering-mirrored RCP8.5 and RCP8.5, as well as **e** the Geoengineering-stabilized RCP8.5 and SSP3 without climate change. Each line represents a specific country with color representing the country's initial GDP per capita in 2010. See Supplementary Materials for other SSPs, climate-economy model specifications (Figures Figure A.23 and Figure A.36).

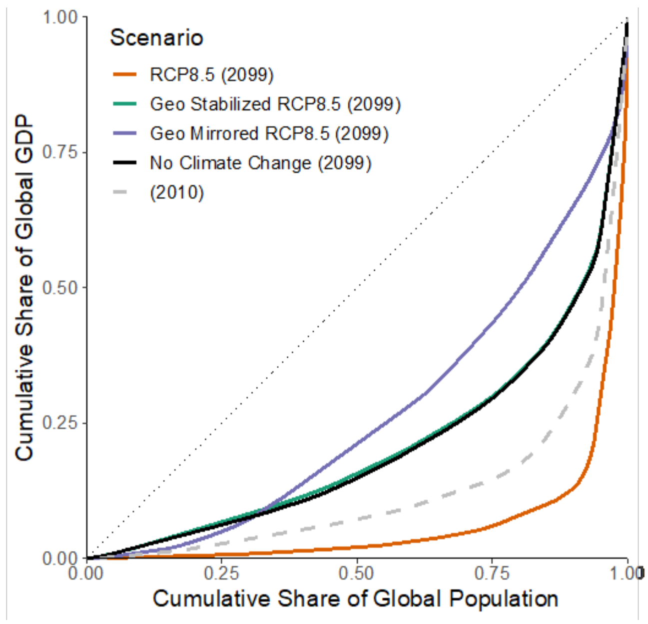


Figure 3.3: **Lorenz curves of global income distribution in 2100.** Curves are estimated using the model in column (1) of Table A.1 for Shared Socioeconomic Pathway (SSP) 3. Cumulative global income vs. cumulative global population, with global warming (RCP8.5, orange), no warming, geoengineering stabilized global temperature (geo-stabilized, green) and global cooling (geo-mirrored, purple). Lorenz curve for present day income distribution is indicated by dashed line. The distribution that would be observed with perfect equality is represented by the dotted line. See Supplementary Materials for other SSPs, climate-economy model specifications (Figure A.47).

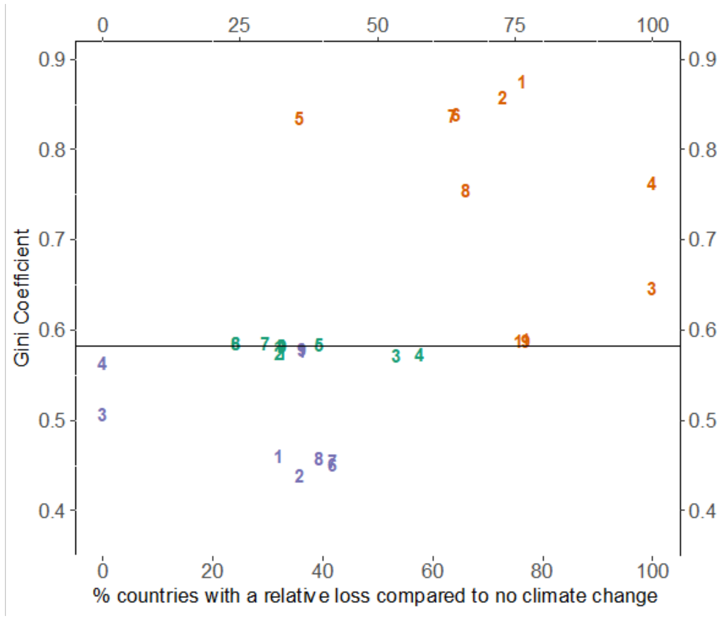


Figure 3.4: **Percentage of countries with a relative loss compared to no climate change versus country-level Gini Coefficients in 2099.** Values represent median projections for Shared Socioeconomic Pathway 3 for RCP8.5 (orange), geoengineering-stabilized RCP8.5 (green) and geoengineering-mirrored RCP8.5 (purple) simulations. Numbers represent models specified as follows: Model 1 estimates a pooled growth model with quadratic temperature and precipitation, year fixed effects, and a quadratic country time trend. Model 2 estimates a growth model with quadratic temperature and precipitation and lags up to 5 years, year fixed effects, and a quadratic country time trend. Model 3 estimates a growth model with quadratic temperature and precipitation for rich and poor countries separately, year fixed effects, and a quadratic country time trend. Model 4 estimates a growth model with quadratic temperature and precipitation for rich and poor countries separately lagged up to 5 years, year fixed effects, and a quadratic country time trend. Model 5 estimates a growth with linear temperature separately for rich and poor countries, region-year fixed effects, and no country time trend. Model 6 estimates a pooled growth model with quadratic temperature, region-year fixed effects, and no country time trend. Model 7 estimates a pooled growth model with quadratic temperature and precipitation, region-year fixed effects, and no country time trend. Model 8 estimates a pooled growth model with quadratic temperature and precipitation lagged up to 5 years, region-year fixed effects, and no country time trend. Model 9 estimates a pooled levels model with quadratic temperature and precipitation, region-year fixed effects, and a quadratic country time trend. Model 10 estimates a pooled levels model with quadratic temperature and precipitation, year fixed effects, and a quadratic country time trend. Model 11 estimates a pooled levels model with quadratic temperature and precipitation, region-year fixed effects, and no country time trend.

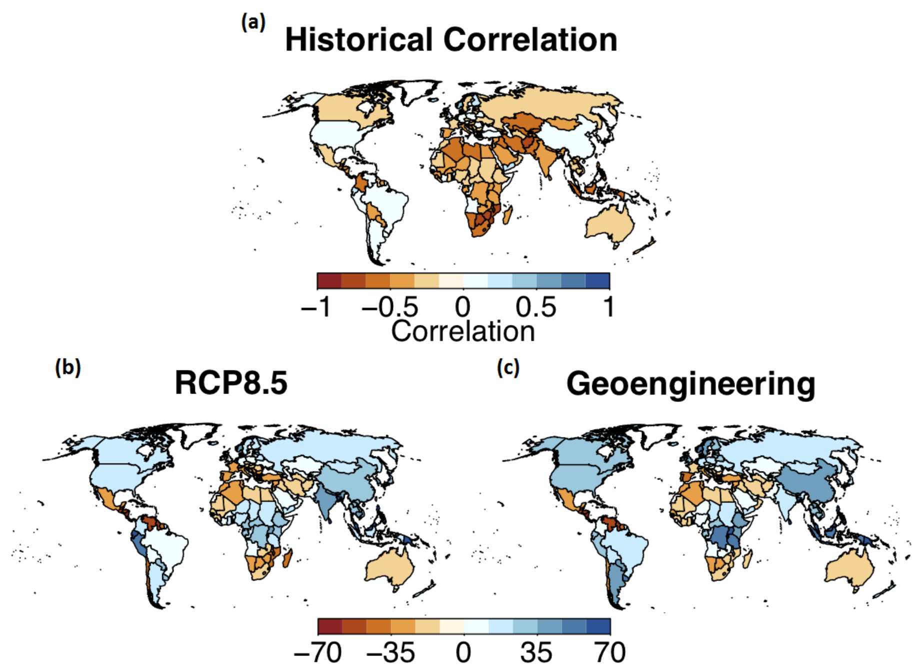


Figure 3.5: **Historical and projected relationship between surface temperature and annual precipitation.** **a** Historical correlation between temperature and precipitation. Change in precipitation relative to change in temperature projected by **b** a CMIP5 ensemble for RCP8.5 and by **c** a GeoMIP ensemble for solar geoengineering to reduce the global the mean temperature by an equal amount as the warming under RCP8.5. The sign of the projected relationship between precipitation and temperature changes for 76 of 165 countries under RCP8.5 and 73 of 165 countries under solar geoengineering.

CHAPTER 4
FROM MICRO-LEVEL WEATHER SHOCKS TO MACROECONOMIC IMPACTS

Macroeconomic empirical studies have consistently found the US, along with other developed economies, to be insensitive to weather shocks. This stands in direct contrast to prevailing microeconomic empirical findings. In this paper, I provide evidence that this empirical paradox is a consequence of the industrial composition and spatial distribution of economic activity in the US. I introduce weather shocks into a general equilibrium model and show that microeconomic labor productivity shocks driven by local weather fluctuations aggregate according to established growth accounting methods. I then construct estimates of the annual macroeconomic impacts of microeconomic weather shocks across 3,080 counties and 14 NAICS 2-digit industries in the US from 2002 to 2017 according to the growth accounting framework. I first estimate a historical relationship between weather and labor productivity growth at the county-by-industry level. I find evidence of significant but heterogeneous sensitivity to weather shocks at the microeconomic level. However, after aggregating across the industrial composition and spatial distribution of economic activity this sensitivity becomes masked by the aggregation. This result suggests that macroeconomic impact estimates may obscure important underlying heterogeneity in weather impacts.

4.1 Introduction

Precise measurement of the economic impacts of climate is a pressing issue in the face of climate change. To better understand the potential future impacts of climate change, recent empirical analyses estimate a historical relationship between climate, or more often weather, and economic activity. These studies typically approach the measurement of impacts from distinctly microeconomic or macroeconomic perspectives. For the US, and other developed economies, these two perspectives have come to contrasting conclusions.

Microeconomic studies examine causal relationships and mechanisms for the impact of climate on a variety of economic outcomes. These microeconomic analyses have found causal evidence of an impact of weather on agricultural yields [106, 82, 107] and labor productivity in industries with high climate exposure [108]. Focusing on the human physiological impacts of weather, recent evidence suggests that temperature causally impacts human capital formation [109]. These studies suggest that, at a microeconomic scale, factors and drivers of US economic activity can be sensitive to weather.

Macroeconomic studies, however, find the US and other developed economies to be insensitive to weather. In seminal work, Dell et al. (2012) and Burke et al. (2015) examine the impact of country-level weather on the growth of GDP per capita [71, 72]. Dell et al. (2012) find a significant impact of temperature on economic growth for poor countries only. Burke et al. (2015) find a non-linear relationship between temperature and economic growth with significant impacts only for countries hotter or colder than the peak growth temperature of around 13°C. Both studies find that the US, along with other rich countries in the case of Dell et al. (2012) and countries with similar temperatures in the case of Burke et al. (2015), are insensitive to weather. This insensitivity to weather for the US is robust to other measures and drivers of economic growth, including employment, capital stock, and total factor productivity [110, 111].

I develop a theoretical framework that introduces localized weather through its effect on the labor productivity of region-industry pairs. Applying this framework, I describe how the microeconomic impact of local weather shocks across the industrial composition and spatial distribution of economic activity translates into macroeconomic impacts in equilibrium. I find that the equilibrium macroeconomic impacts of a micro-level weather shock depend on a region-industry's sensitivity to weather shocks, the size of the weather shock, and the size of the region-industry, measured as their value-added share of GDP. This result is consistent with previous findings in the growth accounting literature [112]. Applying this result, I construct macroeconomic impacts of weather shocks across the US by aggregating their estimated microeconomic impacts.

Information on the historical size of weather shocks and the size of region-industries can be directly observed in data. However, the sensitivity of labor productivity to weather shocks at a microeconomic scale is unobserved, so I empirically estimate the relationship. I estimate a historical relationship between weather and novelly constructed labor productivity growth measures at the county-industry level for 3,080 US counties and 15 NAICS 2-digit industries from 2002 to 2017. To establish causal inference, I follow recent literature in applying panel data fixed effects methods [83]. At the microeconomic level, I find evidence of a heterogeneous, statistically significant, and non-linear impact of changes in temperature and precipitation on labor productivity growth. Sensitivity is largest for industries whose labor is typically more exposed to climate, such as the agriculture, mining, construction, and utilities industries. Counties that are richer and colder tend to be less sensitive to changes in weather.

Combining empirically estimated sensitivities of county-industry pairs to local weather shocks with data on the size of weather shocks and the size of county-industries as a fraction of GDP, I construct annual estimates of the macroeconomic impact of micro-level weather shocks by aggregating across the industrial composition and spatial distribution of economic activity according to the findings of my theoretical framework. I find that the sign and size of the macroeconomic impacts vary over the sample period, however annual macroeconomic impacts are consistently statistically insignificant. Decomposing macroeconomic impacts into county, industry, and county-industry contributions, I show that the significance of weather shocks diminishes when aggregated. This finding highlights the importance of considering underlying heterogeneity in macroeconomic weather shock impact estimates.

This paper contributes to bridging the gap between micro-level and macro-level analyses of climate impacts by providing a simple theoretical framework for aggregating micro-level shocks into macro-level impacts. The most closely related research is [113], who find that the spatial aggregation of highly heterogeneous precipitation levels within a country explains the lack of statistical significance of rainfall in macroeconomic analyses. The results of this paper build on this finding by showing that the spatial and industrial aggregation of highly heterogeneous weather shock impacts within a country can explain the lack of statistical significance of weather shocks in macroeconomic analyses.

This paper proceeds as follows. In section 4.2 I present a general equilibrium theoretical framework that introduces weather shocks through local labor productivity. In section 4.3 I apply the equilibrium of the model to examine the aggregate impact of micro-level weather shocks. In section 4.4 I describe the data and empirical methods used to estimate a historical relationship between weather and labor productivity growth in the US and in section 4.5 I present the results of those estimates. In section 4.6 I apply the theoretical findings of section 4.3 to aggregate the empirical estimates from section 4.5. In section 4.7 I conclude.

4.2 Theoretical Framework

A causal relationship between weather, often measured as temperature, and productivity has been well documented by empirical microeconomic studies. At the individual, firm, and regional level, these studies find a causal relationship between weather and productivity for different productivity measures, such as labor productivity, agricultural yield, and total factor productivity, across different industries [82, 114, 107, 115, 109, 116]. However, it is less clear how these microeconomic weather-driven productivity shocks aggregate into macroeconomic fluctuations.

Here, I introduce a general equilibrium theoretical framework where local weather shocks enter through labor productivity to demonstrate how local microeconomic weather shock impacts aggregate to generate macroeconomic fluctuations. The key contribution of this framework is to provide a concise and tractable description of how the microeconomic impacts of local weather shocks aggregate to generate macroeconomic fluctuations in an economy. The model identifies important channels for spillovers in impacts, such as through common labor markets and trade in intermediate inputs, which are important for the empirical identification of weather impacts as well as distributional outcomes.

I begin with a static multisector model of the economy has two sets of actors: producers and households [117, 118]. Households, characterized by a single representative consumer for the economy, inelastically provide labor to producers and consume final goods. To allow for differential weather shocks across space within the economy, I extend the model by disaggregating production across N industries and R regions. Each producer in the economy is considered to produce a distinct good based on their industry and regional location. Weather shocks are modeled to impact the economy through a supply-side shock to the labor productivity of firms local to the weather shock. In this framework, labor is modeled as the only primary factor of production, though the results are generalizable to productivity shocks to other factors of production [119].

4.2.1 Households

A homogeneous mass of households in the economy is characterized by a representative consumer with constant elasticity of substitution (CES) preferences for final goods and services. Households' sole source of income is from labor. Households inelastically supply labor endowment $\bar{L}$ and receive income $M = w\bar{L}$ based on an economy-wide wage rate w. The representative consumer's consumption is derived from the following utility maximization problem.

$$\begin{aligned} U(c_{11}, ..., c_{NR}) &= \max_{c_{11},...,c_{NR}} \left[\sum_{i=1}^{N} \sum_{r=1}^{R} \alpha_{ir}^{\frac{1}{\sigma}} c_{ir}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \\ \text{s.t. } M &= \sum_{i=1}^{N} \sum_{r=1}^{R} p_{ir} c_{ir} \end{aligned} \tag{4.1}$$

where U is the total utility of the representative consumer, c_{ir} is the consumption of final goods from industry i and region r, α_{ir} represents the households' tastes for the distinct goods and services, and p_{ir} is the price of the final good.

From the consumer's utility maximization problem in Equation (Equation 4.1), I derive the consumer's demand for each distinct final good produced in an industry i and region r from the first-order conditions as

$$c_{ir} = \alpha_{ir} \left(\frac{p_{ir}}{P_h} \right)^{-\sigma} \frac{M}{P_h} \tag{4.2}$$

P_C represents the consumer price index, which I set as the numeraire.

$$P_C = \left(\sum_{i=1}^{N} \sum_{r=1}^{R} \alpha_{ir} p_{ir}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} = 1$$

4.2.2 Producer

To analyze how micro-level shocks aggregate across industries and space, production in the economy is disaggregated across N industries and R regions. A representative producer for each industry-region pair produces a distinct good or service. With a constant-returns-to-scale CES production technology, producers choose combinations of labor, the only primary factor of production, and intermediate inputs to minimize costs. Producers are assumed to operate in a competitive market and take prices and the economy-wide wage rate as given.

To introduce weather into the model, I assume that labor productivity, A_{ir}, of each representative producer in industry i and region r is a function of the weather in their region. This follows microeconomic evidence that labor productivity is sensitive to weather. For now, I do not assume any functional form for how weather impacts labor productivity, but I do assume that the sensitivity of labor productivity to local weather is flexibly individual to each producer.

Together, the output y_{ir} of each producer in industry i and region r is given as

$$y_{ir} = \left[\gamma_{ir}^{\frac{1}{\sigma}} (A_{ir}(W_r) L_{ir})^{\frac{\sigma-1}{\sigma}} + \sum_{j=1}^{N} \sum_{s=1}^{R} \omega_{jsir}^{\frac{1}{\sigma}} x_{jsir}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{4.3}$$

where γ_{ir} is the labor share parameter, $A_{ir}(W_r)$ is labor productivity, L_{ir} is labor input, ω_{jsir} is the share parameter for intermediate inputs from representative producers in industries j and regions s, x_{jsir} is intermediate inputs from producers js, and σ is the elasticity of substitution.[1]

Given their production technology, each representative firm chooses labor and intermediate inputs given wage and prices to minimize their costs. The cost minimization problem for each sector i and region r is described as

$$\begin{aligned} &\min_{L_{ir}, x_{jsir}} wL_{ir} + \sum_{j=1}^{N} \sum_{s=1}^{R} p_{js} x_{jsir} \\ &\text{s.t. } y_{ir} = \left[\gamma_{ir}^{\frac{1}{\sigma}} (A_{ir}(W_r) L_{ir})^{\frac{\sigma-1}{\sigma}} + \sum_{j=1}^{N} \sum_{s=1}^{R} \omega_{jsir}^{\frac{1}{\sigma}} x_{jsir}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \end{aligned} \tag{4.4}$$

From the first-order conditions for the cost minimization problems given by Equation (Equation 4.4), I derive the conditional intermediate input and labor demand.

$$x_{jsir} = \omega_{jsir} \left(\frac{p_{js}}{\mu_{ir}} \right)^{-\sigma} y_{ir} \tag{4.5}$$

$$L_{ir} = \frac{\gamma_{ir}}{A_{ir}(W_r)^{1-\sigma}} \left(\frac{w}{\mu_{ir}} \right)^{-\sigma} y_{ir} \tag{4.6}$$

Here μ_{ir} is the marginal cost of producing a good in industry i and region r.

$$\mu_{ir} = \left[\frac{\gamma_{ir}}{A_{ir}(W_r)^{1-\sigma}} w^{1-\sigma} + \sum_{j=1}^{N} \sum_{s=1}^{R} \omega_{jsir} p_{js}^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{4.7}$$

[1]The elasticity of substitution is assumed to be the same as the elasticity of substitution in the consumer's utility function to allow for a closed solution. This assumption does not meaningfully change the results of the model. The appendix shows robust results for the empirics of this paper across a range of elasticities.

4.2.3 Equilibrium

Before characterizing the equilibrium of the economy, I introduce a key economic measure called the Leontief Inverse matrix, given by

$$\boldsymbol{\mathcal{L}} = [\mathbf{I} - \boldsymbol{\Omega}]^{-1} \tag{4.8}$$

where $\mathbf{I}$ is the identity matrix and $\boldsymbol{\Omega}$, known as the direct requirements matrix, is a matrix composed of the intermediate input share parameters ω_{jsir}. The Leontief Inverse is a measure of the direct and indirect interdependence of an economy. Elements $\mathcal{L}_{jsir}$ of the Leontief Inverse capture the use, both direct and indirect, of output from a producer js to produce a unit of output for producer ir.

Equations (Equation 4.1) and (Equation 4.4) fully describe the objectives of households and producers in the economy subject to the constraints they face. Following these objectives, the general equilibrium of the competitive economy is described as a collection of prices, quantities, and wage such that the following four conditions are satisfied:

1. **(Perfect Competition)** Markets are perfectly competitive, so equilibrium prices equal marginal cost, $p_{ir} = \mu_{ir} \; \forall i, r$.

2. **(Utility Maximization)** The representative consumer chooses consumption c_{ir} to solve the budget constrained utility maximization problem in Equation (Equation 4.1) given equilibrium prices p_{ir}.

3. **(Cost Minimization)** Representative producers choose factor demands L_{ir} and x_{jsir} to solve the cost minimization problem in Equation (Equation 4.4) subject to their production technology given equilibrium prices p_{ir}.

4. **(Market Clearing)** Markets for output of each region-sector pair and the labor market clear, such that $y_{ir} = c_{ir} + \sum_{j=1}^{N} \sum_{s=1}^{R} x_{irjs}$ and $\bar{L} = \sum_{i=1}^{N} \sum_{r=1}^{R} L_{ir}$.

Equilibrium Prices

I first solve for equilibrium prices in the economy by applying the assumption of perfectly competitive markets. Setting the price of output equal to marginal cost, as given in Equation (Equation 4.7), I solve for equilibrium prices in vector form as

$$\mathbf{P} = (\boldsymbol{\mathcal{L}}'\boldsymbol{\gamma}^*)^{\frac{1}{1-\sigma}} w \tag{4.9}$$

In equilibrium, price of an industry's output depends on the equilibrium wage rate, the elasticity of substitution, the productivity adjusted labor share parameter, $\gamma_{ir}^* = \gamma_{ir} A_{ir} (W_r)^{\sigma-1}$, and the Leontief Inverse. Together, the price of output for a producer is determined by the price of labor and the producer's direct and indirect demand for labor inputs.

Equilibrium Output

Next, I solve for an equilibrium measure of output by applying the market clearing condition for the output of producers. Specifically, I multiply both sides of the output market-clearing condition by p_{ir}^{σ}, substitute final and intermediate input demand from Equations (Equation 4.2) and (Equation 4.5) and solve for output measure $p_{ir}^{\sigma} y_{ir}$. In vector form, this gives

$$\mathbf{P}^{\sigma} \odot \mathbf{Y} = \boldsymbol{\mathcal{L}} \boldsymbol{\alpha} M \tag{4.10}$$

where $\odot$, called the Hadamard product, represents the element-wise multiplication of matrices.

In equilibrium, output depends on household income, M, household tastes, α_{ir}, and the Leontief Inverse. Together, the output of a producer is determined by the income of households and their demand, both direct and indirect, for output from the producer.

Equilibrium Wage Rate

Finally, I solve for the equilibrium economy-wide wage rate by applying the labor market clearing condition. Substituting conditional labor demand, given in Equation (Equation 4.6), into the equation for household income, $M = w\bar{L}$, I find the economy-wide equilibrium wage rate as

$$w = \left((\boldsymbol{\mathcal{L}} \boldsymbol{\alpha})' \boldsymbol{\gamma}^* \right)^{\frac{1}{\sigma - 1}} \tag{4.11}$$

In equilibrium, the economy's wage rate depends on the elasticity of substitution, the productivity-adjusted labor share, households' tastes, and the Leontief Inverse. Together, the equilibrium wage, or the price of labor, is determined by the demand, both direct and indirect, for labor, which is captured by the demand, both direct and indirect, for output from producers and the share of labor in those producers' output.

4.3 Comparative Statics

Having characterized the general equilibrium of the economy, in this section I perform comparative static analyses to describe the aggregation and distributional impacts of the microeconomic impacts of weather shocks.

To provide a tractable exhibition of how weather-driven microeconomic impacts affect macroeconomic outcomes in an economy, I present a comparative static analysis of an idiosyncratic weather shock to a single industry i in the region r. Specifically, I assume that all other industries j in the region r are not directly affected by the weather shock in that region. In other words, those industries are insulated from or resilient to their local weather. While these assumptions are inconsistent with reality, where weather shocks can be expected to occur throughout the economy and will affect all industries in a county dependent on their sensitivity to local weather, it allows for a clearer analysis of aggregate and distributional macroeconomic impacts of a micro-level weather shock.

4.3.1 Channels

Before presenting the aggregate and distributional impacts of an idiosyncratic weather shock, I present three channels through which weather shocks impact economic outcomes: the composition effect, the wage effect, and the scale effect. The aggregate and distributional impacts can be decomposed into a combination of these three effects.

Composition Effect

The composition effect accounts for the change in the productivity-adjusted labor input share following a weather shock. Following an idiosyncratic weather shock to producer ir, the composition effect for the producer representing industry j and region s is given as

$$\frac{\partial \log \gamma_{js}^*}{\partial W_r} = \begin{cases} (\sigma - 1)\frac{\partial \log \left(A_{js}(W_r)\right)}{\partial W_r}, & \text{if } j, s = i, r \\ 0, & \text{if } j, s \neq i, r \end{cases} \tag{4.12}$$

For all producers other than the producer in industry i and region r that is directly affected by the weather shock, the composition effect is 0. This is because those producers are not directly affected by the weather shock, and thus their labor productivity is not affected. For producer ir, the composition effect depends on the elasticity of substitution and the direct effect of the weather shock on labor productivity. If producers are complementary, $\sigma < 1$, the composition effect for producer ir a positive productivity shock gives a negative composition effect. Producer ir uses less labor to produce the same quantity of output because it needs less to produce the same amount of output while complementary producers demand more labor. If producers are substitutes, $\sigma > 1$, a positive productivity shock gives a positive composition effect. Producer ir uses more labor because it has become more productive, drawing demand away from substitute producers. In the edge case of Cobb-Douglas production technologies, $\sigma = 1$, the composition effect is 0 for all producers. This is consistent with the property that factor input shares are constant under

Cobb-Douglas production technologies.

Wage Effect

The wage effect accounts for the change in equilibrium economy-wide wage rate following a weather shock. Following an idiosyncratic weather shock to producer ir, the wage effect is given as

$$\frac{\partial \log(w)}{\partial W_r} = \lambda_{ir} \frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r} \tag{4.13}$$

where $\lambda_{ir} = \frac{wL_{ir}}{wL}$ is the share of value added in the economy provided by producer ir.

The wage effect shows that an idiosyncratic weather shock to producer ir has a proportional effect on the economy-wide wage rate, scaled by the labor compensation share, or equivalently value-added share, of producer ir relative to the economy. If a weather shock boosts the labor productivity of the producer directly affected by the shock, this increases the demand for labor in the economy, in turn increasing the value and thus the price of labor based on the size of producer ir as an employer of labor in the economy.

Scale Effect

The output effect accounts for the change in output of a producer following a weather shock. Following an idiosyncratic weather shock to producer ir, the scale effect for the producer representing industry j and region s is given as

$$\frac{\partial \log(p_{js}^{\sigma} y_{js})}{\partial W_r} = \lambda_{ir} \frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r} \tag{4.14}$$

The scale effect shows that an idiosyncratic weather shock to producer ir has a proportional effect on the output of all producers in the economy, scaled by the value-added share of producer ir relative to the value-added of the economy. If a weather shock boosts the labor productivity of the producer directly affected by the shock, this increases the wage rate of the economy, in turn increasing the income of households. This increase in income increases the demand for final goods and thus the output of producers.

4.3.2 Aggregate Impacts

I first analyze the aggregate impact of an idiosyncratic weather shock to the representative producer for industry i in the region r on the equilibrium GDP of the economy. I maintain the assumption that the idiosyncratic weather shock in the region r that only directly affects industry i in the region r to facilitate interpretation.

Theorem 4.3.1. Aggregate value-added effect

$$\frac{\partial \log(M)}{\partial W_r} = \lambda_{ir} \frac{\partial \log \left(A_{ir}(W_r)\right)}{\partial W_r} \tag{4.15}$$

Proof. See Appendix section B.2.

For an idiosyncratic weather shock to producer ir, the macroeconomic impact, measured as the change in (log) GDP of an economy, is proportional to the impact of the weather shock on labor productivity of producer ir. The weather-driven labor productivity shock is scaled by the value-added share, or share of labor compensation, of the affected producer relative to the aggregate economy. This result implies that the impact of a weather shock on a producer's labor productivity and the share of value-added of that producer are sufficient statistics for measuring how a micro-level weather shock to a producer impacts aggregate economic outcomes in an economy.

Theorem 4.3.1 is a direct consequence of the wage effect shown in Equation (Equation 4.13). The GDP of the economy, or equivalently the income of households, is equal to the wage rate times the labor endowment since labor is inelastically supplied. Thus, the impact of an idiosyncratic weather shock on aggregate household income for the economy is simply given as the impact on the wage rate since the labor endowment is constant.

This result implies that the impact of weather shocks on labor productivity and the share of value-added of a producer are sufficient statistics for how micro-level weather shocks to a producer impact aggregate economic outcomes in an economy. This finding is consistent with previous theoretical findings for the macroeconomic impacts of micro-level productivity shocks [112]. As discussed by [120], to a first-order approximation for any constant returns to scale production technology in a competitive economy, a factor-augmenting shock impacts aggregate output proportionally to the cost of the factor for the producer as a share of GDP of the economy.

4.3.3 Distributional Impacts

Here I analyze the distributional impacts of an idiosyncratic weather shock on the value-added of producers throughout the economy. This highlights important channels of reallocation and spillovers following micro-level weather shocks.

Before describing these distributional impacts, I provide an important measure, which I term the labor demand effect. This measure captures the change in labor input for a producer following an idiosyncratic weather shock. Applying the equation for labor demand, given in Equation (Equation 4.6), the labor demand effect can be further disaggregated into a composition effect, wage effect, and scale effect. Together, the change in labor demand for producer js following an idiosyncratic weather shock to producer ir is given as

$$\frac{\partial \log(L_{js})}{\partial W_r} = \begin{cases} (\lambda_{ir} - 1)(1 - \sigma)\frac{\partial \log\left(A_{ir}(W_r)\right)}{\partial W_r}, & \text{if } j, s = i, r \\ \lambda_{ir}(1 - \sigma)\frac{\partial \log\left(A_{ir}(W_r)\right)}{\partial W_r}, & \text{if } j, s \neq i, r \end{cases} \tag{4.16}$$

The change in labor demand for producer js depends on the value-added share of producer ir relative to the economy, the elasticity of substitution, and the size of the impact of the weather shock on labor productivity for producer ir. Since, by definition, $\lambda_{ir} < 1$, the sign of the impacts critically depend on the elasticity of substitution.

The intuition of the labor demand effect is as follows. I first consider complementary factors of production, where $\sigma < 1$. Consider a weather shock that boosts labor productivity for producer ir. As a result, labor input decreases for producer ir and increases for complementary intermediate inputs $js \neq ir$. Following a productivity shock to producer ir, there is an increase in demand for its output as well as producers of complementary intermediate inputs. Since producer ir requires less labor input to provide the same quantity of output, labor shifts from producer ir to other producers js.

Next, I consider substitute factors of production, where $\sigma > 1$. Consider a weather shock that boosts labor productivity for producer ir. As a result, labor input increases for producer ir and decreases for substitute intermediate inputs $js \neq ir$. Following a productivity shock to producer ir, there is an increase in demand for its output and a decrease in demand for producers of substitute intermediate inputs. As a result, producer ir requires more labor input to satisfy the increase in demand. Thus, labor shifts from other producers js to producer ir.

Finally, I consider the case of Cobb-Douglas production technologies, where $\sigma = 1$. In this edge case, the labor demand effect is 0 for all producers. This directly follows from the properties of Cobb-Douglas production technologies where the distribution of factor inputs is constant across producers.

Following from the assumption that labor is the only primary factor of production, the value-added of a producer is given by the economy-wide wage rate time their labor input. Thus, the value-added effects that I analyze next are composed of a wage effect given by Equation (Equation 4.13) and the labor demand effect.

Own Effect

I first describe the effect of an idiosyncratic weather shock to producer ir on its value added.

Theorem 4.3.2. Own value-added effect

$$\frac{\partial \log(wL_{ir})}{\partial W_r} = \Big((\sigma - 1) + \lambda_{ir}(2 - \sigma)\Big)\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r} \tag{4.17}$$

Proof. See Appendix section B.2.

Theorem **??** illustrates that the change in value-added for producer ir following an idiosyncratic weather shock to that producer depends on the size of the resulting labor productivity shock, the elasticity of substitution, and the size of the producer measured as their share of value-added.

To describe the intuition of the own-value added effect, I first consider the case of complementary producers, where $\sigma < 1$. Considering a weather shock that boosts the labor productivity of producer ir, the net sign of the value-added effect is indeterminant. In the case of complementary producers, the wage effect and the labor demand effect work against each other. When the producer represents a large fraction of the economy, the value-added effect is more likely to be positive because the wage effect becomes stronger. When the producer is small, the change in productivity has a smaller effect on the overall wage of the economy and the labor demand effect dominates.

Next, consider the case of substitute factors of production and final goods, where $\sigma > 1$. In this case, the wage effect and the labor demand effect work in the same direction. Considering a weather shock that boosts the labor productivity of producer ir, the value-added effect is positive, meaning that the change in productivity proportionally translates into an increase in value-added.

Finally consider the edge case of Cobb-Douglas production technologies, where $\sigma = 1$. In this case, the labor demand effect becomes 0 because of the properties of Cobb-Douglas technologies as discussed above. As a result, the own-value added effect becomes equivalent to the wage effect.

Spillover Effect

Next, I describe the effect of an idiosyncratic weather shock to producer ir on the value-added of other producers, $js \neq ir$. Since these industries are assumed to not directly experience weather shocks, these effects constitute spillover impacts of a weather shock through the general equilibrium economy.

Theorem 4.3.3. Indirect value-added Effect

$$\frac{\partial \log(wL_{js})}{\partial W_r} = \lambda_{ir}(2-\sigma)\frac{\partial \log\left(A_{ir}(W_r)\right)}{\partial W_r} \tag{4.18}$$

Proof. See Appendix section B.2.

Following an idiosyncratic weather shock to producer ir, the change in value-added of other producers js depends on the size of the resulting labor productivity shock, the elasticity of substitution, and the size of producer ir measured as their share of value-added.

To describe the intuition of the indirect-value added effect, I first consider the case of complementary producers, where $\sigma < 1$. Considering a weather shock that boosts the labor productivity of producer ir, the net sign of the value-added effect is positive. This suggests that a positive weather-driven labor productivity shock to producer ir increases the value-added of other producers js. In the case of complementary producers, the sign of the indirect-value added effect is unambiguous because the wage effect and the labor demand effect work in the same direction.

Next, consider the case of substitutable producers, where $\sigma > 1$. In this case, the wage effect and the labor demand effect work against each other. Considering a weather shock that boosts the labor productivity of producer ir, the value-added effect is positive for any elasticity of substitution less than 2. When producers are less substitutable, the wage effect dominates the labor demand effect. However, for sufficiently substitutable producers, $\sigma > 2$, the labor demand effect begins to dominate the wage effect, and the sign of the indirect value-added becomes negative.

Finally, consider the edge case of Cobb-Douglas production technologies, where $\sigma = 1$. In this case, the labor demand effect becomes 0 because of the properties of Cobb-Douglas technologies as discussed above. As a result, the indirect-value added effect becomes equivalent to the wage effect.

These comparative static analyses provide two key takeaways. The first takeaway is that aggregating the microeconomic impacts of weather shocks throughout an economy into macroeconomic impacts requires information on just the microeconomic impacts of weather shocks on primary factors of production, such as labor productivity, and the size of the economic agents, producers, affected. In the empirical analysis below, I apply the findings of Theorem 4.3.1, using data on the size of producers and empirical estimates of the impact of weather on their labor productivity to construct estimates of the macroeconomic impacts of weather shocks for the US economy.

The second key takeaway is that the economic variable of interest used in empirical analyses of weather impacts is important. Often empirical studies of the impact of weather shocks on economic outcomes focus on value-added as an outcome of interest, the dependent variable in regression analyses. Theorem **??** importantly illustrates that how weather shocks translate into impacts on value-added depends critically, both in magnitude and sign, on fundamental characteristics of the economy, such as the substitutability of producers, and the granularity of the study. Further, Theorem **??** illustrates that, in general equilibrium, weather shocks can spillover through the economy. This suggests that using an equilibrium economic measure such as value-added rather than an economic determinant such as labor productivity as the outcome of interest could lead to biased estimates.

4.4 Empirical Context

In this section, I introduce the empirical setting in which I demonstrate how to aggregate microeconomic weather impacts into macroeconomic impacts following the theoretical framework above. In this quantitative exercise, I estimate the macroeconomic impacts of weather shocks across the United States from their local microeconomic impacts on labor productivity at the county-industry level. I focus on impacts through labor productivity because of the abundance of empirical evidence documenting a causal relationship and due to data availability limitations [108, 109]. From Theorem 4.3.1, this analysis requires information on the size of county-industry producers, the size of the weather shocks, and the sensitivity of labor productivity growth to local weather shocks. The first two can be measured with data. The last I empirically estimate. Below I present the data I use in the analysis.

4.4.1 Economic Data

To measure the economic size of region-industries and their labor productivity growth, I use data provided by the Bureau of Economic Analysis (BEA). This data covers 15 2-digit NAICS industry classifications across 3,080 counties in the contiguous United States from 2001 to 2017. These industry classifications span agriculture, manufacturing, and services and are listed in Table B.1. For this analysis, I drop the government industry. The economic size of county-industries, represented by value-added, is provided directly by the BEA. Labor productivity growth at the county-industry level, however, is not. Thus, I construct a novel measure of county-industry labor productivity growth as described below. Panel **A** of Table 4.1 presents the summary statistics of the economic data used in the empirical analysis.

Due to the level of resolution for these measures, the BEA censors select observations primarily based on their size for privacy concerns. These censored data comprise only around 2% of the aggregate GDP in any year, suggesting that they will have little impact on the aggregate impacts estimates constructed below. I also argue this censorship is unlikely to bias empirical estimates of the sensitivity of labor productivity growth to weather shocks because the data is not censored based on labor productivity growth, the constructed variable of interest.

Labor Productivity

For data on labor productivity growth at the county-industry resolution level, I construct a novel dataset of labor productivity growth measures for 14 2-digit NAICS industries across

Table 4.1: Summary Statistics

Panel A: Economic	Mean	Std. Dev.	Min	Max
Year	2009	4.9	2001	2017
Value Added per capita ($US2012)	3,461.0	90,924.4	0	48,648,796
Growth Value Added per capita	0.00821	0.276	-7.898	9.359
Population	98,646.1	315,531.8	55	10,120,540
Employed	4,933.0	19,725.8	0	986,040
Growth Labor Productivity	0.0222	0.841	-19.63	20.23
Compensation	225,131.4	1,269,437.0	0	123,169,232
Industry Value Added	992.8	816.4	95.60	4,088.5
Industry Gross Output	1,771.1	1514.7	195.5	6,590.8
Growth Industry Gross Output Price Index	0.0233	0.0549	-0.315	0.265
Panel B: Weather	Mean	Std. Dev.	Min	Max
Temperature (°C)	12.66	4.530	1.339	25.10
Precipitation (mm/year)	97.32	36.55	4.842	222.8
Mean Temperature (°C)	12.66	4.477	3.228	24.32
Mean Precipitation (mm/year)	97.32	32.97	13.56	185.1
Δ Temperature (°C)	0.0320	0.886	-3.362	2.910
Δ Precipitation (mm/year)	0.570	23.54	-107.6	92.14

Unit of observation is a county in a year. There are 3,080 counties, 15 industries, and 17 years, totalling 785,400 observations.

counties in the United States. Due to the high correlation in weather across space, how this measure is constructed is important for generating unbiased estimates of the sensitivity of labor productivity growth to weather shocks.[2]

Starting with the assumption of perfect competition, which implies that labor is compensated its marginal product, I derive a measure of labor productivity growth that will provide unbiased estimates of sensitivity to weather shocks under the CES production technology from Equation (Equation 4.3). Solving for labor productivity and differencing to get labor productivity growth gives[3]

$$\Delta \log(A_{irt}(W_{rt})) = \frac{\sigma}{\sigma - 1}\Delta \log\left(\phi_{irt}\right) + \Delta \log\left(\frac{p_{irt}y_{irt}}{L_{irt}}\right) - \Delta \log\left(p_{irt}\right) \tag{4.19}$$

[2]See Appendix section B.2 for a discussion of bias in empirical estimates based on labor productivity growth measure.

[3]The derivation of this measure is in Appendix section B.2

where $\phi_{irt} = \frac{wL_{irt}}{p_{irt}y_{irt}}$ represents the fraction of sales revenues that go to the compensation of labor. This result suggests that labor productivity growth can be captured by the combination of the growth in labor compensation as a fraction of sales and the growth of sales relative to physical labor input, controlling for price changes.

From Equation (Equation 4.19), constructing a measure of county-industry labor productivity growth requires data on the elasticity of substitution (σ), labor compensation (wL_{irt}), labor input (L_{irt}), gross output ($p_{irt}y_{irt}$), and prices (p_{irt}). I set the elasticity of substitution to $\sigma = 0.5$ following previous empirical estimates [121, 122].[4] Data on labor compensation and labor input for county-industries is directly observable in data provided by the BEA. However, data on gross output and prices are not available at the county-industry level, they are only reported at the industry level.

To get an approximate measure of county-industry prices, I assume that for a given industry i, all counties r face the same growth of prices for output of that industry. That is, I assume

$$\Delta \log \left(p_{irt}\right) = \Delta \log \left(p_{it}\right)$$

The growth of industry-level price indices is directly observable, as reported by the BEA.

To approximate county-industry gross output, I assume that the gross output for each region r in industry i is proportional to the gross output of the aggregate industry based on the region r's share of the aggregate value-added of the industry. That is, I assume

$$p_{irt}y_{irt} = \kappa_{irt}p_{it}y_{it}$$

where $\kappa = \frac{VA_{irt}}{VA_{it}}$ is the proportional scaling factor.

Together, applying these assumptions, I construct an approximate measure of county-

[4]The appendix provides a sensitivity analysis with respect to the elasticity of substitution.

industry level labor productivity growth as

$$\Delta \log(A_{irt}(W_{rt})) = \frac{\sigma}{\sigma - 1}\Delta \log\left(\frac{w_t L_{irt}}{\kappa_{irt} p_{it} y_{it}}\right) + \Delta \log\left(\frac{\kappa_{irt} p_{it} y_{it}}{L_{irt}}\right) - \Delta \log\left(p_{it}\right) \quad (4.20)$$

To provide suggestive evidence of the validity of this labor productivity growth measure, Figure 4.1 displays county-industry labor productivity growth in 2005 measured based on Equation (Equation 4.20) against the commonly used labor productivity measure of the ratio of value-added to labor input. There is a high but imperfect correlation between the measures. Across the sample years, the measures share a correlation coefficient of 0.92.

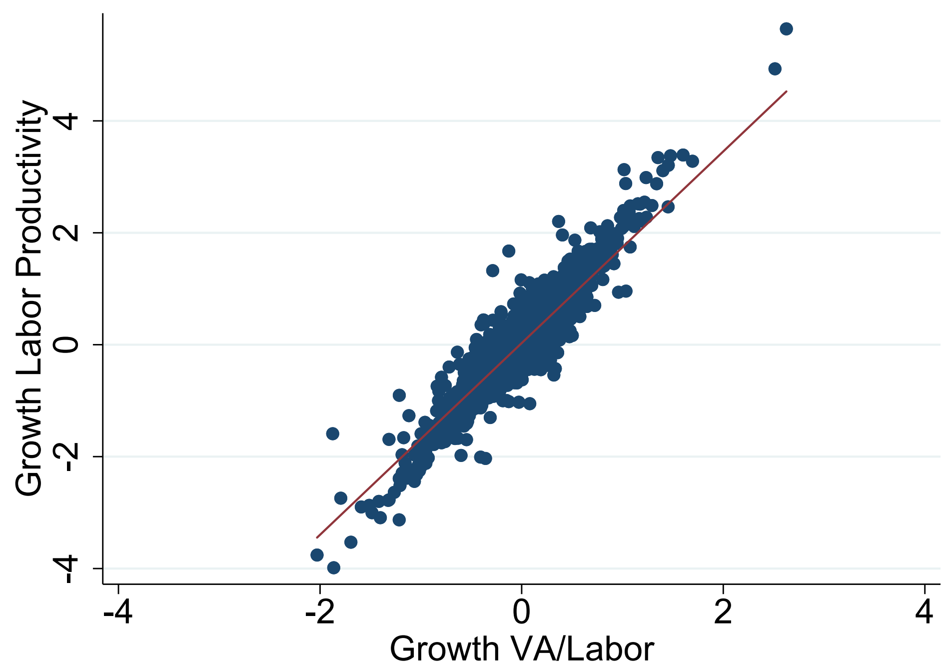


Figure 4.1: **Growth of Labor Productivity Measures in 2005** Growth of labor productivity versus growth of value added per labor employment in 2005.

4.4.2 Weather Data

To measure weather shocks, I follow previous work in using aggregate measures of temperature and precipitation as a proxy. Specifically, I use population-weighted measures of country-level annual mean temperature and precipitation from *Terrestrial Air Tempera-*

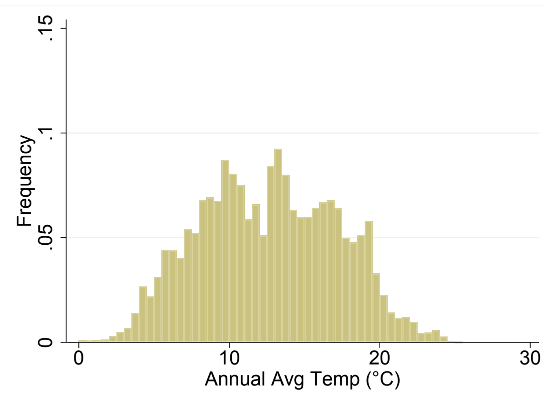
ture and Precipitation: 1900-2017 Gridded Monthly Time Series (version 5.01) [123, 71, 72, 110]. These gridded temperature and precipitation measures come from interpolated weather station data and have a resolution of 0.5×0.5 degrees, or about 56km$\times$56km at the equator. Concerns of biased estimates from the use of weather station data are unlikely to apply since this analysis focuses on the US [124]. I aggregate the gridded weather measures to annual population-weighted county-level measures using gridded population data for 2000 [71]. This weighting accounts for the spatial heterogeneity in the importance of weather fluctuations, giving greater weight to areas where there are more people, and thus, often more production.

While economic data is at the county-industry level, due to lack of spatial data for the economic activity of industries within a county, weather data for each industry within a county is proxied by weather at the county-level. On average, a county in the US is around 1,000 miles^2 and within a county there is a high correlation in weather fluctuations year to year. This suggests that county-level measures of weather are a good proxy for weather fluctuations for industries within each county.

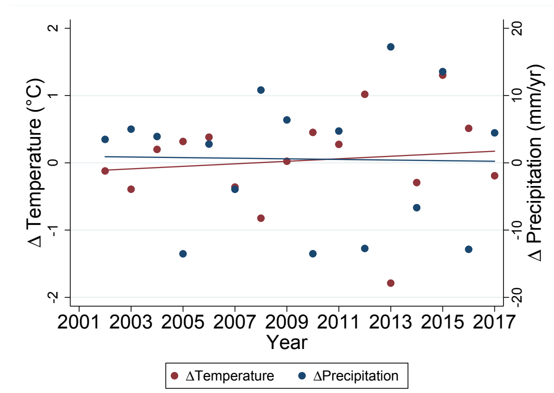
Panel **B** of Table 4.1 displays the weather-related summary statistics for the counties analyzed in this paper. Figure 4.2 displays the distribution of population-weighted annual average temperature observations as well as a simple average of county-level changes in population-weighted temperature over the sample period. The summary statistics and figures show that there is significant variation in temperature and weather observations across the sample. Further, there is significant variation and fluctuation in the year-to-year changes in temperature and precipitation with a slight average increase in temperatures over the sample period.

4.5 Empirical Estimation

With data on the economic size of producers and the size of weather shocks, I lastly need information on the sensitivity of labor productivity to local weather shocks. Here, I estimate



(a)



(b)

Figure 4.2: **Weather Data (a)** displays the distribution of temperature observations across counties and years in the sample. **(b)** displays the simple average of annual county temperature and precipitation changes in the sample.

a causal relationship between county-industry labor productivity growth and local weather shocks using panel data fixed effect methods. I follow the regression model of [110] and estimate different variations of the following regression estimation equation.

$$\Delta \log(A_{irt}) = \alpha_{ir} + \alpha_t + \beta_1 \Delta \text{Temp}_{rt} + \beta_2 \Delta \text{Precip}_{rt} + \epsilon_{irt} \tag{4.21}$$

On the left-hand side of the regression equation is growth in labor productivity in an industry i in county r at time t. On the right-hand side are county-industry fixed effects α_{ir}, time fixed effects α_t, and changes in temperature and precipitation. Panel data fixed effects methods exploit the exogeneity of weather fluctuations, allowing for the identification of a causal relationship between weather and economic outcomes. While this approach has been employed in a variety of settings (see [83] for a review), the appropriate choice of functional form for the estimating equation is still debated.

The inclusion of panel data fixed effects controls for potential omitted variables that could bias the coefficient of interest, β_1 and β_2. County-industry fixed effects control for factors that are specific to each county-industry pair and time-invariant over the sample, such as policy differences or demographic differences. Year fixed effects control for time-varying shocks that are common to all county-industries, such as a recession. Once controlling for these fixed effects, identification of the relationship of interest relies on the exogeneity of weather fluctuations and the assumption that any drivers of county-industry deviations in labor productivity are not correlated with weather shocks.

I estimate a growth effect for labor productivity for two reasons. First, by differencing the left-hand-side, we alleviate potential concerns of non-stationarity. Not controlling for the non-stationarity of productivity growth could lead to spurious results. Second, recent empirical estimates comparing the growth and level effects of weather shocks on economic outcomes provide evidence of weather shocks having a growth effect ([71]).

4.5.1 Pooled Estimates

I begin with a pooled estimate of Equation (Equation 4.21). This model assumes a homogeneous relationship between weather shocks, measured as temperature and precipitation changes, and labor productivity growth for all county-industry pairs.

Table 4.2: **Linear Labor Productivity Sensitivity Sigma 0.5**

	Labor Productivity Growth Rate
Δ Temp	0.386
	(0.376)
Δ Precip	0.00839
	(0.00488)
Obs.	457,625
R sq.	0.0696

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Temperature is measured in C. Precipitation is measured in mm/year. The unit of observation is a county-industry in a year. Regression includes county-by-industry fixed effects and state-by-year fixed effects. Standard errors are clustered by county and industry.

The results of this estimation are shown in Table 4.2. The temperature coefficient suggests that a 1°C increase labor productivity growth rates by 0.39%. An increase in temperature of 0.66°C, the average change in temperature in a given year across counties in the sample, would increase labor productivity growth rates by 0.26%. However, I find no evidence of a statistically significant relationship between weather shocks and labor productivity growth rates for these pooled estimates. This is consistent with previous macroeconomic estimates that have found no significant relationship between temperature and economic growth for the United States [71, 72]. The same holds for precipitation.

4.5.2 Differences Across Industries

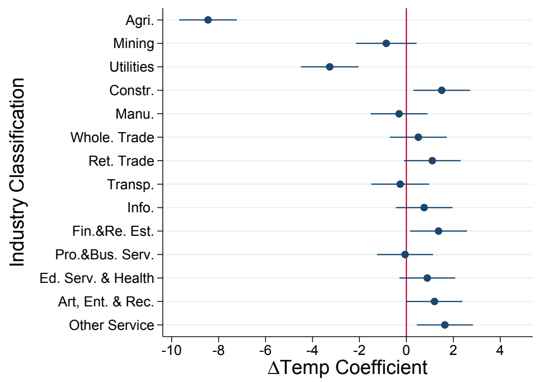
The nature of production in each industry is considerably different, so it is naive to expect the sensitivity of labor productivity to weather shocks across industries to be homogeneous. For example, industries with greater exposure to outdoor weather, such as agriculture, mining, utilities, construction, and manufacturing, are likely to be more sensitive to weather shocks [108].

To account for a heterogeneous relationship between weather shocks and labor productivity growth across the 14 different NAICS 2-digit industries, I estimate a model that allows for heterogeneous relationships between weather changes and labor productivity growth for each industry. This regression estimating equation takes the form

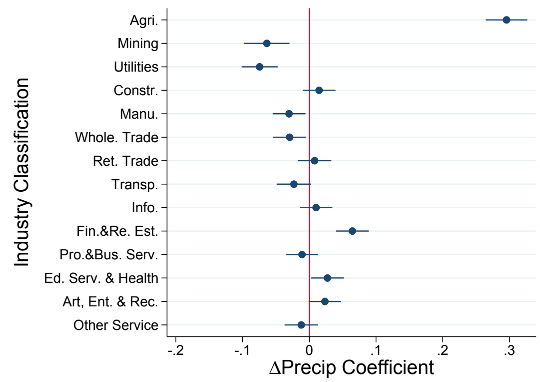
$$\Delta \log(A_{irt}) = \alpha_{ir} + \alpha_t + \sum_{i=1}^{15} \left(\beta_i^T \Delta \text{Temp}_{rt} + \beta_i^P \Delta \text{Precip}_{rt} \right) + \epsilon_{irt} \tag{4.22}$$

$$\begin{aligned} \Delta \log(A_{irt}) = & \sum_{i=1}^{15} \left(\beta_{i1}^T \Delta \text{Temp}_{rt} + \beta_{i1}^P \Delta \text{Precip}_{rt} \right) \\ & + \sum_{i=1}^{15} \overline{\text{Temp}}_{rt} \times \left(\beta_{i2}^T \Delta \text{Temp}_{rt} + \beta_{i2}^P \Delta \text{Precip}_{rt} \right) + \alpha_{ir} + \alpha_t + \epsilon_{irt} \end{aligned} \tag{4.23}$$

Figure 4.3 displays the regression coefficient estimates for Equation 4.23 and 95% confidence intervals. Contrary to the pooled response, these results provide suggestive evidence of a statistically significant and heterogeneous relationship between weather shocks and labor productivity growth rates across industry classifications.



(a) Temperature Coefficients.



(b) Precipitation Coefficients.

Figure 4.3: **Heterogeneous Industry Response** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification with 95% confidence intervals. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0737.

Consistent with previous empirical findings, industries that are likely to have higher exposure to outdoor weather are also found to be the most sensitive to weather shocks, both in terms of temperature and precipitation changes. For example, agriculture is found to be the most sensitive. Results suggest that a 1°C increase in annual temperature decreases labor productivity growth rates for agriculture production in a county by around 8.4%. A 10mm increase in annual precipitation in a county increases agriculture labor productivity growth rates by around 3%. For the utilities industry, a 1°C increase in temperature in a county decreases labor productivity growth rates by 3.3% and a 10mm increase in annual precipitation in a county decreases labor productivity growth rates by 0.74%. These results suggest a need for industrial disaggregation to allow for heterogeneous responses to weather shocks.

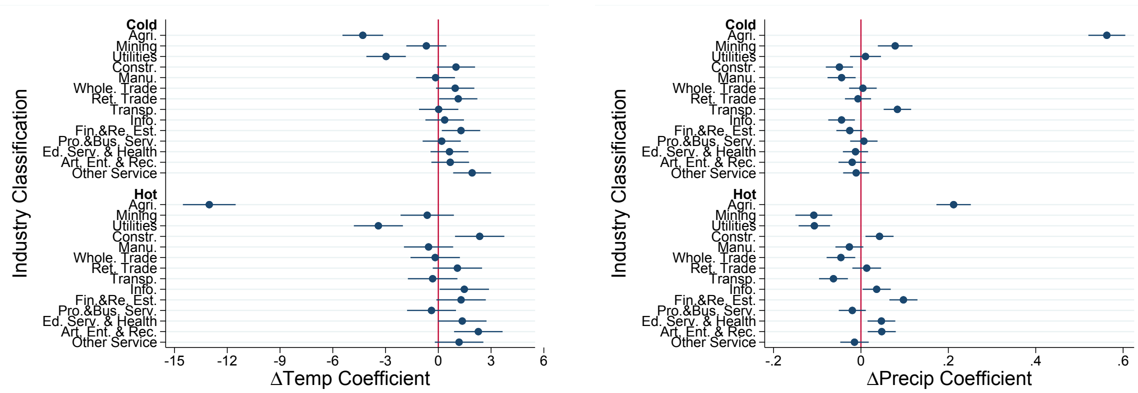
I find evidence that the relationship between weather shocks and labor productivity growth rates varies across industry classifications not just in magnitude but also in sign. Labor productivity growth in some industries is found to be harmed by increases in temperature, while others benefit. Exploring mechanisms for the heterogeneous relationships between weather shocks and factor productivities is an important area for future work.

4.5.3 Differences in Climate

The above estimates allow for heterogeneous sensitivity across industry classifications, however, it maintains a pooled response within industry classifications across the spatial distribution of economic activity across the United States. As with industrial composition, it is naive to consider a homogeneous response across US counties. For example, there may be a difference in sensitivity to weather shocks across counties on the basis of climate. A 1°C increase in temperature in Koochiching, MN where the average annual temperature is below 2°C can be expected to have a different effect than a 1°C increase in temperature in Palm Beach, FL where the average annual temperature is above 24°C. Thus, I next estimate a new empirical model that allows for differential responses both across industry classification and across counties based on whether a county is a hot county, where a hot county is defined as having an average temperature over the sample above the median of around 13°C. In this application, a county's average temperature is used as a proxy, though an imperfect one, of a county's climate.

Figure 4.4 displays the regression coefficient estimates and 95% confidence intervals differentiated by industry classification and separately for hot and cold counties. These results provide further evidence of heterogeneous sensitivity to temperature and precipitation changes across industries, consistent with the estimates shown in Figure 4.3. Again, industries that are more likely to be exposed to outdoor weather, such as agriculture, mining, utilities, and construction have a higher sensitivity to weather shocks.

Comparing regression coefficient estimates between hot and cold counties across the different industry classifications suggests that there is some evidence of a differential response to weather shocks across counties based on their average temperature over the sample. However, the differences in response, both sign, magnitude, and significance, varies



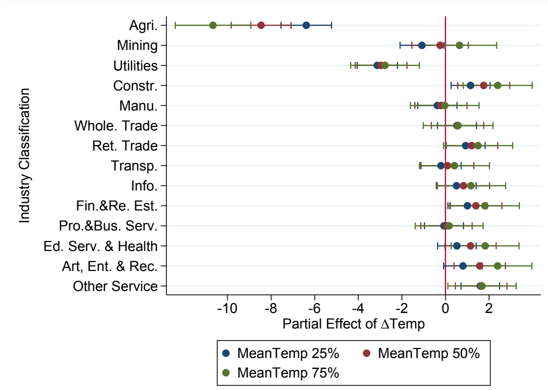
(a) Temperature Coefficients.

(b) Precipitation Coefficients.

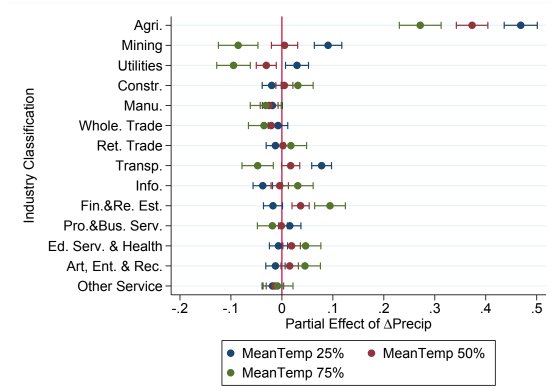
Figure 4.4: **Heterogeneous Industry Response by Hot/Cold** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification and hot/cold counties with 95% confidence intervals. Hot counties are those with mean temperatures above the median. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0749.

across industries. For temperature sensitivity, being a hot county significantly increases sensitivity for agriculture; construction; information; educational services, health care, and social assistance; and arts, entertainment, and recreation. However, wholesale trade and other services are found to be less sensitive to temperature changes in hot counties. For precipitation sensitivity, utilities; wholesale trade; educational services, health care, and social assistance; arts, entertainment, and recreation are more sensitive to changes in precipitation in hot counties. Agriculture is found to be less sensitive to precipitation changes in hot counties. For mining, construction, transportation, information, the sign of the relationship changes between hot and cold counties. Though not true for all industries, most industries appear to be more sensitive to weather shocks in hotter counties. This again suggests the importance of allowing for heterogeneous responses across industry classifications.

To allow for greater flexibility in heterogeneous sensitivity to weather shocks across counties on the basis of their climate, proxied by a county's average temperature over the sample period, I estimate a non-linear relationship that includes an interaction of changes in temperature and precipitation with a county's mean temperature over the sample period.



(a) Temperature Coefficients.



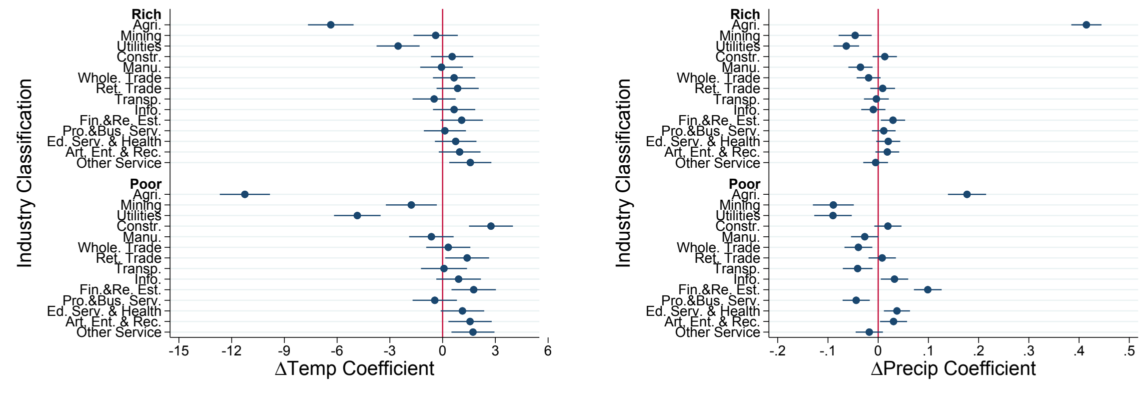
(b) Precipitation Coefficients.

Figure 4.5: **Heterogeneous Industry Response by Mean Temperature** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification and county mean temperature with 95% confidence intervals. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0748.

Figure 4.5 shows the results of interacting ΔTemperature and ΔPrecipitation with a county's average temperature. Specifically, I plot the partial effects of the coefficient estimates for each industry classification across counties in the 25th, 50th, and 75th percentile of average temperature along with the 95% confidence intervals. I find a heterogeneous relationship across industry classifications and a non-linear relationship across counties that is consistent with the hot dummy variable estimation approach.

4.5.4 Differences in Income

Previous empirical studies of the effect of weather on economic outcomes have found evidence that economic development can be an important determinant of the sensitivity of a region to weather [71, 110]. For example, regions with higher income levels may have a greater ability to invest in adaptation mechanisms to reduce climate sensitivity. Thus, I examine for any evidence of differential sensitivity to weather shocks across counties on the basis of their economic status. Specifically, I first estimate a new regression model that includes an interaction between changes in temperature and precipitation with an indicator variable for poor counties, where a county is indicated as poor if its mean income per capita for the sample period is below the median of around \$15,000.



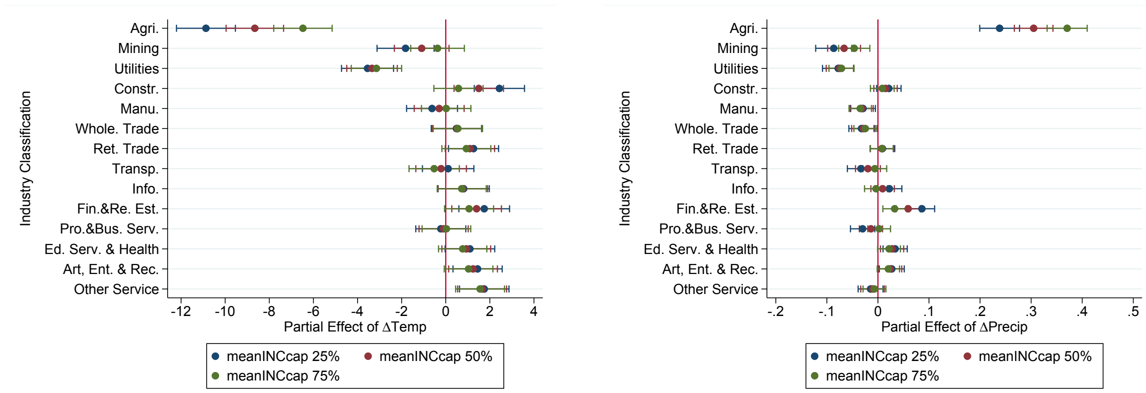
(a) Temperature Coefficients.

(b) Precipitation Coefficients.

Figure 4.6: **Heterogeneous Industry Response by Rich/Poor** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification and rich/poor counties with 95% confidence intervals. Counties are considered poor if the mean income per capita is below the median. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0742.

Figure **??** displays the regression coefficient estimates and 95% confidence intervals differentiated by industry classification as well as by poor and rich counties. Comparing the regression coefficients between poor and rich counties across the different industry classifications suggests that differences in economic development or status on the basis of its average income per capita can be an important factor in determining the impact of a weather shock. Unlike hot versus cold counties, across nearly every industry classification poor counties are more sensitive to weather shocks, both temperature changes or precipitation changes. This result suggests that even in the United States, a developed economy, differences in economic status across regions of the country can be important for the impact of weather shocks.

To allow for greater flexibility in heterogeneous sensitivity to weather shocks across counties on the basis of their economic status or development, I estimate a non-linear relationship that includes an interaction of changes in temperature and precipitation with a county's mean income per capita over the sample period.



(a) Temperature Coefficients. (b) Precipitation Coefficients.

Figure 4.7: **Heterogeneous Industry Response by Mean Income per capita** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification and county mean income per capita with 95% confidence intervals. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0743.

Figure 4.7 shows the results of interacting ΔTemperature and ΔPrecipitation with a county's average income per capita. Specifically, I plot the estimated partial effect of ΔTemperature for each industry for counties in the 25th, 50th, and 75th percentile of average income per capita along with the 95% confidence intervals. Again there is evidence of a heterogeneous response to weather shocks both across industries and across counties with poorer counties typically more sensitive to weather shocks than richer counties.

4.6 Aggregate Impacts

In this section, I construct macroeconomic estimates of the microeconomic impacts of climate shocks across the United States. From Theorem 4.3.1, the aggregate impact of a microeconomic weather shock is equal to the product of the size of the producer, measured as their share of GDP in the economy, and the effect of the local weather shock on their labor productivity. To construct these estimates I combine data on the economic size of county-industries and the size of the weather shocks discussed in section 4.4 with the estimated sensitivity of labor productivity growth rates to local weather shocks from section 4.5.

To construct an estimate of the macroeconomic impacts for the US in any given year from the micro-level weather shocks, I sum the contributions of the microeconomic impacts to macroeconomic growth across spatial distribution and industrial composition. Specifically, building on Theorem 4.3.1 I calculate the macroeconomic impact of weather shocks in discrete form for a year t as

$$\Delta M_t = M_{t-1} \sum_{i=1}^{N} \sum_{r=1}^{R} \lambda_{irt-1} \hat{\beta}_{it} \Delta f(W_{rt}) \tag{4.24}$$

With data on λ_{irt-1}, the share of GDP, and $\Delta f(W_{rt})$, the change in relevant weather variables, and empirical estimates of β_{it}, the sensitivity of local labor productivity to changes in weather, I calculate the annual macroeconomic impacts of weather shocks in the US over the sample period. This impact on macroeconomic growth is converted into a dollar impact by taking the product with GDP in the previous period.

Figure (Figure 4.8) shows the estimated annual macroeconomic impacts of weather shocks across the US from 2003 to 2017. These estimates apply the microeconomic coefficient estimates for the non-linear model specification that allows for heterogeneity based on the initial climate of counties shown in Figure (Figure 4.5). Results for other empirical specifications are consistent. The point estimates represent the mean macroeconomic impact estimates. The bounds represent the 95% confidence interval which is calculated by appropriately weighting the variance-covariance matrix from the microeconomic regression coefficient estimates. These confidence intervals capture uncertainty in macroeconomic impacts based on uncertainty in sensitivity to microeconomic weather shocks. These estimates do not include county-industry-year observations with missing data on labor productivity growth or GDP. These missing observations represent less than 2% of annual GDP, so they are unlikely to significantly change the qualitative or quantitative findings.

I find that the macroeconomic impacts of weather shocks in the US are statistically insignificant. In each year, the size and even the sign of the macroeconomic impacts vary, ranging from around -\$100 Billion to \$100 Billion or around -0.5% to 0.5% of annual US GDP. This variation is primarily driven by year-to-year weather variation. For example, the

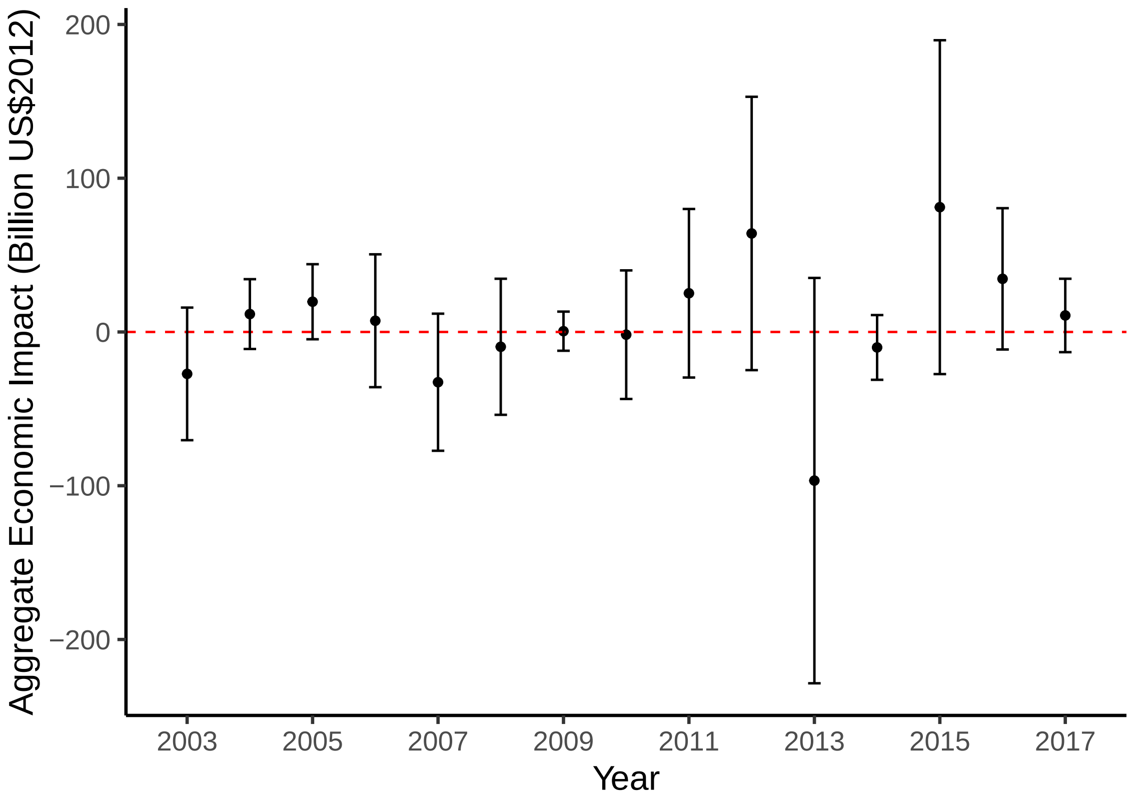


Figure 4.8: **Macroeconomic Impact of Weather Shocks by Year.** Macroeconomic impact of weather shocks across the United States in each year year. Points show the mean estimate. Bounds show the 95% confidence interval.

years 2013 and 2015 have the largest mean macroeconomic impacts in magnitude and similarly have the largest average changes in temperature. Consistently across each year, however, I fail to find evidence of significant macroeconomic impacts at the 95% confidence level. This result is robust to alternative estimates for the sensitivity to microeconomic weather shocks across regression specifications.

The finding that weather shocks have a statistically insignificant impact on macroeconomic outcomes in the US is consistent with previous findings. Existing empirical analyses of the macroeconomic impacts of weather shocks that examine the relationship between country-level weather shocks and economic outcomes, both growth and level, typically measured by GDP per capita, have similarly found statistically insignificant impacts of weather shocks for developed and northern, cooler economies, including the US [71, 72, 110]. Together, these findings stand in contrast to the empirical microeconomic evidence that labor productivity in the US, a fundamental determinant of economic outcomes, is sensitive to weather shocks.

4.6.1 Decomposition

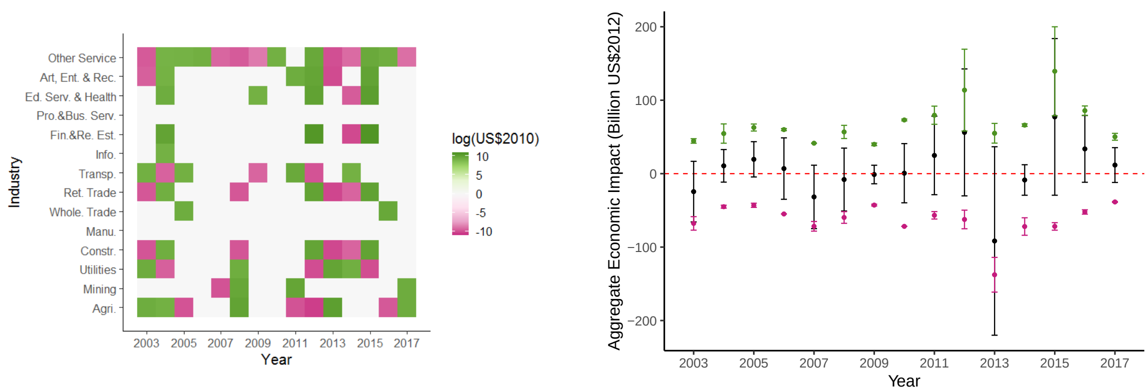
To explore the disconnect between the microeconomic and macroeconomic impacts of weather shocks, I decompose the constructed macroeconomic impact estimates into its underlying contributions. Specifically, I calculate the contributions to macroeconomic impacts of weather shocks across industries, counties, and county-industry pairs. By decomposing the macroeconomic impacts of weather shocks across the economy, I can examine the insignificant macroeconomic impact shown in Figure 4.8 to determine what factors contribute to the insignificant effect.

To perform this decomposition, I calculate on the relevant components of Equation (**??**). For the industry-level contributions to macroeconomic impacts, I only sum macroeconomic impact contributions across counties for each industry. For the county-level contributions to macroeconomic impacts, I only sum macroeconomic impact contributions across industries for each county. For the county-industry-level contributions, I drop both summations.

Here it is important to distinguish between a *contribution* to macroeconomic growth and the net impact of weather shocks for a county, industry, or county-industry, as they are not necessarily identical. As shown by Theorem 4.3.3, weather shocks can have spillover or indirect effects on economic outcomes elsewhere in the economy through labor markets or production networks. Since this analysis is focused on understanding the insignificant effect of weather shocks on macroeconomic outcomes, I focus on the contributions rather than the microeconomic outcomes.

Industry-level Contributions

Figure 4.9 displays the industry-level contributions to the macroeconomic impacts of weather shocks aggregated across the spatial distribution of economic activity. Panel A displays the contributions by industry by year. Industries that statistically significantly boost macroeconomic growth in a year are green, industries that statistically significantly slow macroeconomic growth in a year are in red, and industries that have a statistically insignificant effect on macroeconomic growth in a year are white. Similarly, Panel B displays the aggregate contribution of industries with a statistically significant positive impact on macroeconomic growth with a 95% confidence interval shown in green and the aggregate contribution of industries with a statistically significant negative impact on macroeconomic growth and 95% confidence interval are shown in red.



(a)

(b)

Figure 4.9: **Industry-level Contributions to Macroeconomic Growth** Contribution to macroeconomic growth for statistically significant aggregate industry-level weather impacts by year. Panel **(a)** displays by industry. Panel **(b)** shows the aggregate impacts of the statistically significant positive and negative effects separately.

When aggregated across space, I still observe statistically significant contributions to macroeconomic impacts for many of the industries. Weather shocks to nearly every industry have a significant impact on macroeconomic growth in at least one year, the exceptions being manufacturing and professional and business services. This is likely due to the insignificant relationship between weather shocks and labor productivity for the industries found at the microeconomic scale. Further, weather shocks across half of the industries have a significant impact on macroeconomic growth in at least five of the 15 years in the sample.

The number of industries that experience weather shocks that have a statistically significant impact on macroeconomic growth varies by year, as does the sign of the impact within industries across years. This variation is largely a combination of the variation in weather shocks in any given year and the sensitivity of industries. As shown in Panel B of Figure **??**, while temperatures are rising over the sample, changes in temperature and precipitation fluctuate across the sample years. So if labor productivity is found to grow with an increase in temperatures for an industry, it will have a positive impact on macroeconomic growth in years where temperatures are predominantly rising and will have a negative impact in years where temperatures are predominantly falling.

As evidenced in the microeconomic analysis above, industries have heterogeneous sensitivity to weather shocks. This goes for both the sign and significance of the effect. Thus, in a year where temperatures are rising, we can expect heterogeneous contributions to macroeconomic growth across industries depending on whether they are found to benefit from rising temperatures or are harmed. Additionally, in years with smaller changes in temperatures, we can expect that only industries with the strongest sensitivity to weather fluctuations to have a significant impact on macroeconomic growth at the aggregate level.

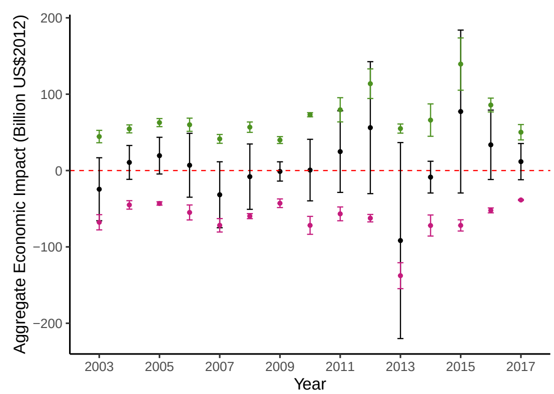
These significant industry-level aggregate impacts on macroeconomic growth can be economically significant as well. For example, focusing on the industries that have a significant negative impact on macroeconomic growth in each year, Panel B of Figure 4.9 shows that these slowdowns in labor productivity can reduce macroeconomic growth by anywhere from \$50 to \$100 Billion in a year. This represents around 0.5% of the annual US GDP.

These results suggest that it is not the aggregation of microeconomic impacts of weather shocks across the spatial distribution of economic activity alone that leads to statistically insignificant macroeconomic impacts. There is evidence of contributions for select industries in select years, however, due to the heterogeneity in these contributions as well as the uncertainty in impacts for others, when aggregated again across industries, the significance of weather shocks becomes masked.

County-level Contributions

Figure 4.10 displays the county-level contributions to the macroeconomic growth of weather shocks aggregated across the industrial composition of economic activity within each county. Panels A and B are the county-level comparable of Panels A and B of Figure 4.9 discussed above. Counties are sorted on the vertical axis of Panel A by the frequency of statistically significant weather impacts. This sorting is chosen to visually demonstrate the persistence of weather shocks at the county level.

(a)



(b)

Figure 4.10: **County-level Contributions to Macroeconomic Growth** Contribution to macroeconomic growth for statistically significant aggregate county-level weather impacts by year. Panel **(a)** displays by county, sorted by the frequency of significant aggregate county-level impacts. Panel **(b)** shows the aggregate impacts of the statistically significant positive and negative effects separately.

When aggregated across industries, I still observe statistically significant macroeconomic impacts by county. Two-thirds of counties experience weather shocks across their industrial makeup that, when aggregated, have a significant impact on macroeconomic growth. These significant impacts are persistent across the sample years for around half of US counties.

The magnitude and sign of the county-level aggregate contributions to macroeconomic growth vary across years both across and within counties. As with the industry-level aggregate contributions, much of the variation is explained by variation in annual weather shocks. How this annual variation translates into variation at the county-level depends on the industrial makeup of a county as well as the county's sensitivity to weather shocks. Based on the microeconomic sensitivity estimates, hotter counties are more likely to have a significant impact on macroeconomic growth in a given year. For example, of the 21 counties that have a significant impact in every year of the sample, 15 are hot counties.

Additionally, counties with a larger economic composition of sensitive industries are more likely to have a significant impact on macroeconomic growth in a given year. For example, Missouri has six counties that have a significant impact on macroeconomic growth in each year of the sample. Each of those counties has an agriculture industry that composes over 20% of its annual GDP. On the national scale, agriculture composes less than 1% of annual GDP. Agriculture is consistently found to be the most sensitive industry to weather shocks, so counties with a higher composition of agriculture are likely to be more sensitive to weather shocks.

These significant county-level aggregate impacts on macroeconomic growth can be economically significant as well. For example, focusing on the counties that have a significant negative impact on macroeconomic growth each year, Panel B of Figure **??** shows that these slowdowns in labor productivity can reduce macroeconomic growth by anywhere from \$50 to \$100 Billion in a year, comparable to the industry-level aggregate slowdowns. This represents around 0.5% of the annual US GDP.

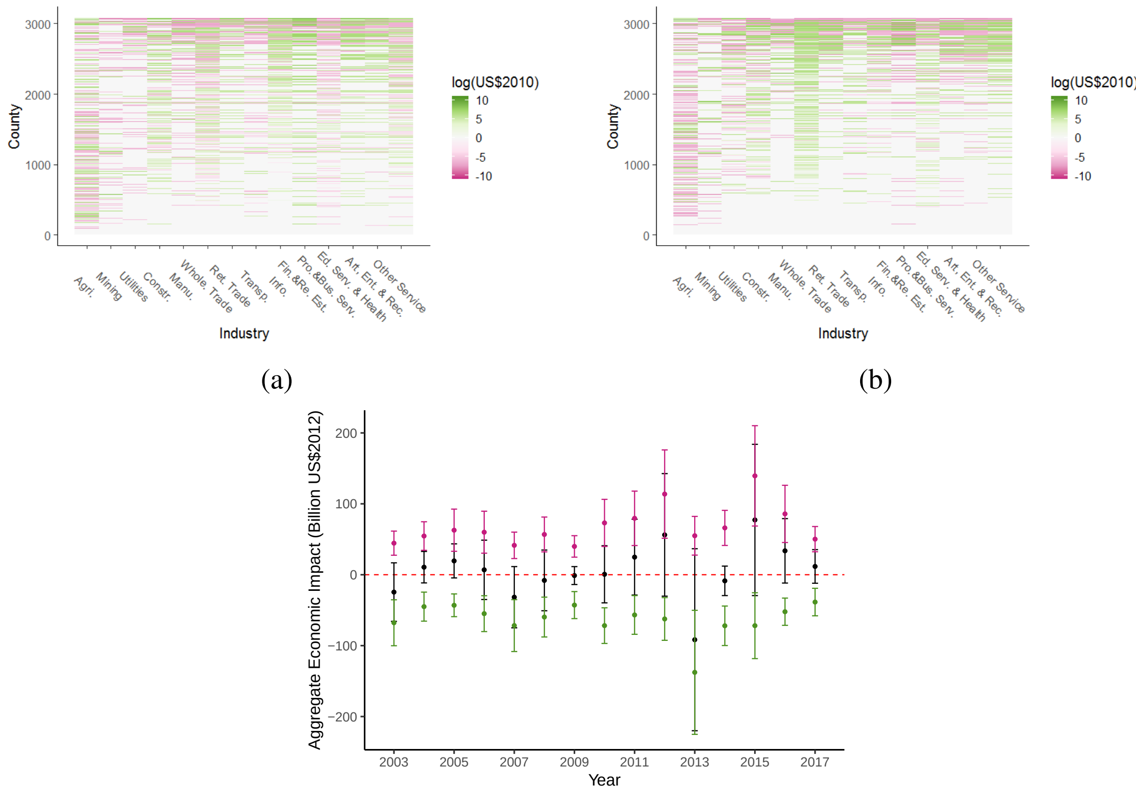
These results suggest that it is also not the aggregation of microeconomic impacts of weather shocks across the industrial composition of economic activity alone that leads to statistically insignificant macroeconomic impacts. There is evidence of contributions for select counties in select years; however, when aggregated again across counties, the significance of weather shocks becomes masked because of variation in the size and, importantly, in the sign of these contributions as well as the uncertainty in impacts for others.

County-Industry level Contributions

Finally, I calculate the contributions to macroeconomic growth across county-industry pairs. Figure 4.11 displays the statistically significant county-industry contributions. Panels A and B show the significant contributions by county and industry in 2009 and 2010, respectively. Counties are again sorted by the frequency of significant contributions to macroeconomic growth. Panel C shows the macroeconomic impacts as well as the aggregate contributions from statistically significant positive and negative contributions at the county-industry level separately.

Comparing Panels A and B of Figure 4.11 to Panel A of both Figure 4.9 and Figure 4.10, it can be seen that as the macroeconomic impacts are further disaggregated, significant impacts become more frequently identifiable. The macroeconomic impacts in both 2009 and 2010 are found to be insignificant, and the mean estimates are found to be small. However, when these impacts are decomposed, it can be seen that every industry has a significant impact on macroeconomic growth in at least one county and nearly every county has a significant impact on macroeconomic growth through at least one industry.

Comparing the impacts of weather shocks on macroeconomic growth in 2009 and 2010 at the county-industry level provides insight into what drives the uncertainty in macroeconomic estimates. In both years, the mean estimates are close to zero. However, the uncertainty in the macroeconomic impact is much larger in 2010 than in 2009, as seen in Panel C of Figure 4.11. In panel A of Figure 4.11 there is significant heterogeneity in impacts across both industries and across counties as evidenced by the amount of pink *and* green in each column and row. However, in panel B of Figure 4.11, there is less variation in impacts across industries, with lots of either pink *or* green in any column. This is likely due to the small average change in temperature in 2009, but a larger increase in temperatures



(a) (b) (c)

Figure 4.11: **County-Industry-level Contributions to Macroeconomic Growth** Contribution to macroeconomic growth for statistically significant county-industry-level weather impacts by year. Panel **(a)** and **(b)** display county-by-industry impacts for 2009 and 2010, respectively. Counties are sorted by the frequency of significant aggregate county-level impacts. Panel **(c)** shows the aggregate impacts of the statistically significant positive and negative effects separately.

in 2010 as evidenced in Panel B of Figure 4.2. As a result, aggregating the small, heterogeneous impacts in 2009 leads to a more precise estimate of no macroeconomic impact for that year. In 2010, there are large positive and large negative impacts. Together, these cancel in the aggregate, leading to small mean estimates, but large uncertainty.

This decomposition analysis demonstrates that the finding of no macroeconomic impacts in the United States is a consequence of aggregating heterogeneous and sometimes uncertain microeconomic impacts across the industrial composition and spatial distribution of economic activity. This finding highlights the importance of spatial and industrial disaggregation in weather shock impacts, as aggregation can mask considerable underlying heterogeneity. I show in Appendix section B.3, that these findings are robust to different values of the elasticity of substitution as well as different microeconomic empirical specifications.

4.7 Conclusion

In this paper, I introduce weather shock impacts into a general equilibrium theoretical framework. This provides a growth accounting framework that describes how to aggregate local micro-level weather shocks into macroeconomic impacts. I apply this framework to the US and construct annual estimates of the macroeconomic impacts of micro-level shocks to labor productivity growth rates across the industrial composition and spatial distribution of economic activity within the country from 2002 to 2017.

The growth accounting framework introduced in this paper permits the examination of the seemingly paradoxical result that economic activity in the US is found to be sensitive to weather shocks at the microeconomic scale while macroeconomic studies have predominantly found the US to be insensitive to weather shocks. Consistent with previous findings, I show evidence of a significant, but the heterogeneous relationship between weather shocks and labor productivity growth rates at the county-by-industry level. However, when these impacts are aggregated, I find no evidence of sensitivity to weather shocks at the macroeconomic scale.

Decomposing the macroeconomic impact estimates into the underlying contributions at higher resolution, I show that macroeconomic insensitivity is a consequence of aggregating heterogeneous and uncertain microeconomic weather impacts across the industrial composition and spatial distribution of economic activity in the US. As the level of resolution increases, so does the frequency of identifiable statistically significant impacts. However, these impacts are varied in both sign and magnitude. Thus, when aggregated, the microeconomic impacts become masked.

It is important to reiterate and make clear the limitations of the analysis in this paper.

First, in the theoretical framework, I focus on the first order aggregate impacts of microeconomic shocks. These first-order effects are independent of the underlying production structure of the US economy. This facilitates the analysis conducted in this analysis, since there do not exist, to my knowledge, inter-regional input-output network data for the US. Recent work in the production network literature has shown that second-order impacts can be important [120]. Estimating the second-order macroeconomic impacts for microeconomic weather shocks is an area for future work.

Second, the empirical analysis in this paper focuses on the impact of weather shocks through their effect on labor productivity. As I discuss following Theorem **??**, it is important to focus on the effect of weather shocks on primary factors of production because general equilibrium economic measures, such as value-added or GDP, can lead to biased estimates. I specifically focus on labor productivity growth as the channel for weather shocks both because there is considerable microeconomic evidence of this channel as well as data limitations. It is possible that these estimates may actually capture the impact of weather shocks on other factors of production if they are correlated with labor. Additionally, it is possible that weather shocks can impact economic outcomes through other factors of production, such as capital accumulation. I leave this as an area for future work.

Third, there are potential issues of data quality or measurement error for the constructed measure of labor productivity growth. Because data does not exist for gross output at the county-industry level for the US, I assume that regional gross output within an industry is proportional to industry aggregate gross output based on the region's share of value-added for that industry. Additionally, data on value-added is censored by the BEA. Unfortunately, there is no way to alleviate potential concerns of measurement error or bias due to these data issues. However, for censorship, I argue concerns are partially alleviated because the censored data represents a small proportion of the overall economy and the data is censored on value-added, but the empirical analysis focuses on labor productivity growth, which is not directly correlated with value-added. I show that the key takeaways are robust to the choice of elasticity of substitution.

Fourth, there are potential concerns about the appropriate specification of the microeconomic relationship between weather shocks and labor productivity growth rates. In the paper, I use panel data fixed effects methods to remove many concerns around the potential for omitted variable bias. I additionally regress on first differences of weather variables to mitigate concerns of non-stationarity in the panel analysis. Further, I estimate a variety of empirical specifications to examine factors that have been shown to be important in previous empirical analyses, such as a region's climate or economic development and I find the key takeaways of the analysis are robust across specifications.

Understanding the relationship between climate and economic outcomes is important for informing policymakers in the face of expected climate change. For example, macroeconomic empirical analyses have recently been implemented to estimate country-level social cost of carbon (CSCC), a simplified measure widely recommended by economists as a guide for policymakers [76]. The macroeconomic estimates that provide the foundation of these CSCCs find the US to be relatively insensitive to weather shocks. However, as I show, understanding the underlying heterogeneity that can be masked by these macroeconomic estimates can be critical for effective policy moving forward.

CHAPTER 5

CONCLUSION

The essays composing this dissertation contribute to the discourse in economics around climate change and solar geoengineering. They document the current state of solar geoengineering economics, highlight important areas where economics is well-poised to contribute to the discussion, and push the boundaries of our current perception of both solar geoengineering and climate change impacts. Notably, these essays explore and emphasize the distribution and heterogeneity of impacts, an important contribution particularly for discussions around climate justice and both the ethics and governance of solar geoengineering.

Chapter 2 documents the evolution of economic thinking around solar geoengineering, highlighting the role of its distinctive characteristics as a climate policy option. In the essay, I highlight the distribution of impacts, uncertainties and risk, and strategic decision-making as important avenues for economics to contribute to critical discussions around the ethics and governance of solar geoengineering. Following these findings, Chapter 3 empirically analyzes the distributional impacts of solar geoengineering implementation and finds that, in contradiction to prevailing concerns, solar geoengineering reduces inter-country income inequality by benefiting hotter, poorer countries most. Chapter 4 takes a step back and focuses on the empirical estimation of the relationship between the climate and macroeconomic outcomes. Starting with a theoretical foundation, the paper constructs estimates of the aggregate impacts of weather shocks and demonstrates that the aggregation of weather shock impacts across the spatial distribution and industrial composition of the US economy masks considerable underlying heterogeneity.

While these essays make important contributions to the discussions around climate change and solar geoengineering, they are not the final word. As concluded in Chapter

2, it is important for “economists to embrace this area and go play in the sandbox with other researchers across all the disciplines currently involved in solar geoengineering [and climate change] research, and for other disciplines to play along.”

Appendices

APPENDIX A

SUPPLEMENTARY MATERIALS FOR "CLIMATE ECONOMETRIC MODELS INDICATE SOLAR GEOENGINEERING WOULD REDUCE INTER-COUNTRY INCOME INEQUALITY"

Supplementary Figures

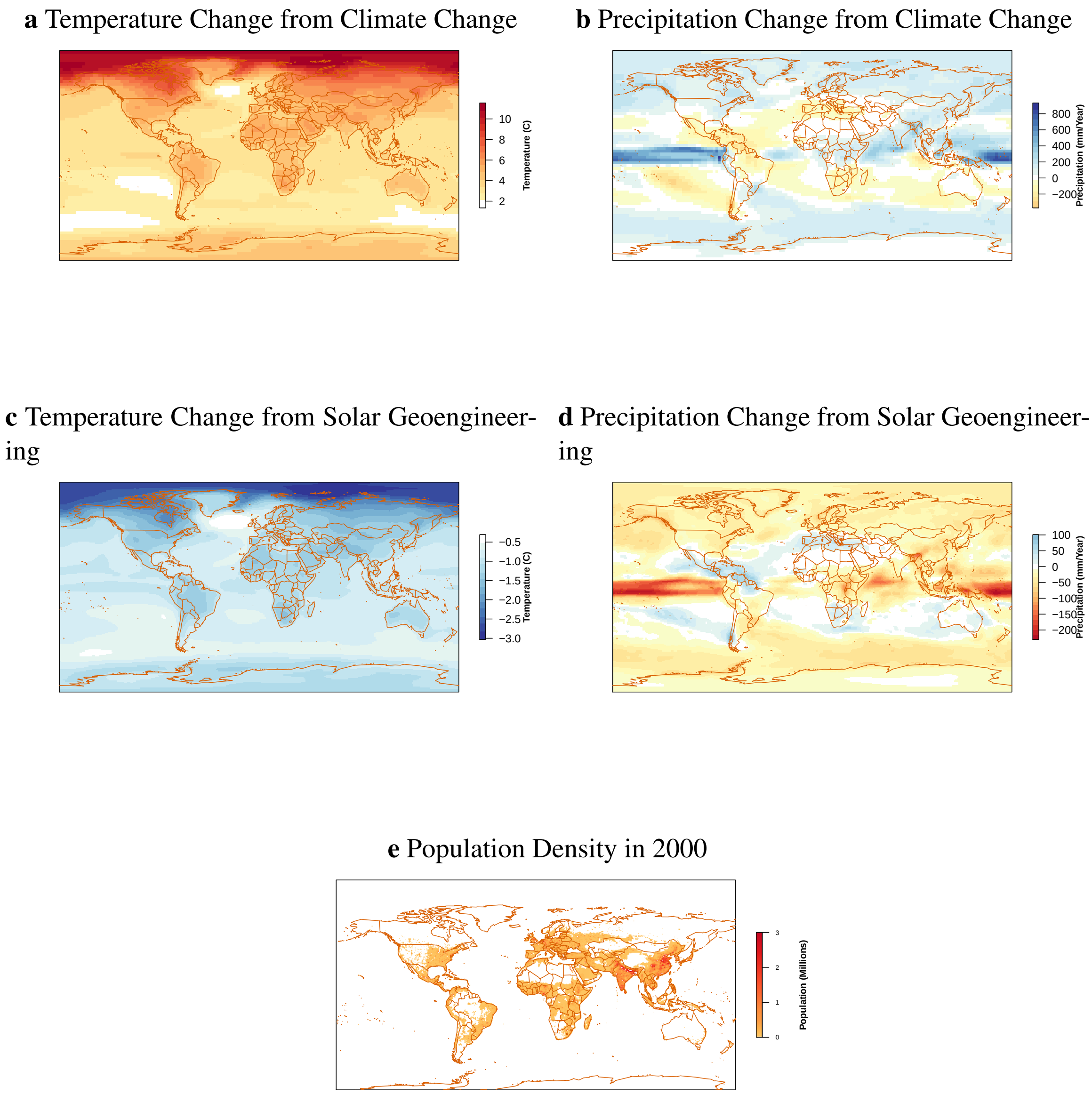


Figure A.1: **Climate Projections a**, ensemble mean of temperature projections for change in near-surface temperature from 2081-2100 relative to 1986-2005 for models participating in CMIP5. **b**, ensemble mean of precipitation projections for change in precipitation from 2081-2100 relative to 1986-2005 for models participating in CMIP5. **c**, ensemble mean of temperature change from a 1°C change in temperature from solar geoengineering for 12 models participating in the GeoMIP G1 experiment. **d**, ensemble mean of precipitation change from a 1°C change in temperature from solar geoenginxeering for 12 models participating in the GeoMIP G1 experiment. **e**, grid-cell population density in year 2000 used for calculating population-weighted country mean values of temperature and precipitation.

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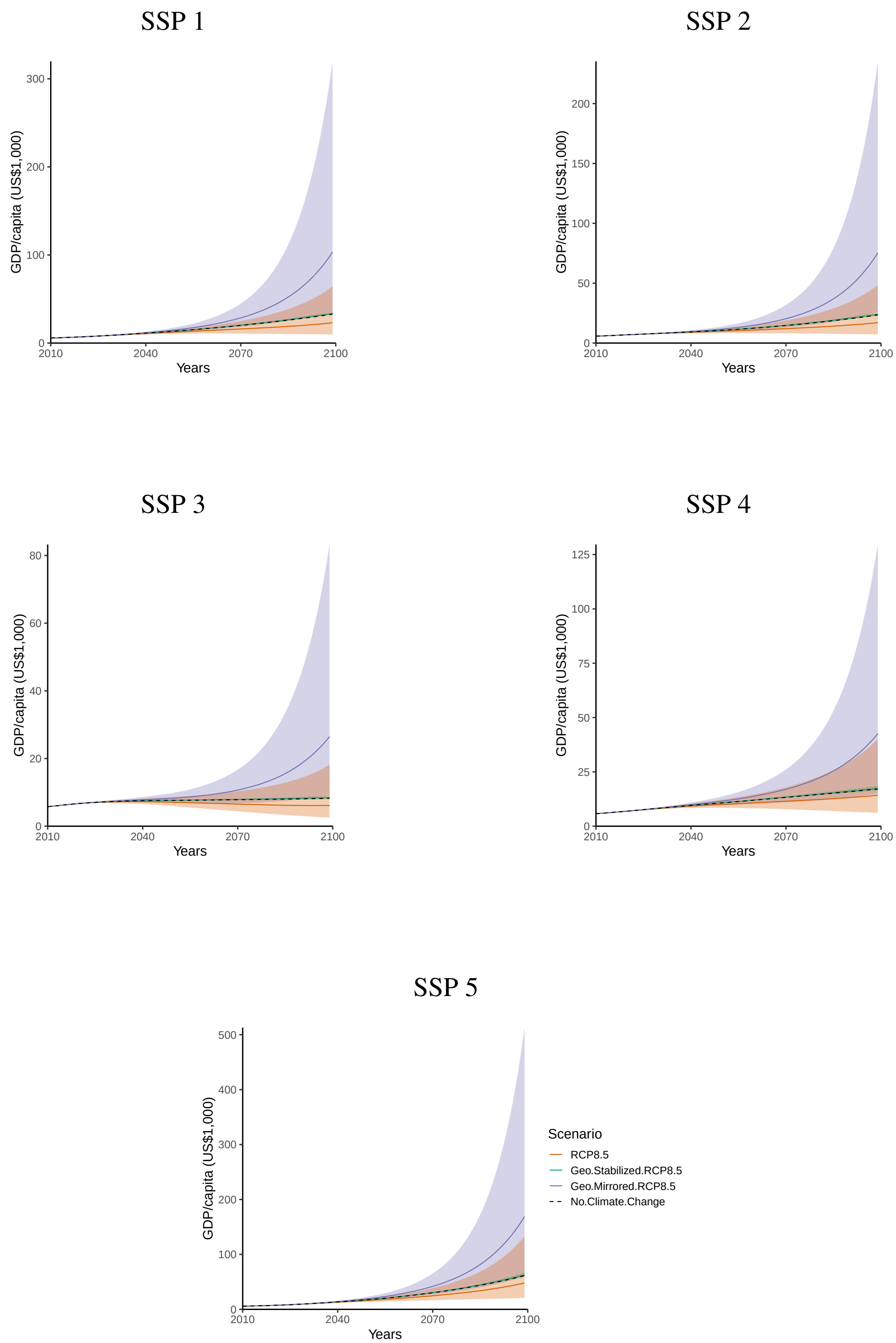
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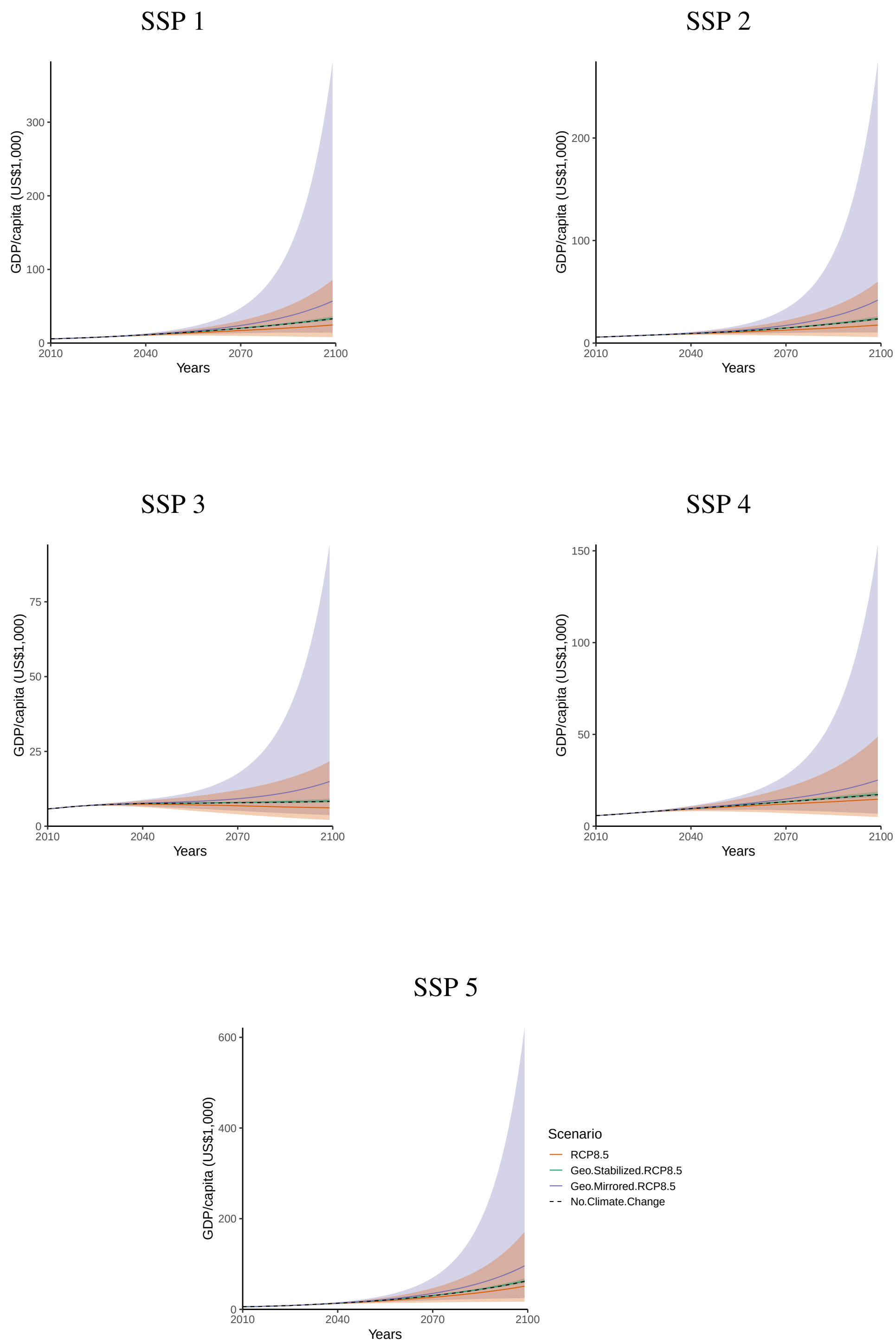
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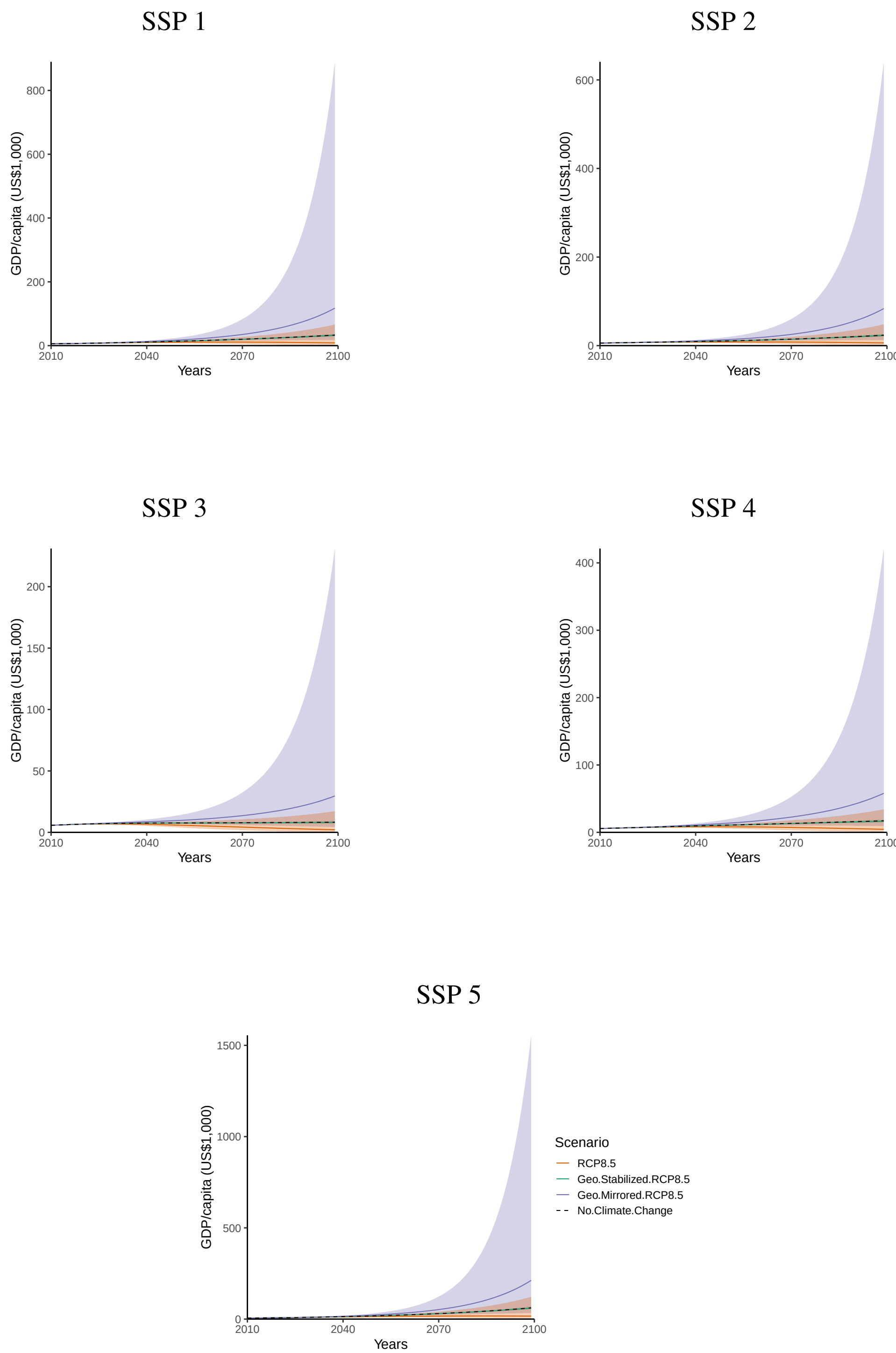
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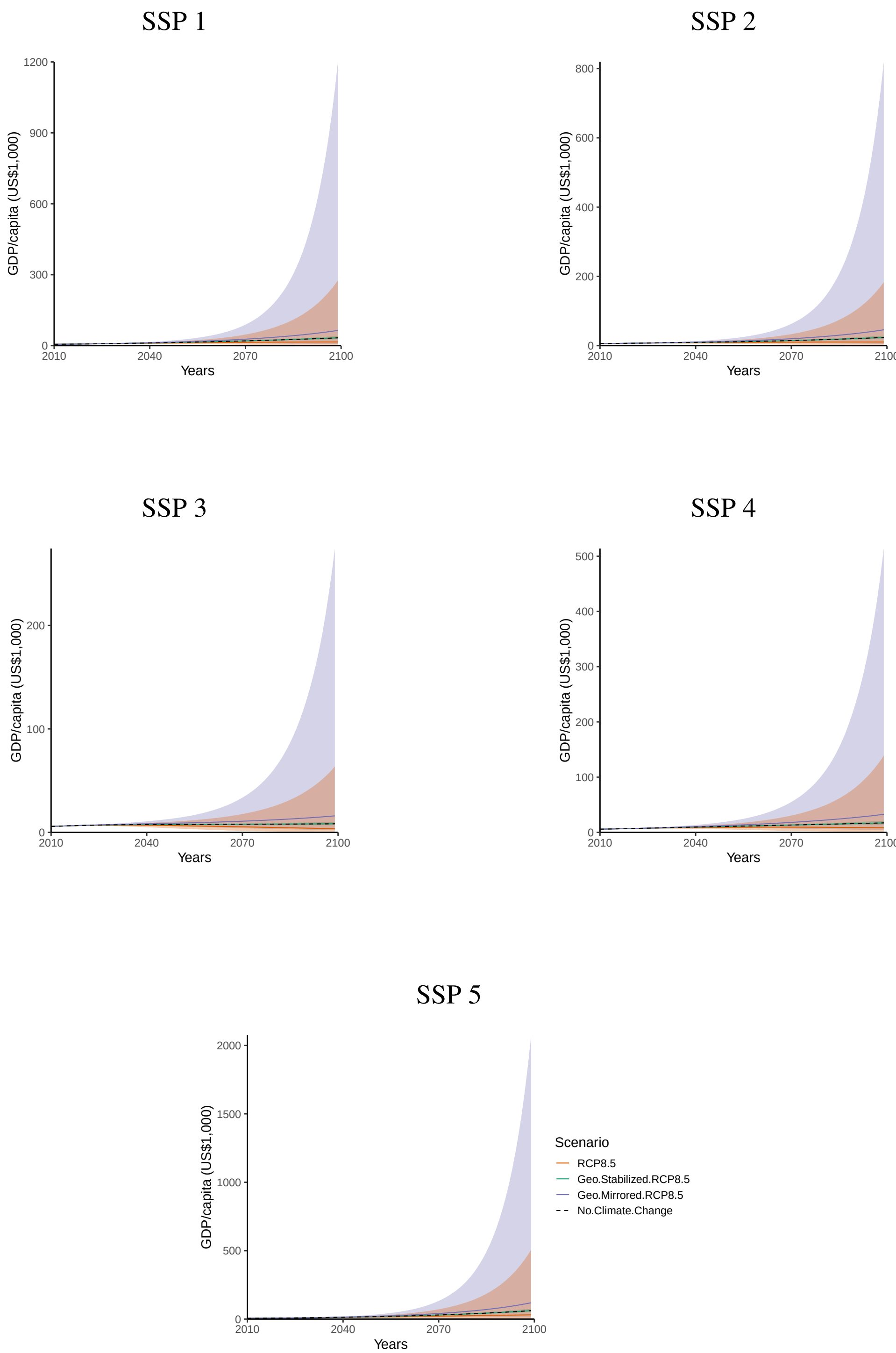
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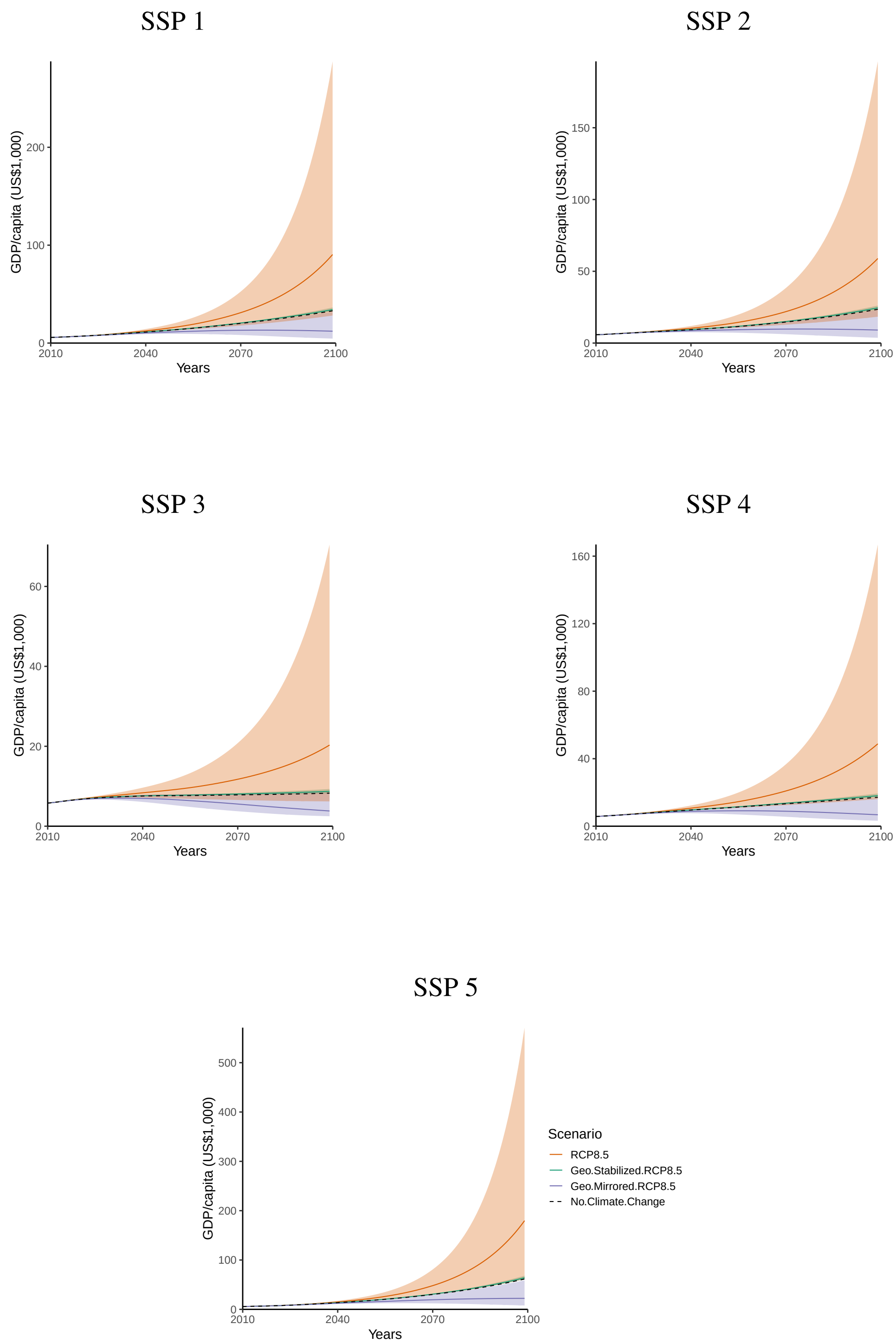
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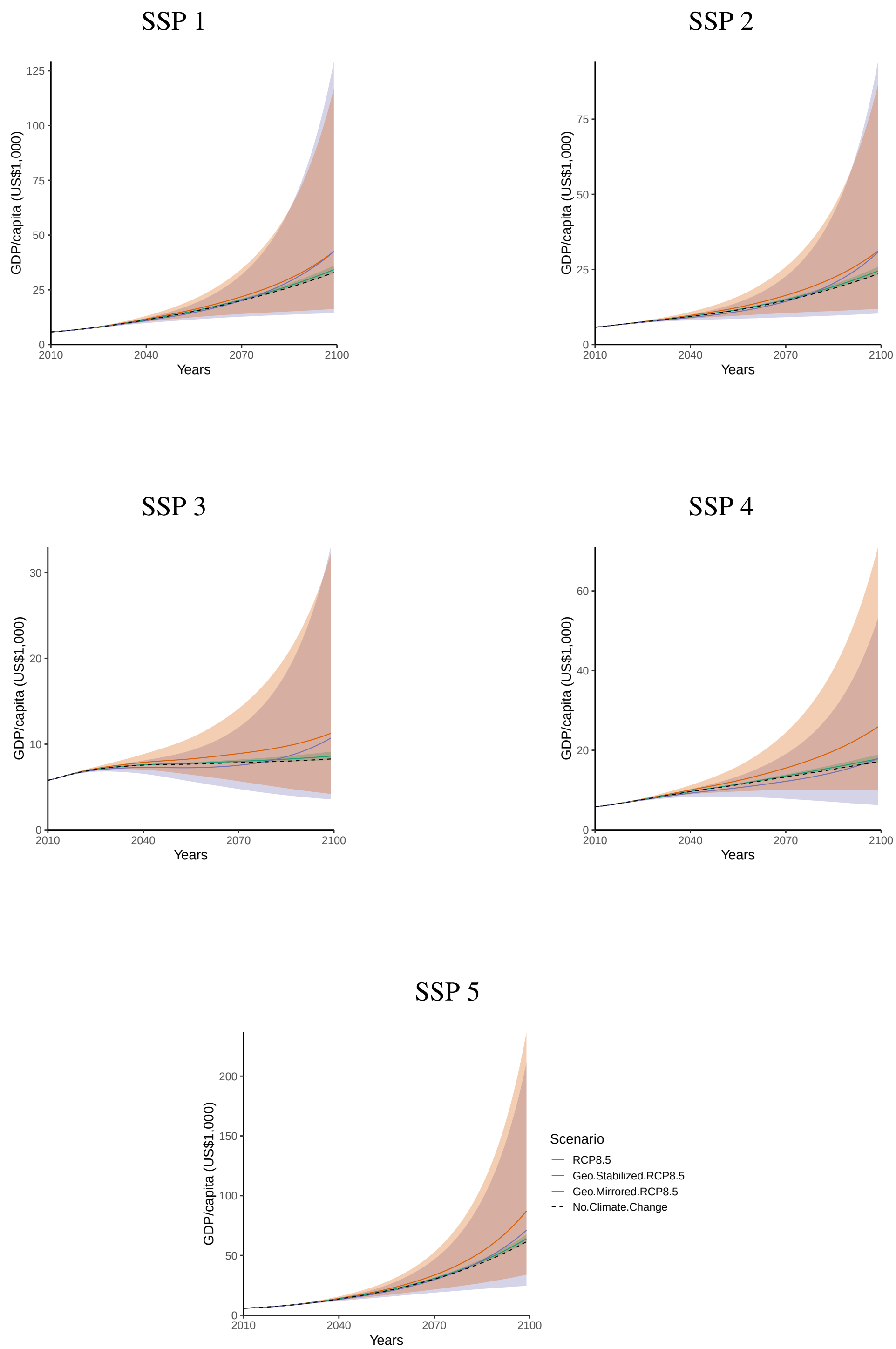
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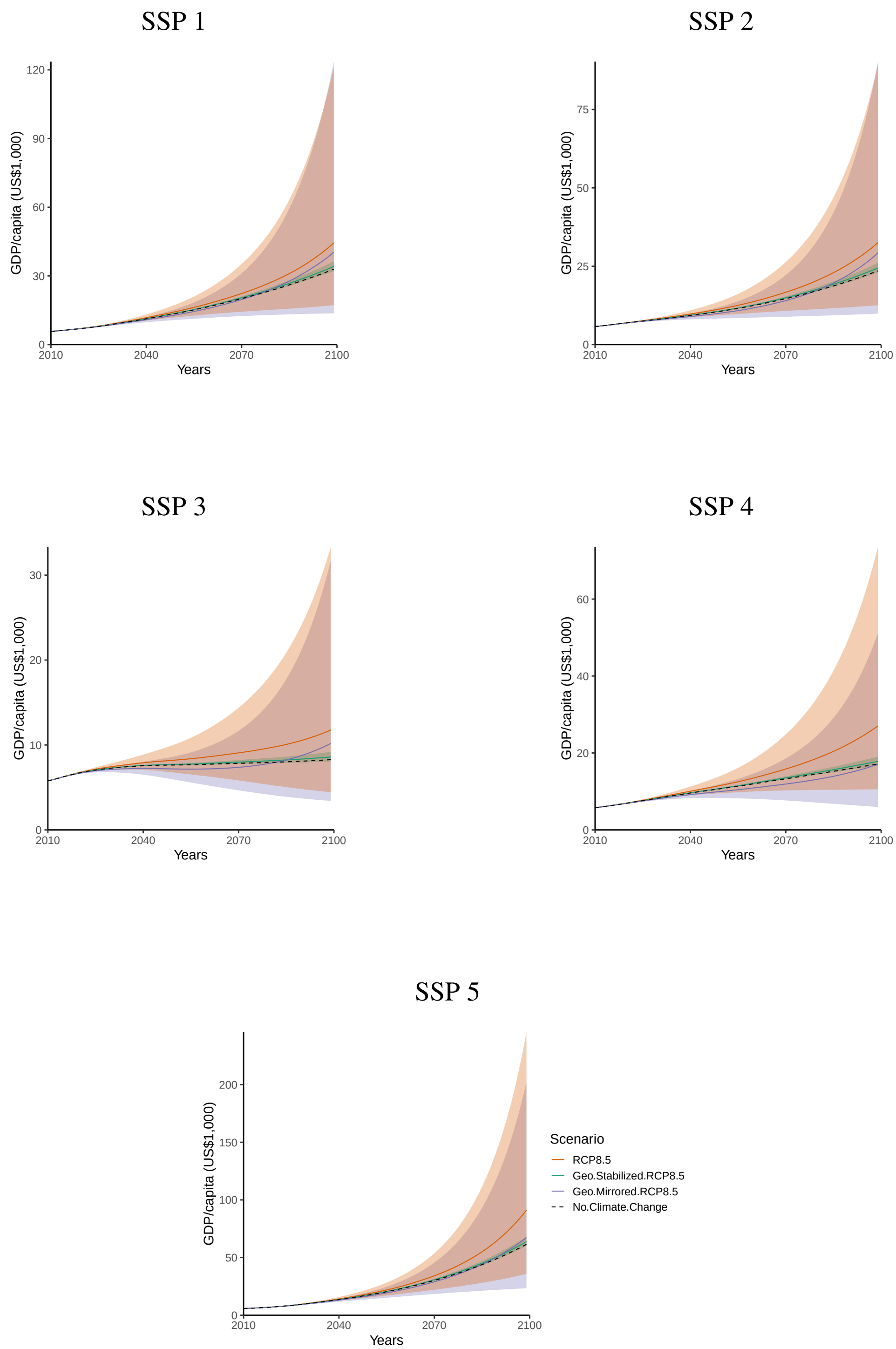
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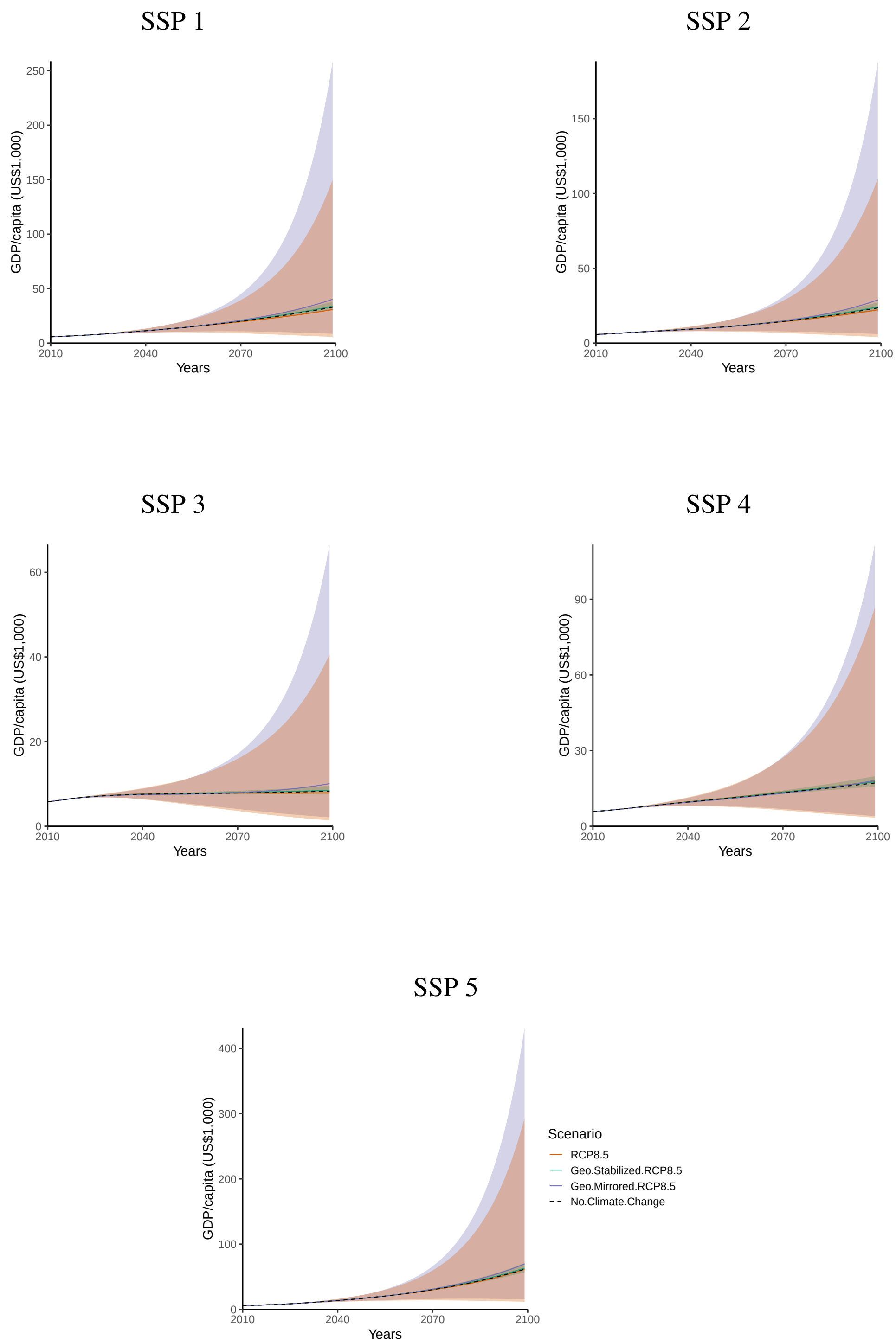
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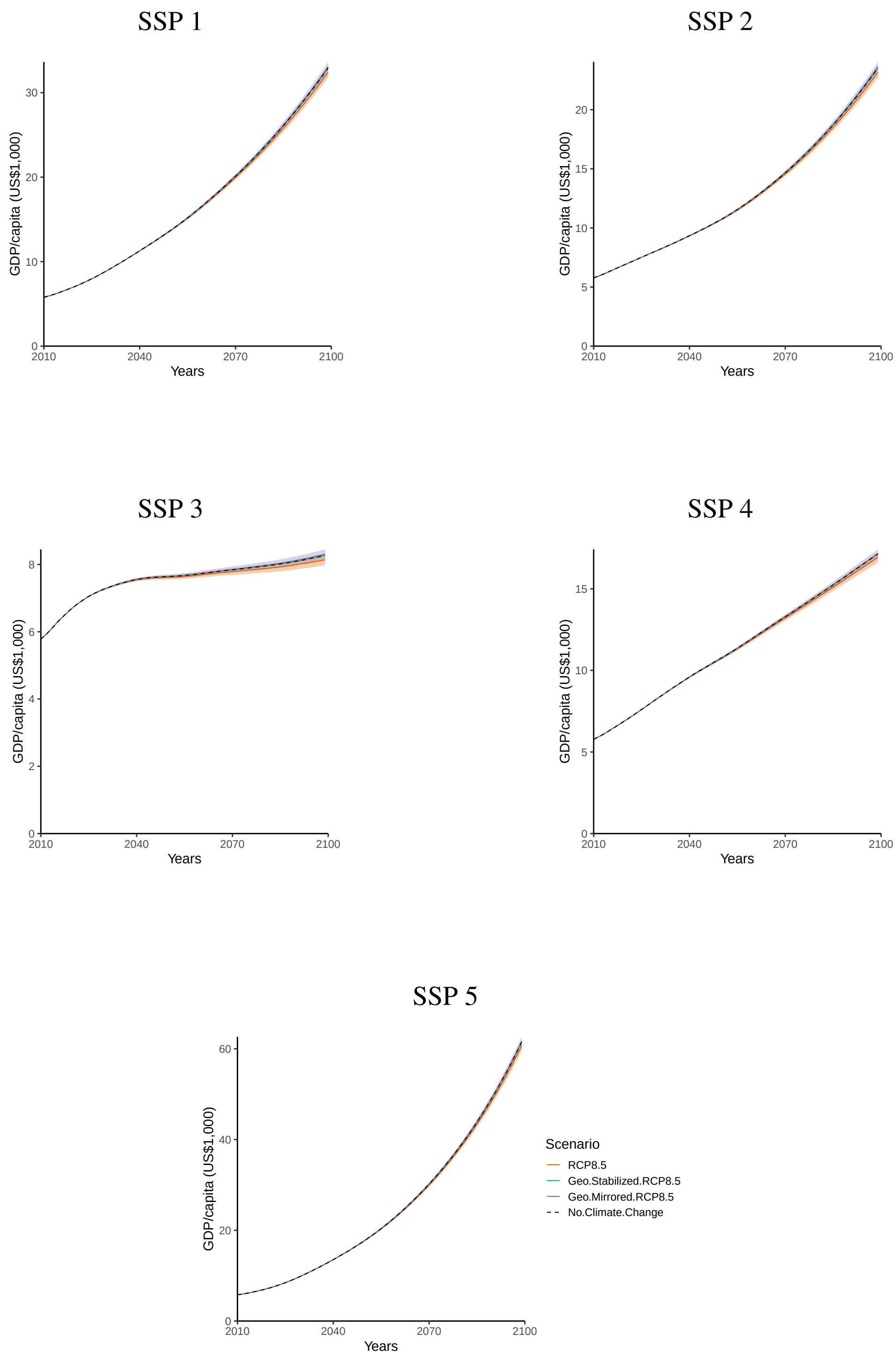
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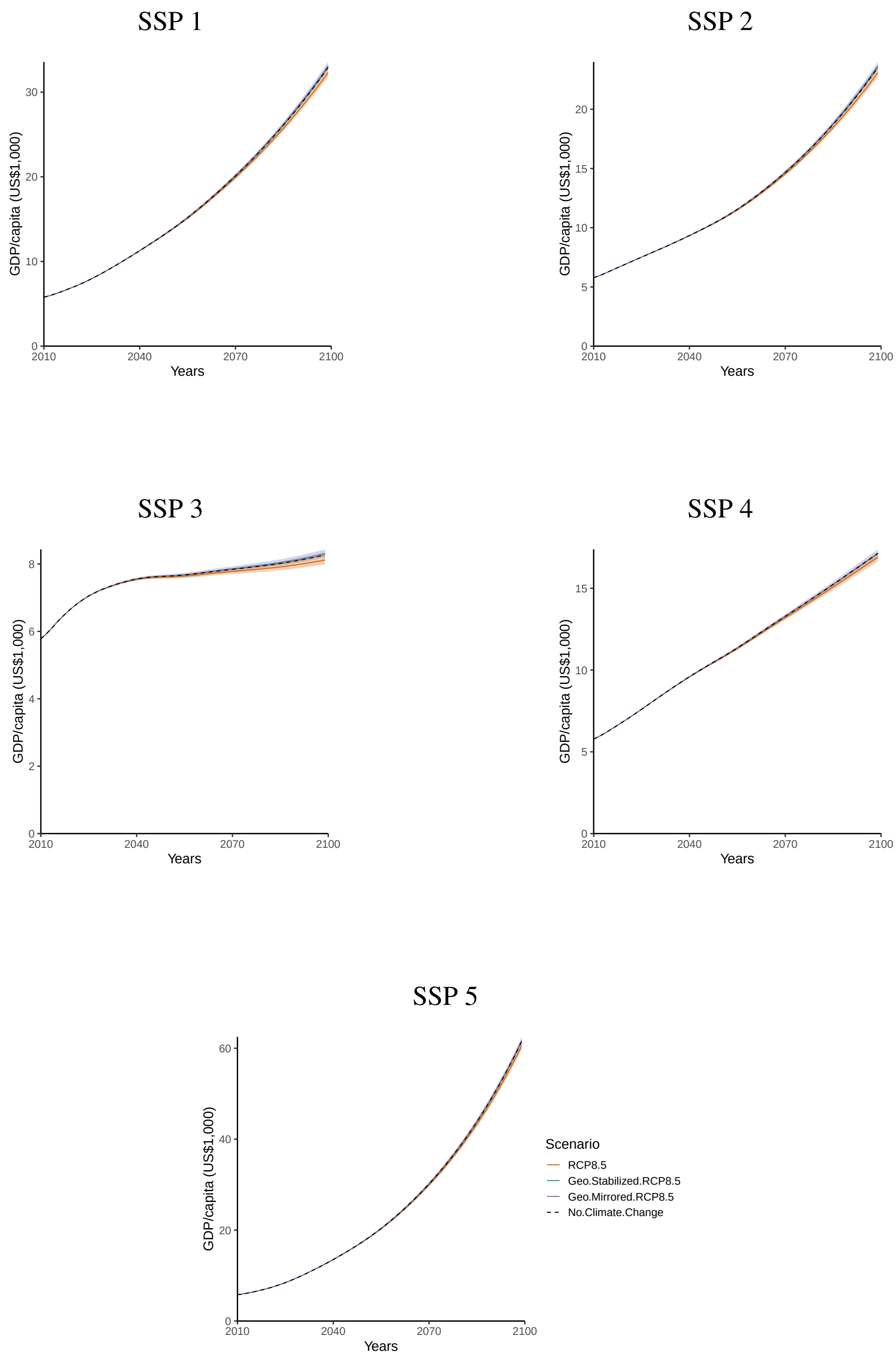
SSP 4
SSP 5
GDP/capita (US$1,000)
Years
Scenario
RCP8.5
Geo.Stabilized.RCP8.5
Geo.Mirrored.RCP8.5
No.Climate.Change

j.


SSP 1
GDP/capita (US$1,000)
0
10
20
30
2010
2040
2070
2100
Years
SSP 2
GDP/capita (US$1,000)
0
5
10
15
20
2010
2040
2070
2100
Years
SSP 3
GDP/capita (US$1,000)
0
2
4
6
8
2010
2040
2070
2100
Years
SSP 4
GDP/capita (US$1,000)
0
5
10
15
2010
2040
2070
2100
Years
SSP 5
GDP/capita (US$1,000)
0
20
40
60
2010
2040
2070
2100
Years
Scenario
RCP8.5
Geo.Stabilized.RCP8.5
Geo.Mirrored.RCP8.5
No.Climate.Change

k.

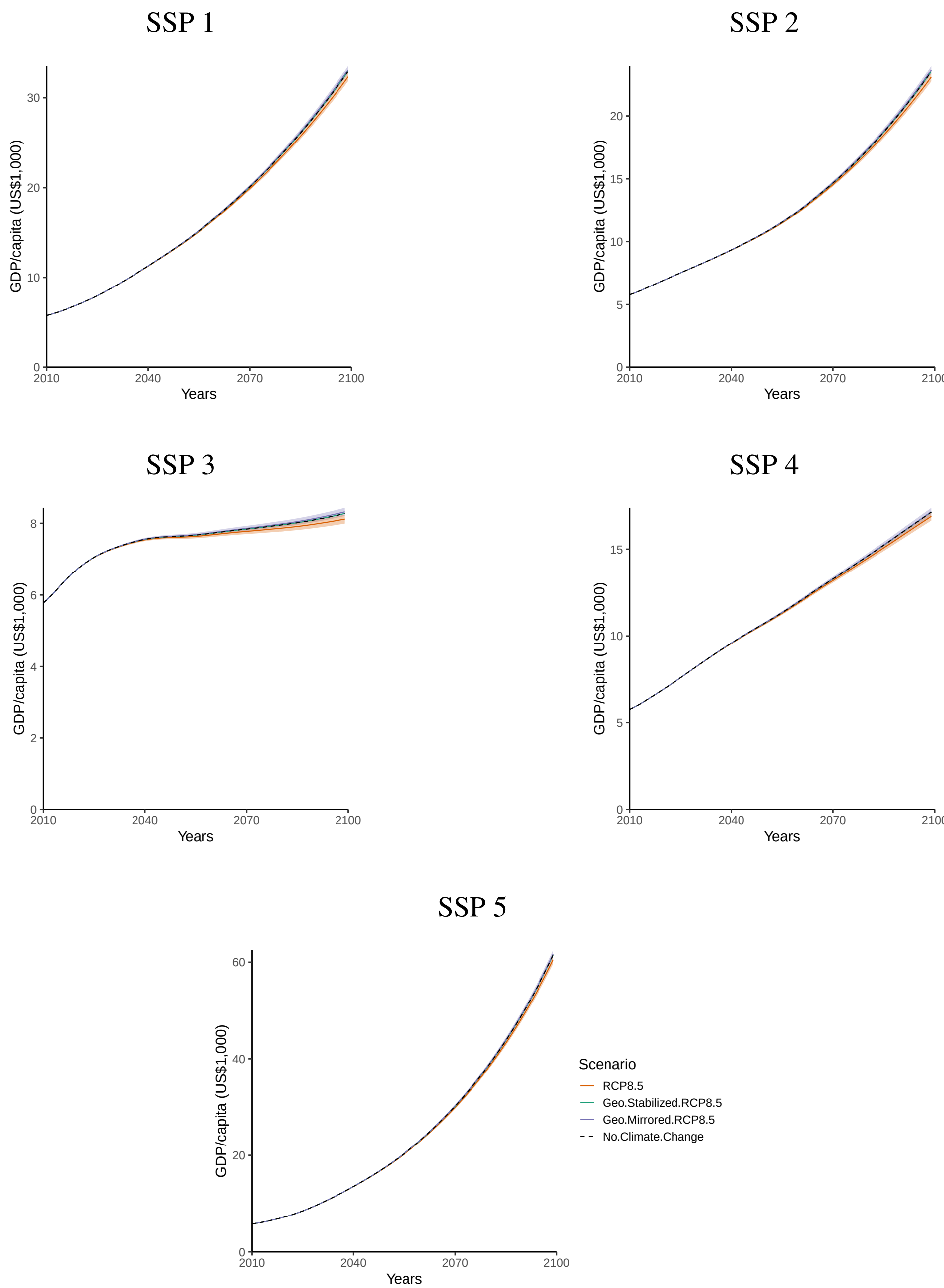
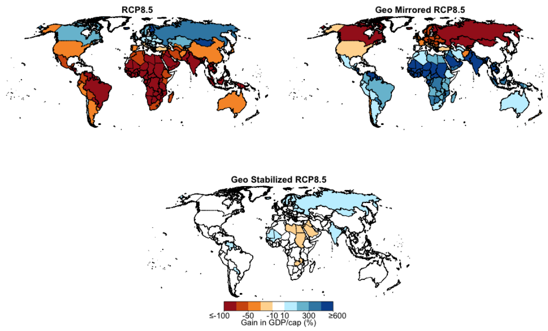


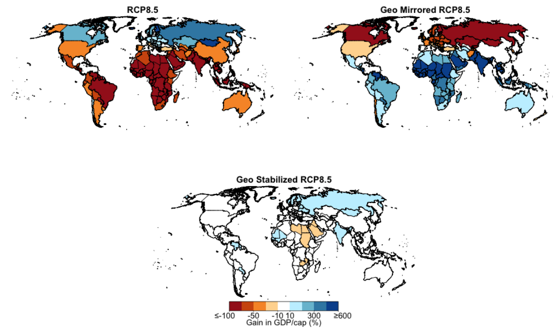
Figure A.12: **Projected global GDP per capita over the 21st Century.** Each line represents the median projection different climate scenario. The filled area represents the 95% confidence interval for climate impacts. Each panel represents the projections from a different Shared Socio-economic Pathway (SSP). **a** uses the model from column (1) in Table Table A.1; **b** uses column (2); **c** uses column (3); **d** uses column (4); **e** uses column (5); **f** uses column (6); **g** uses column (7); **h** uses column (8); **i** uses column (9); **j** uses column (10); **k** uses column (11).

a.

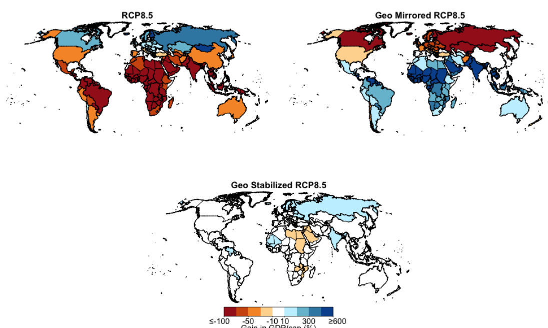
SSP 1



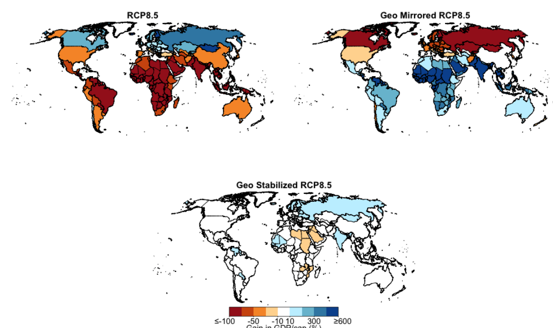
SSP 2



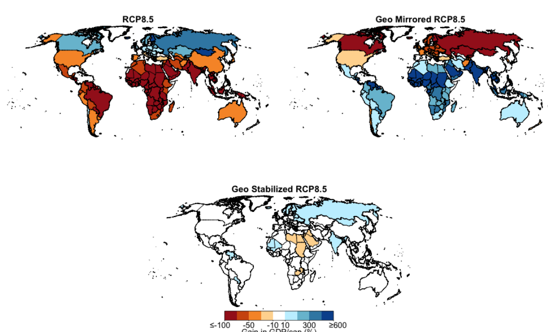
SSP 3



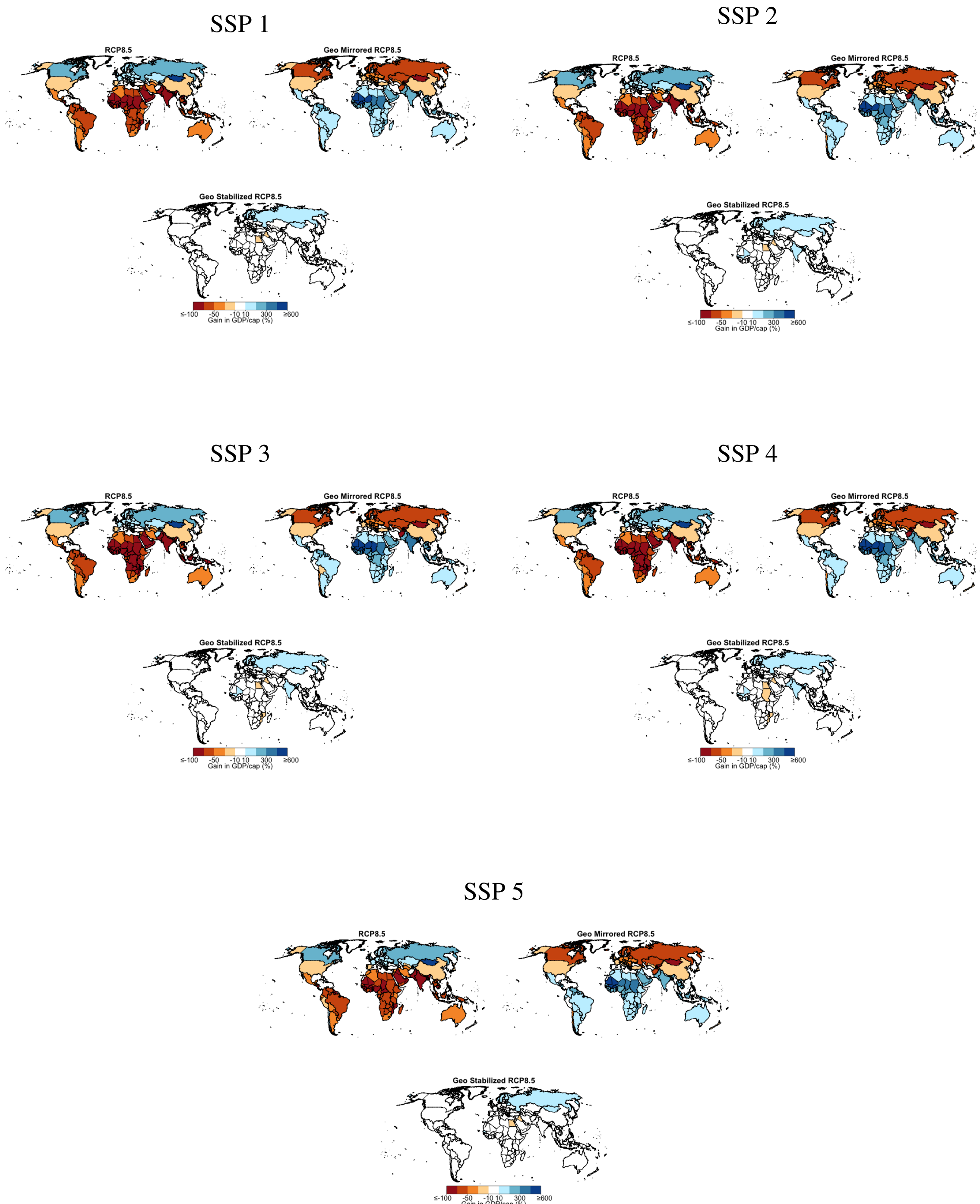
SSP 4



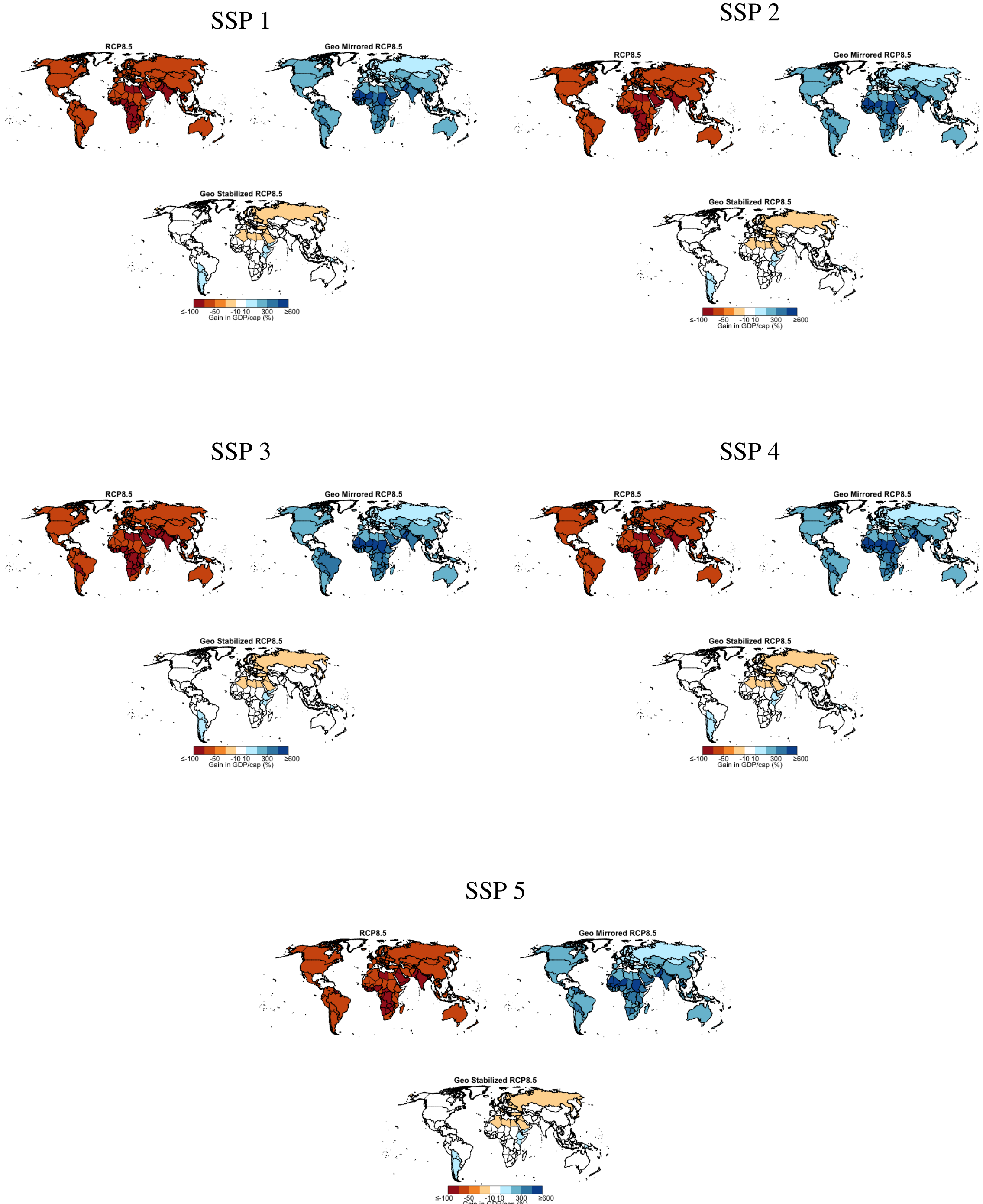
SSP 5



b.

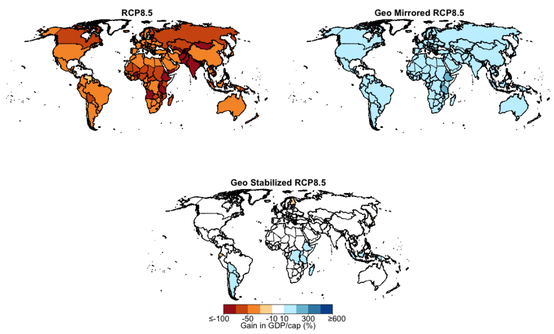

SSP 1
RCP8.5
Geo Mirrored RCP8.5
Geo Stabilized RCP8.5
≤-100 -50 -10 10 300 ≥600
Gain in GDP/cap (%)
SSP 2
RCP8.5
Geo Mirrored RCP8.5
Geo Stabilized RCP8.5
≤-100 -50 -10 10 300 ≥600
Gain in GDP/cap (%)
SSP 3
RCP8.5
Geo Mirrored RCP8.5
Geo Stabilized RCP8.5
≤-100 -50 -10 10 300 ≥600
Gain in GDP/cap (%)
SSP 4
RCP8.5
Geo Mirrored RCP8.5
Geo Stabilized RCP8.5
≤-100 -50 -10 10 300 ≥600
Gain in GDP/cap (%)
SSP 5
RCP8.5
Geo Mirrored RCP8.5
Geo Stabilized RCP8.5
≤-100 -50 -10 10 300 ≥600
Gain in GDP/cap (%)

c.

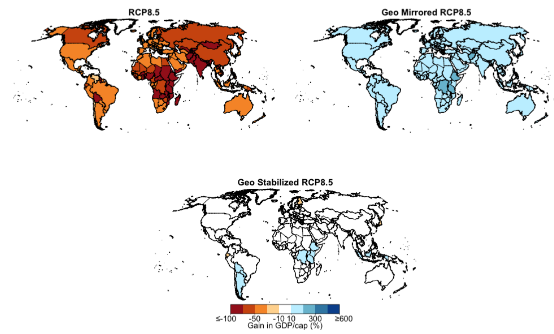

SSP 1
RCP8.5
Geo Mirrored RCP8.5
Geo Stabilized RCP8.5
≤-100 -50 -10 10 300 ≥600
Gain in GDP/cap (%)
SSP 2
RCP8.5
Geo Mirrored RCP8.5
Geo Stabilized RCP8.5
≤-100 -50 -10 10 300 ≥600
Gain in GDP/cap (%)
SSP 3
RCP8.5
Geo Mirrored RCP8.5
Geo Stabilized RCP8.5
≤-100 -50 -10 10 300 ≥600
Gain in GDP/cap (%)
SSP 4
RCP8.5
Geo Mirrored RCP8.5
Geo Stabilized RCP8.5
≤-100 -50 -10 10 300 ≥600
Gain in GDP/cap (%)
SSP 5
RCP8.5
Geo Mirrored RCP8.5
Geo Stabilized RCP8.5
≤-100 -50 -10 10 300 ≥600
Gain in GDP/cap (%)

d.

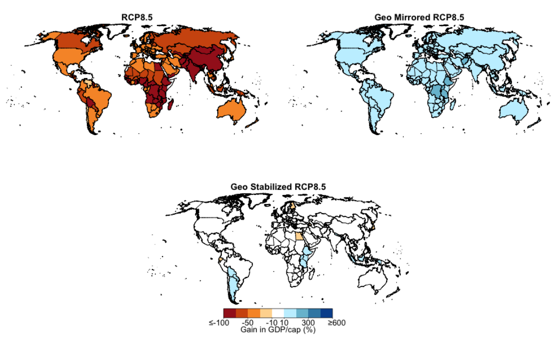
SSP 1



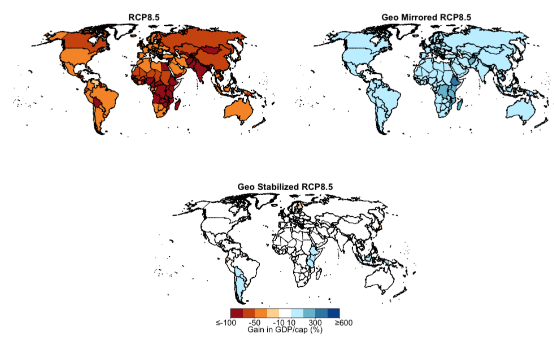
SSP 2



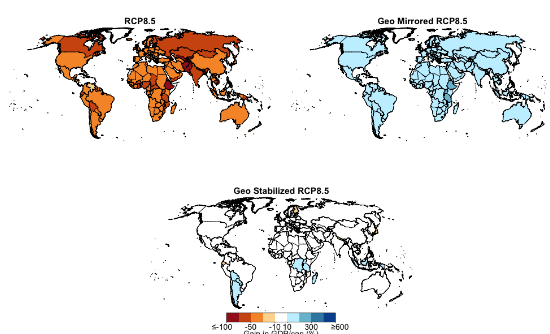
SSP 3



SSP 4

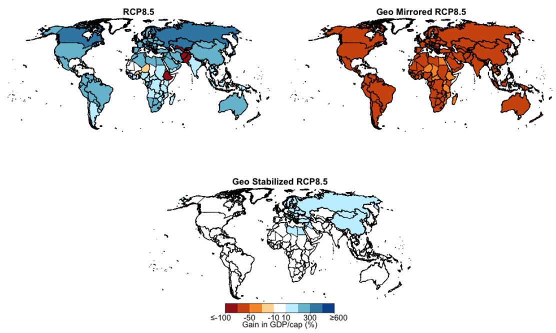


SSP 5

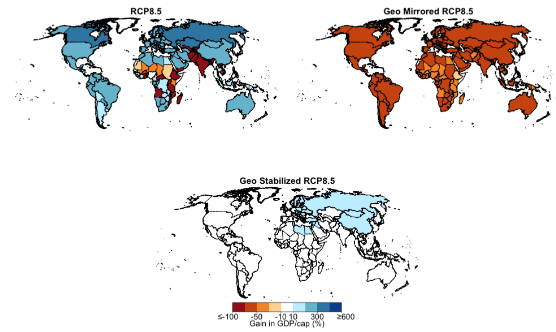


e.

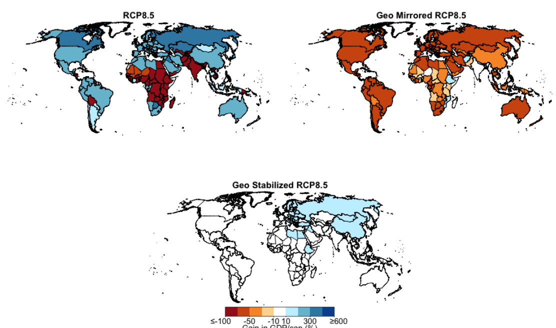
SSP 1



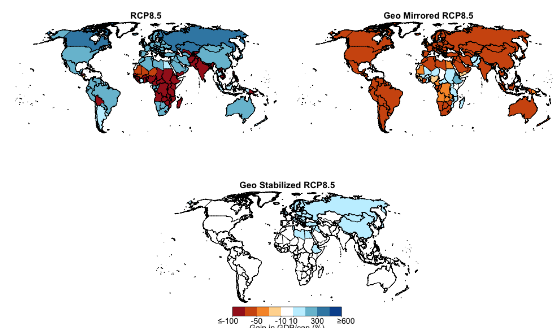
SSP 2



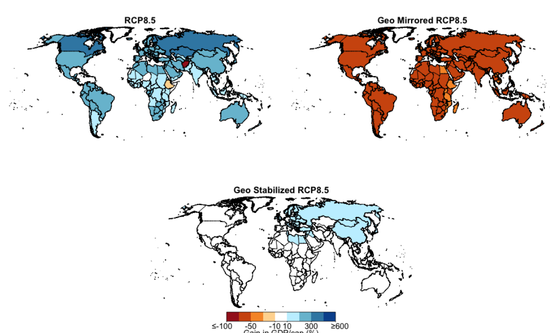
SSP 3



SSP 4

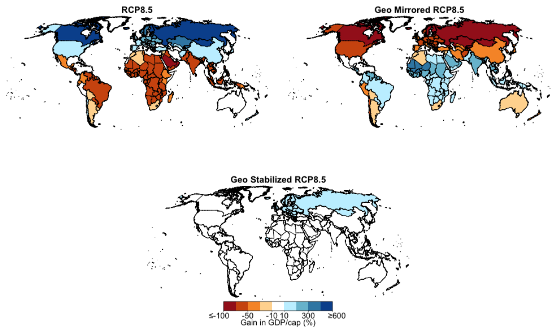


SSP 5

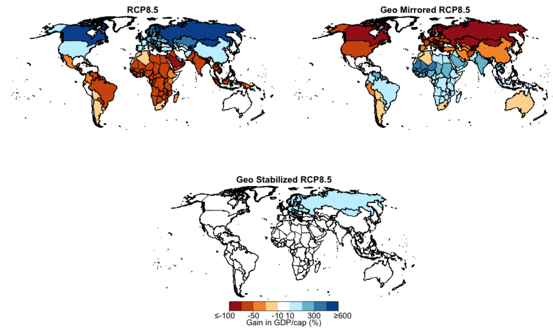


f.

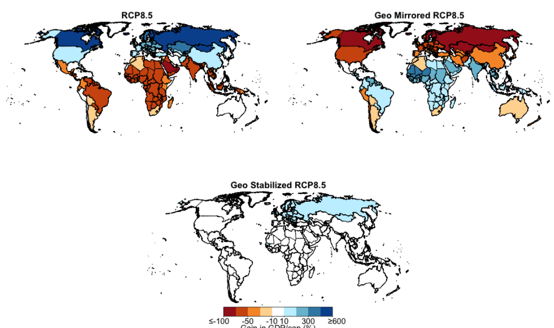
SSP 1



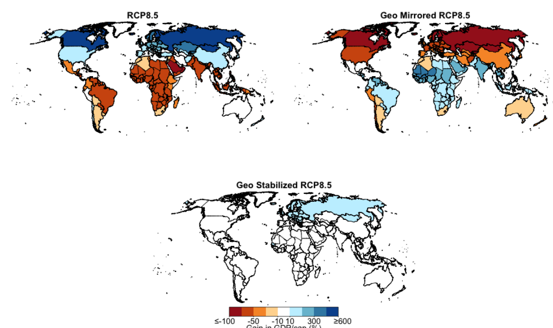
SSP 2



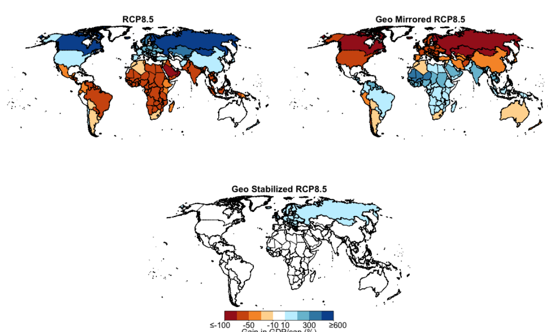
SSP 3



SSP 4

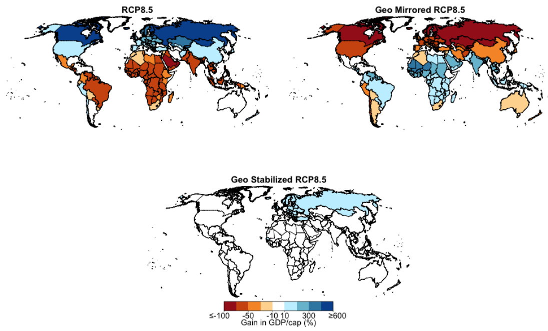


SSP 5

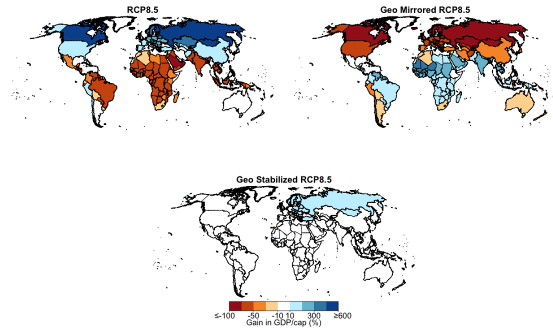


g.

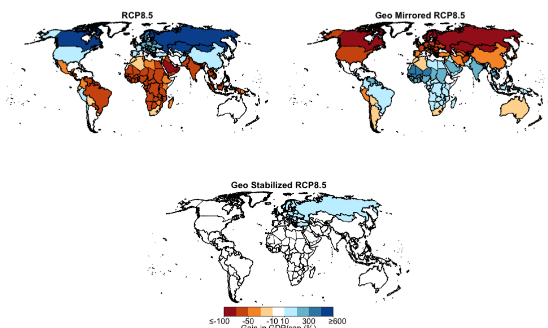
SSP 1



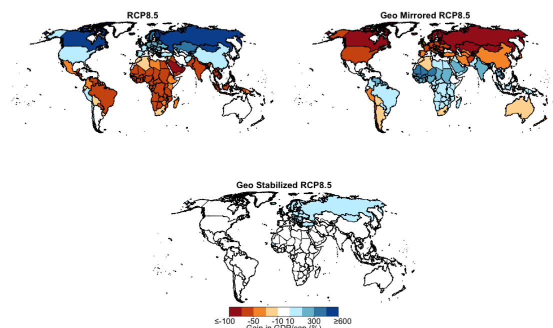
SSP 2



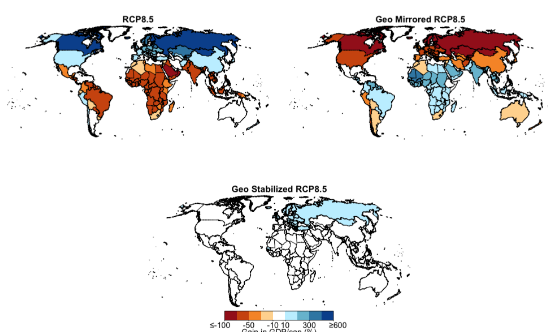
SSP 3



SSP 4

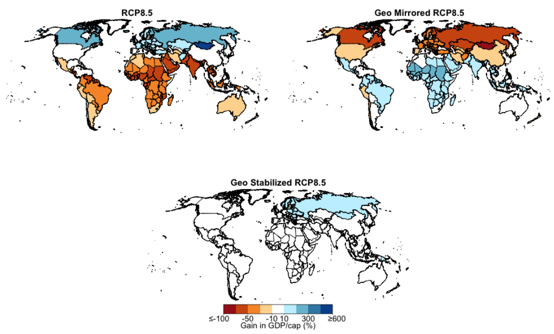


SSP 5

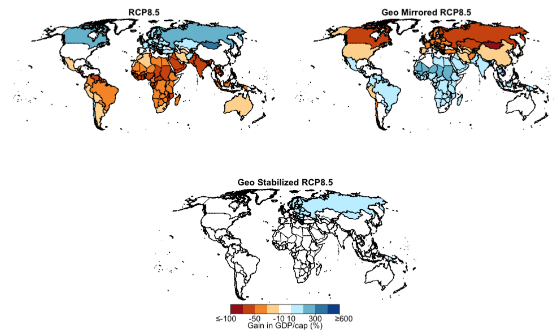


h.

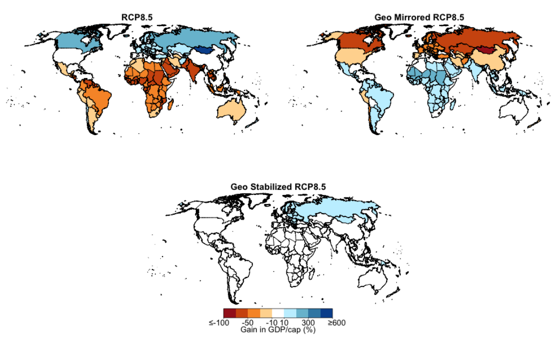
SSP 1



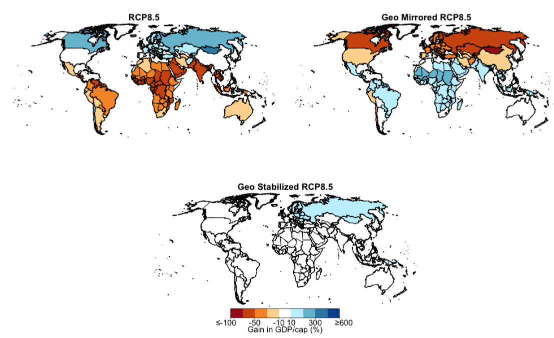
SSP 2



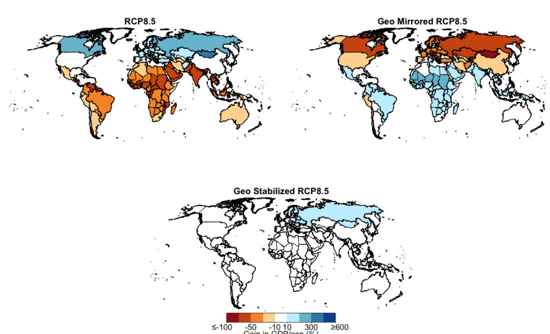
SSP 3



SSP 4

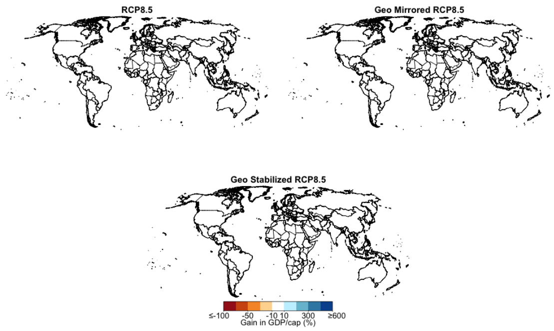


SSP 5

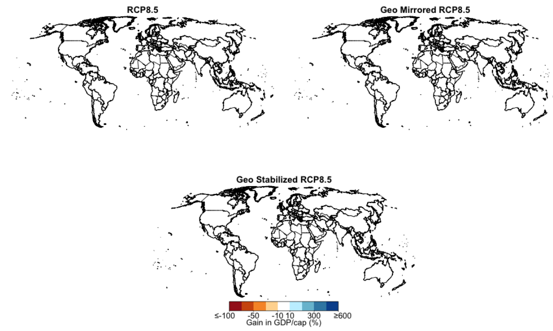


i.

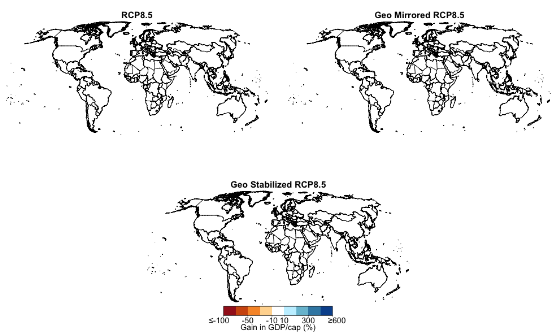
SSP 1



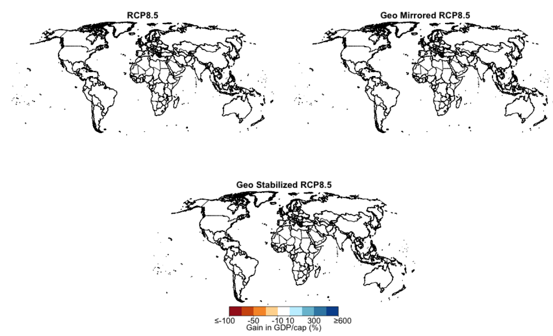
SSP 2



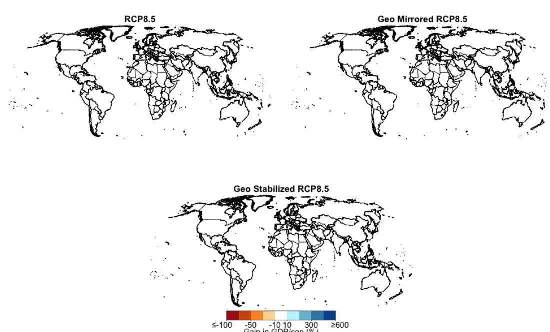
SSP 3



SSP 4

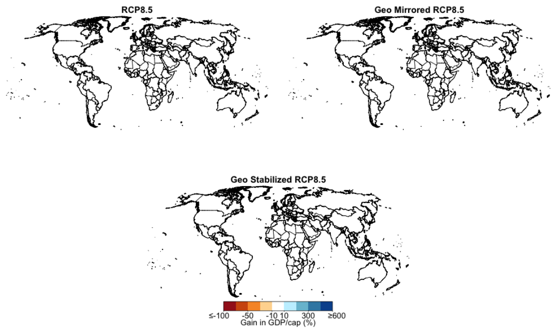


SSP 5

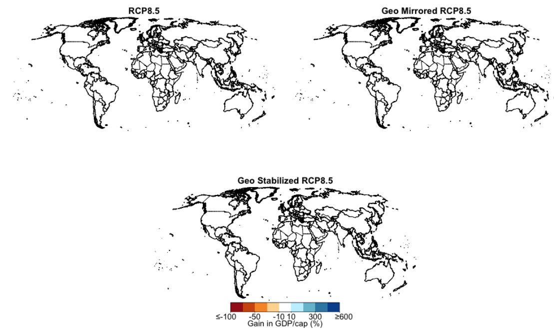


j.

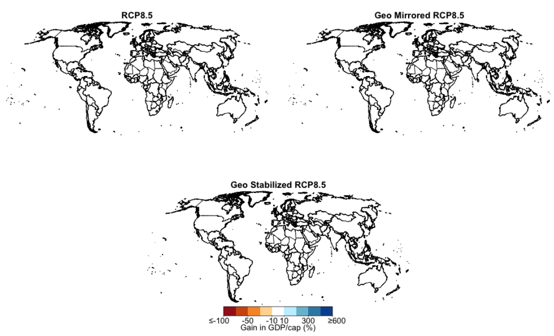
SSP 1



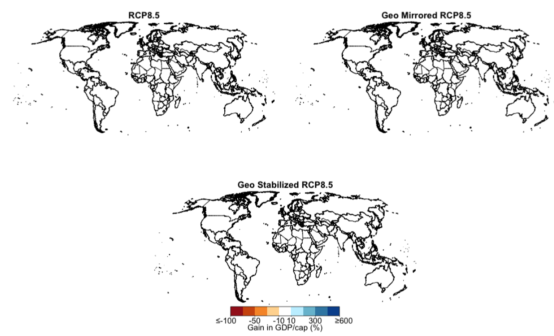
SSP 2



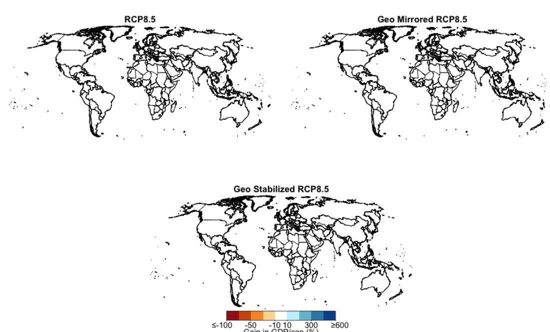
SSP 3



SSP 4

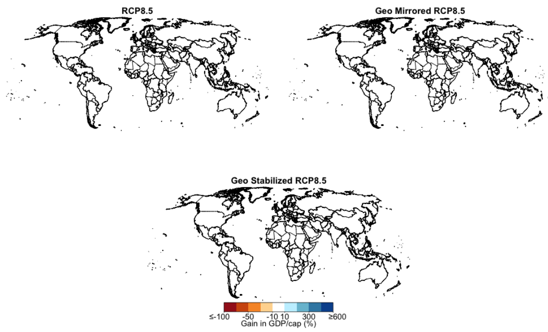


SSP 5

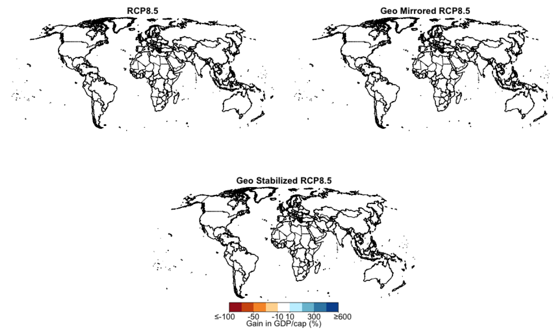


k.

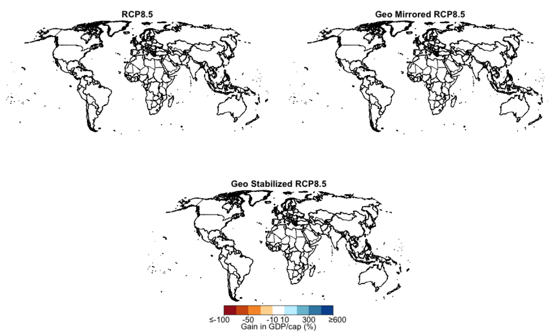
SSP 1



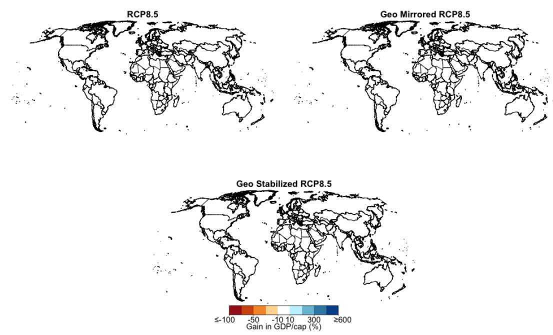
SSP 2



SSP 3



SSP 4



SSP 5

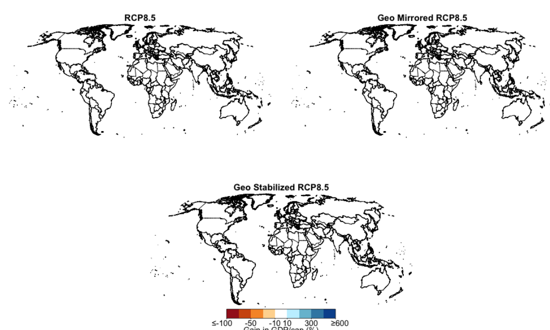


Figure A.23: **Percentage Gain in GDP per capita in 2099 relative to the scenario with no changes.** Each panel displays the country-level percentage gain in GDP per capita for the RCP 8.5, geoengineering mirrored RCP 8.5, and geoengineering stabilized RCP 8.5 scenarios relative no changes scenario in 2099. **a** uses the model from column (1) in Table Table A.1; **b** uses column (2); **c** uses column (3); **d** uses column (4); **e** uses column (5); **f** uses column (6); **g** uses column (7); **h** uses column (8); **i** uses column (9); **j** uses column (10); **k** uses column (11).

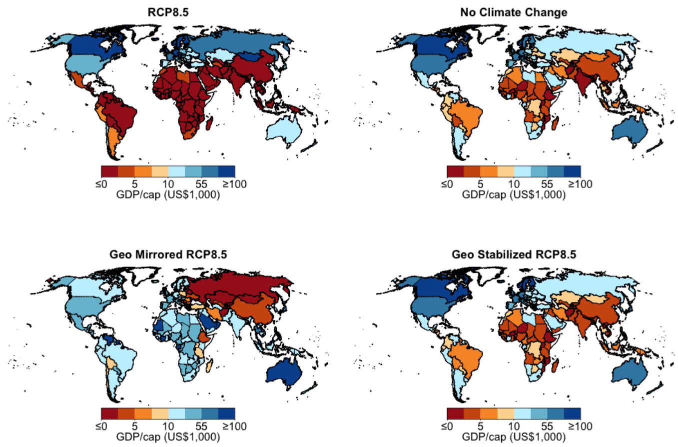


Figure A.24: **GDP per capita in 2099.** Projected country-level GDP per capita in 2099. Results are for the model in column (1) of Table Table A.1 for SSP3.

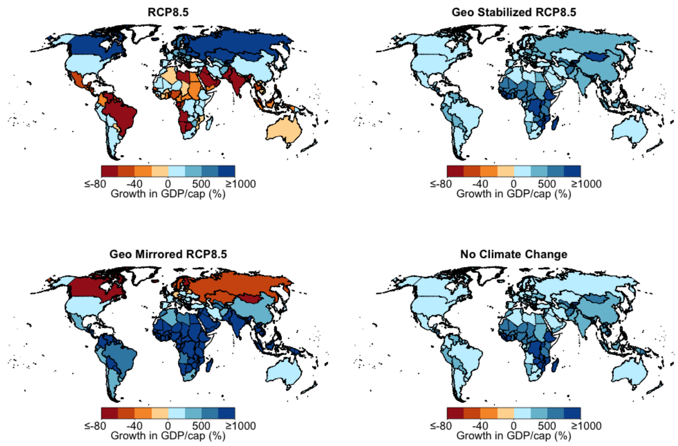
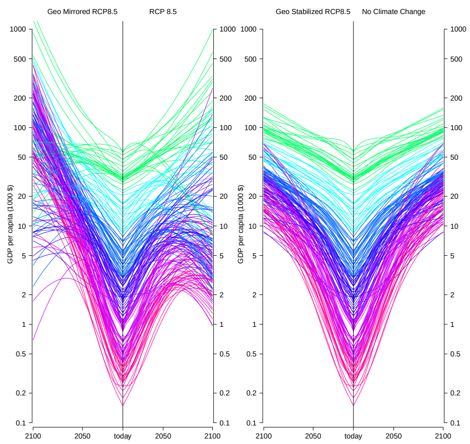


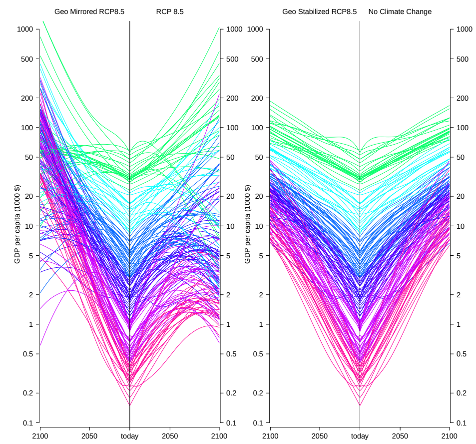
Figure A.25: **Percentage Gain in GDP per capita from 2010 to 2099.** Results are for the model in column (1) of Table Table A.1 for SSP3.

a.

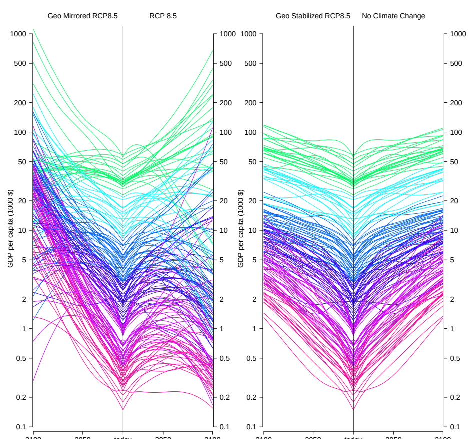
SSP 1



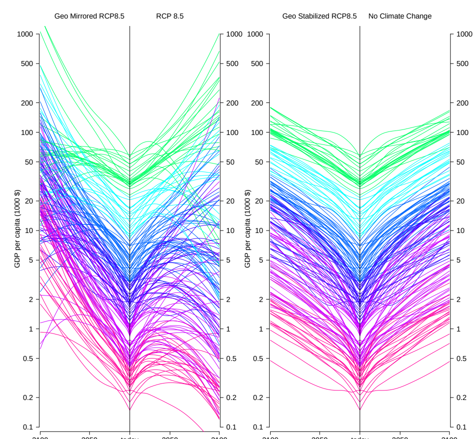
SSP 2



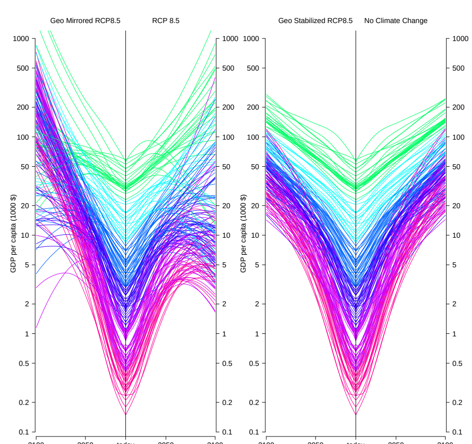
SSP 3



SSP 4

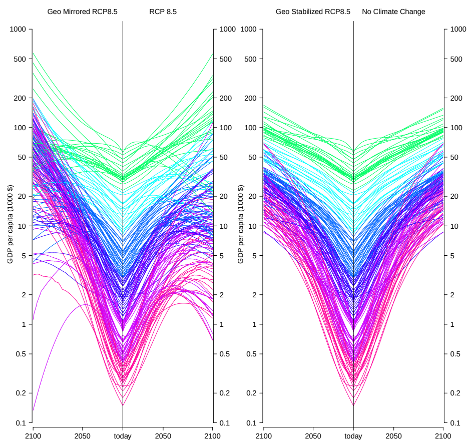


SSP 5

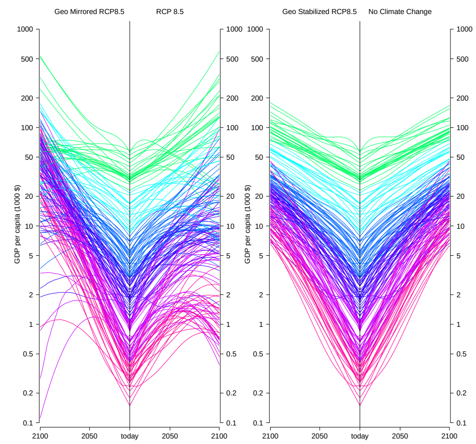


b.

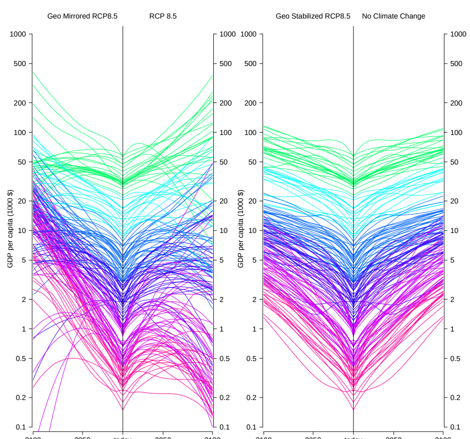
SSP 1



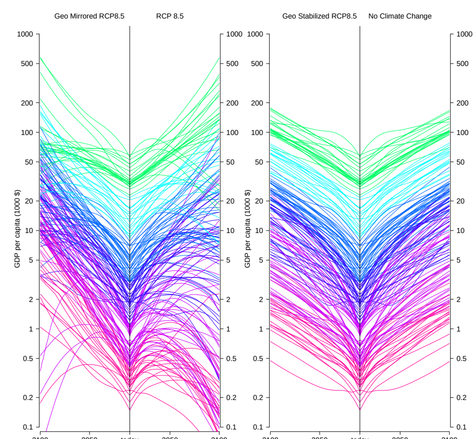
SSP 2



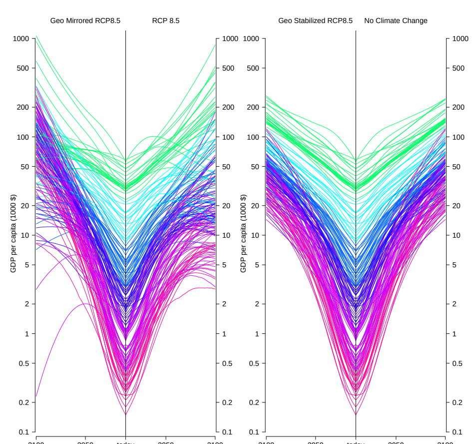
SSP 3



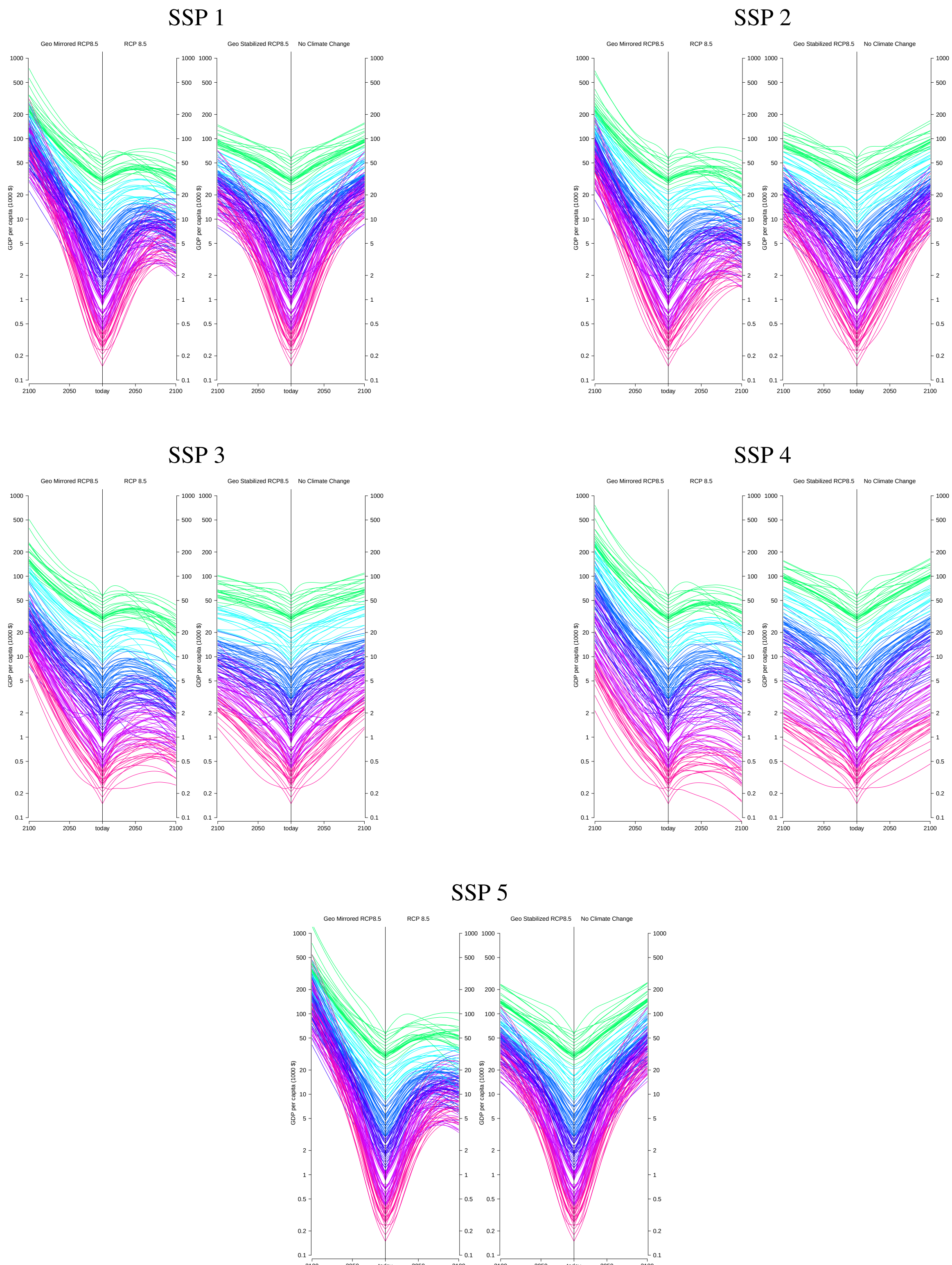
SSP 4



SSP 5

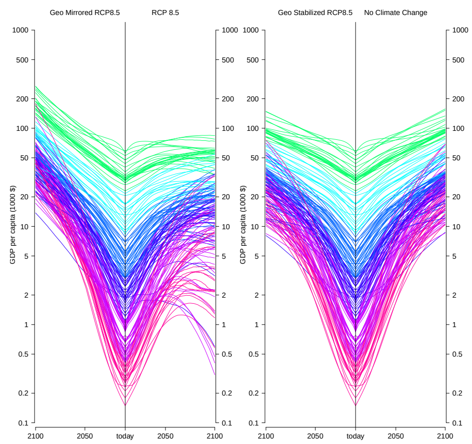


c.

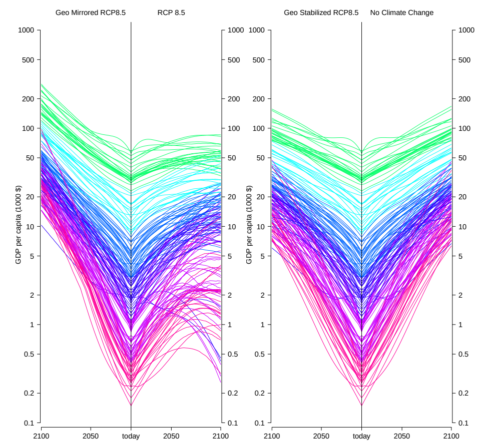

SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Geo Mirrored RCP8.5
RCP 8.5
Geo Stabilized RCP8.5
No Climate Change
GDP per capita (1000 $)
1000
500
200
100
50
20
10
5
2
1
0.5
0.2
0.1
2100
2050
today
2050
2100

d.

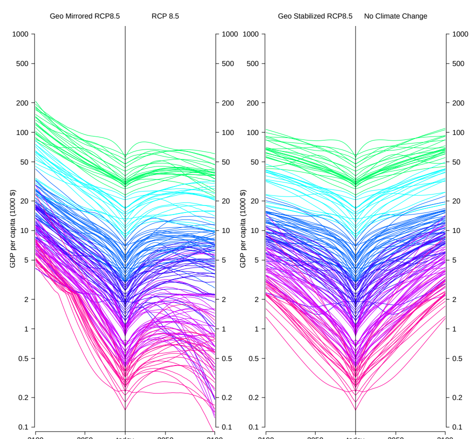
SSP 1



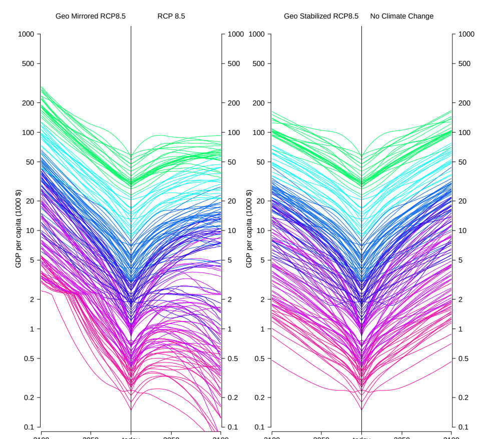
SSP 2



SSP 3



SSP 4



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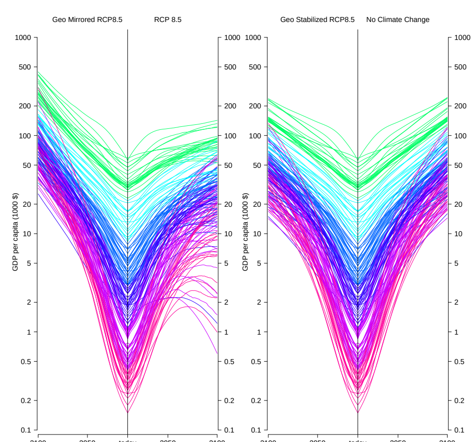
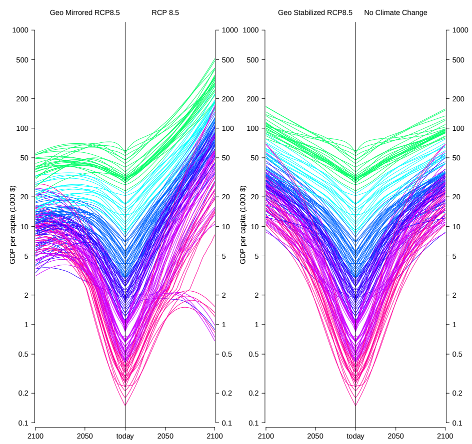


e.

SSP 1



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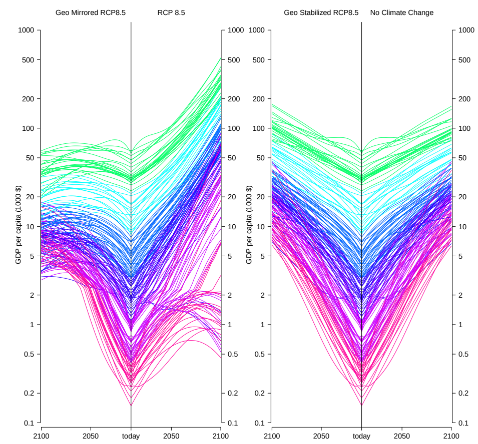

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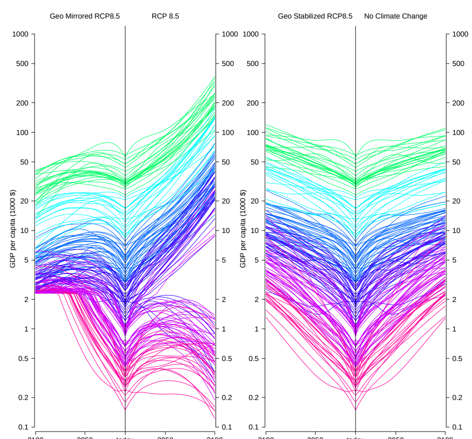
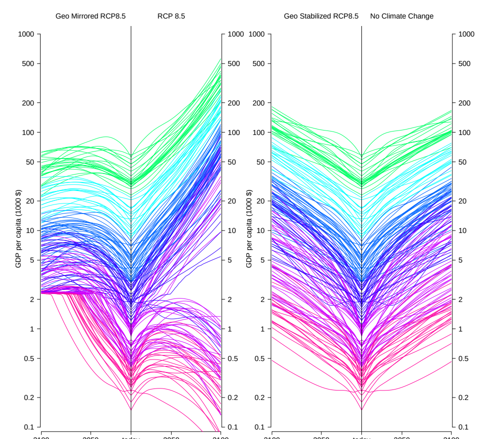
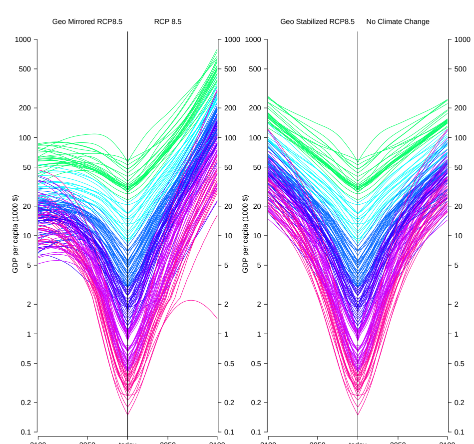


SSP 4

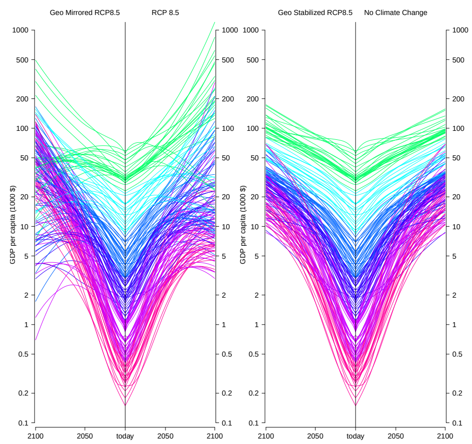


SSP 5



f.

SSP 1



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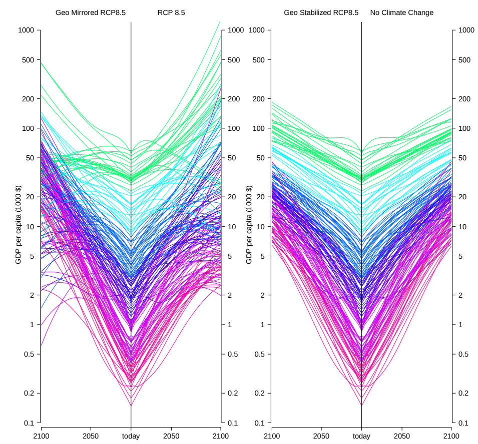
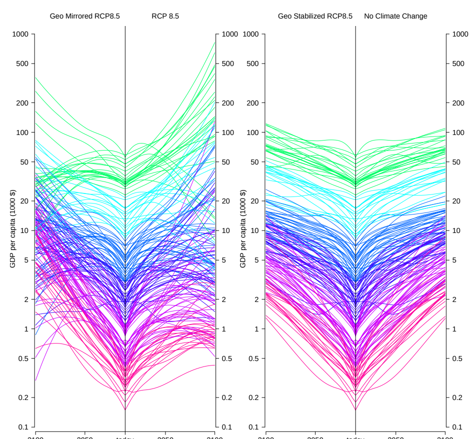
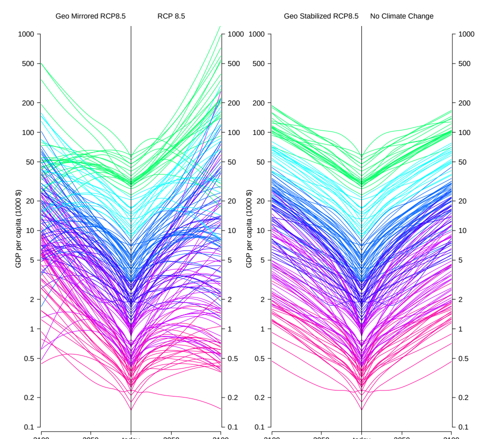


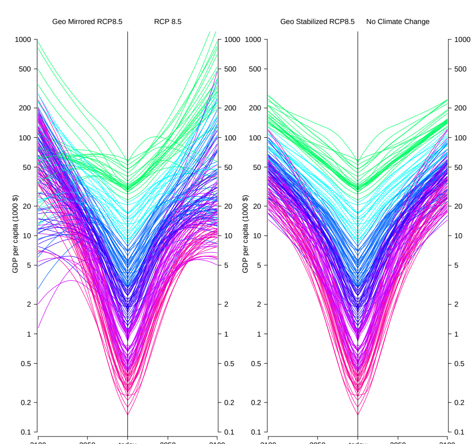
SSP 3



SSP 4

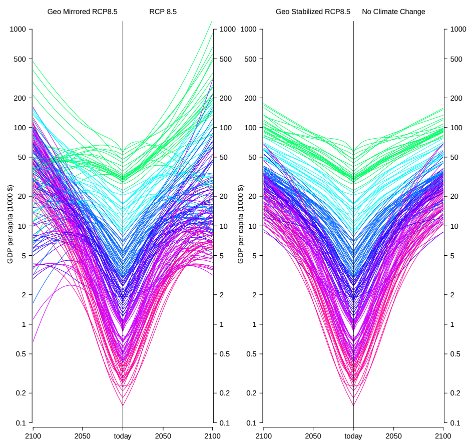


SSP 5

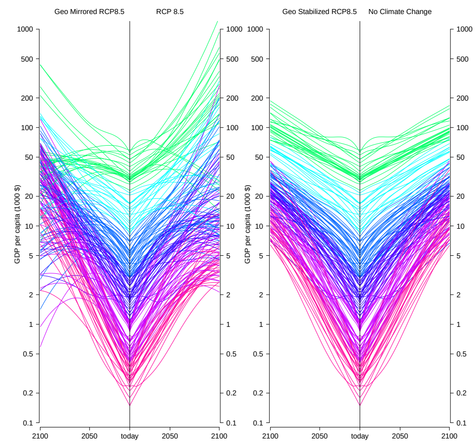


g.

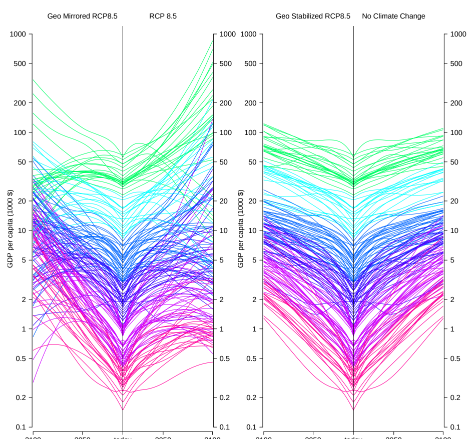
SSP 1



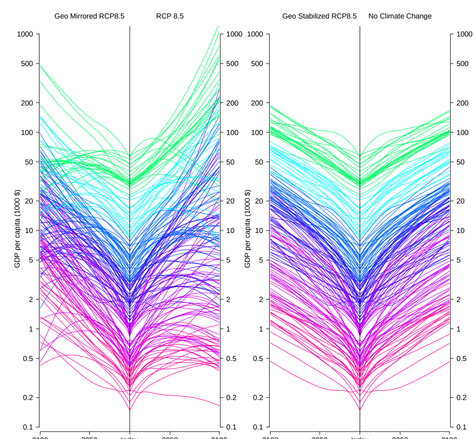
SSP 2



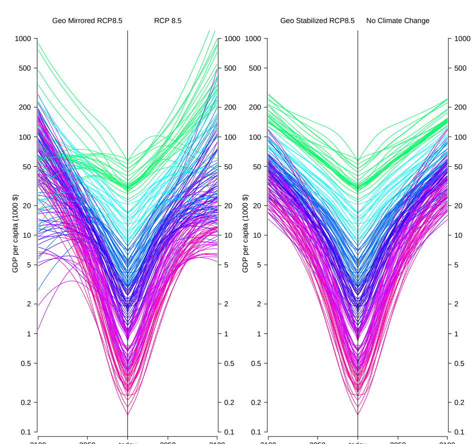
SSP 3



SSP 4

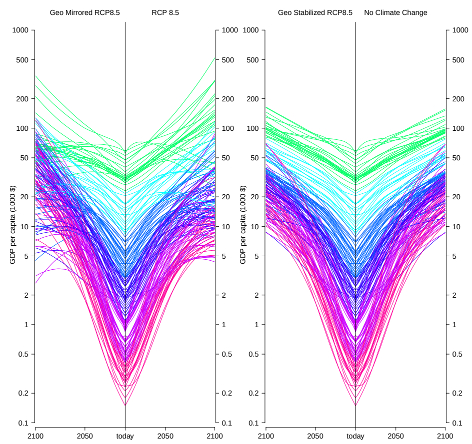


SSP 5

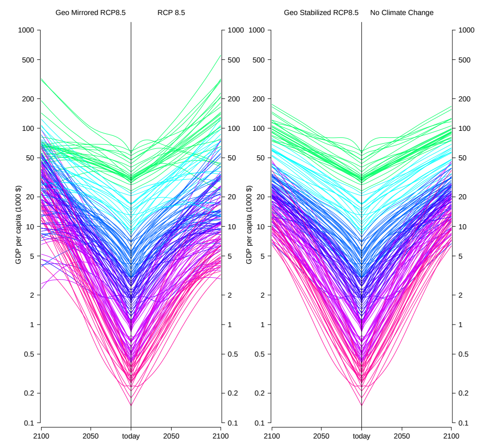


h.

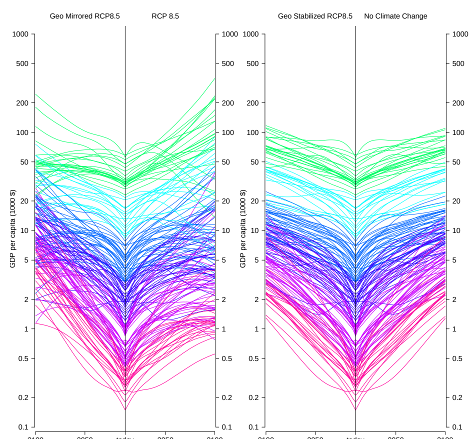
SSP 1



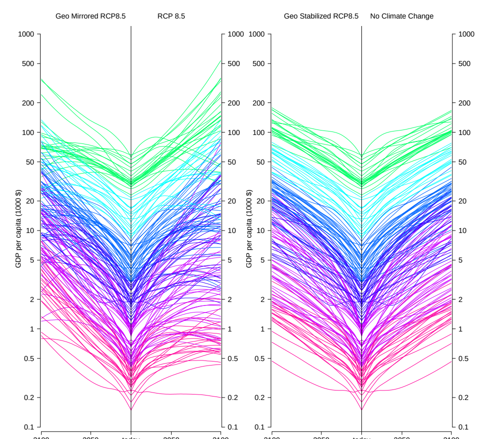
SSP 2



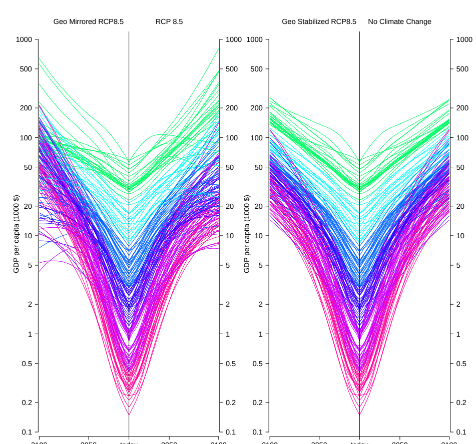
SSP 3



SSP 4

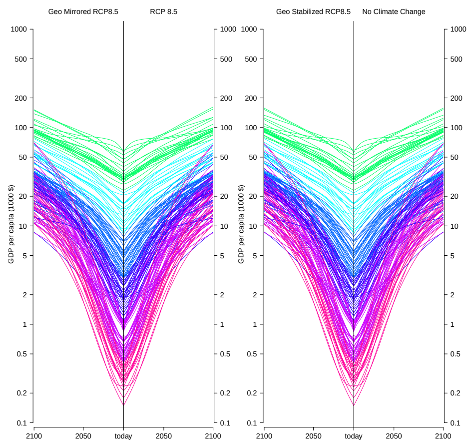


SSP 5

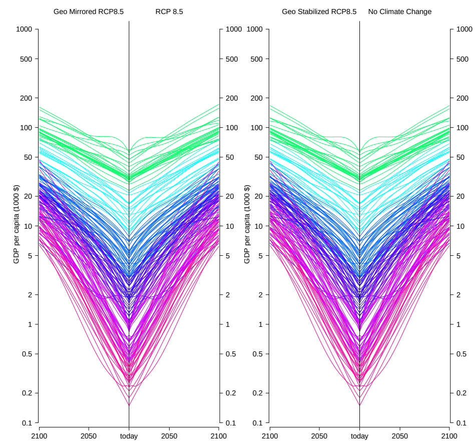


i.

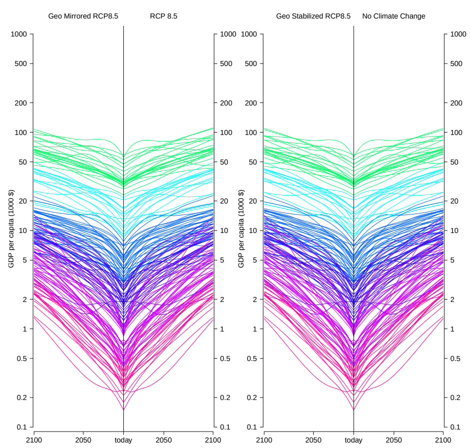
SSP 1



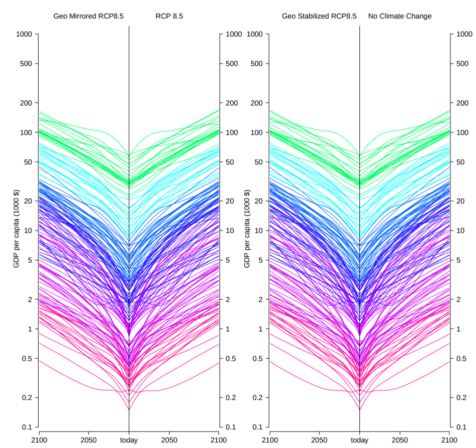
SSP 2



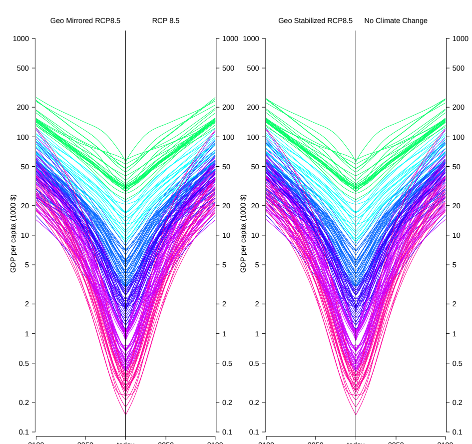
SSP 3



SSP 4

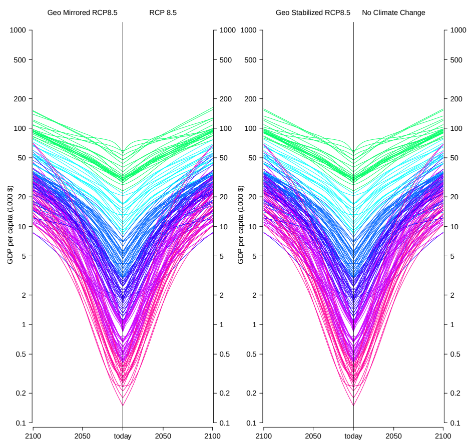


SSP 5

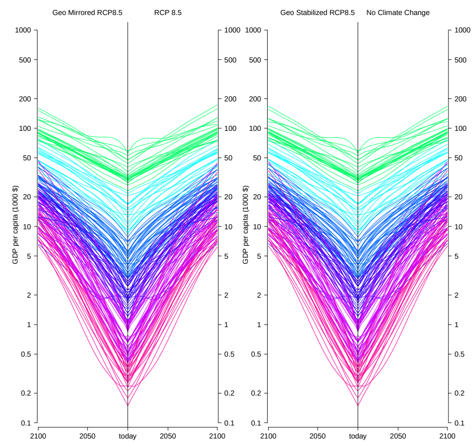


j.

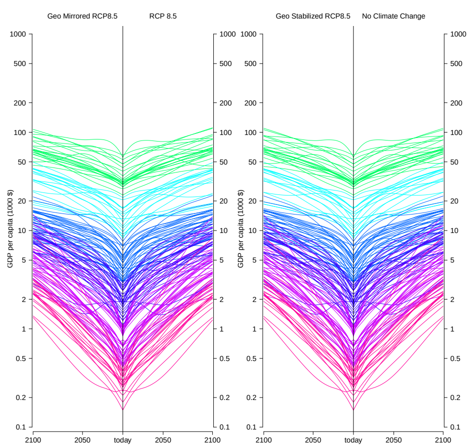
SSP 1



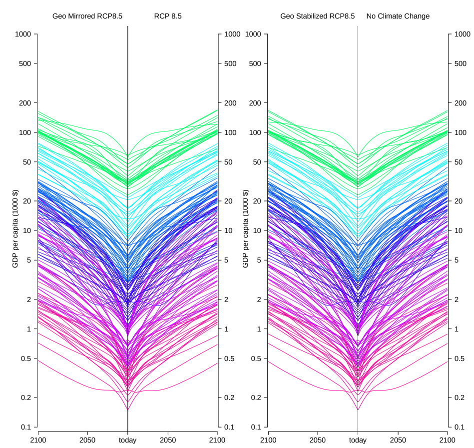
SSP 2



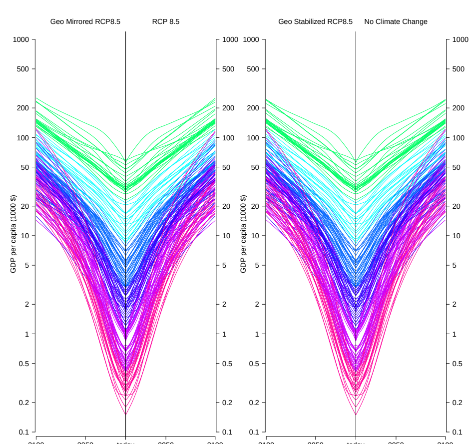
SSP 3



SSP 4



SSP 5



k.

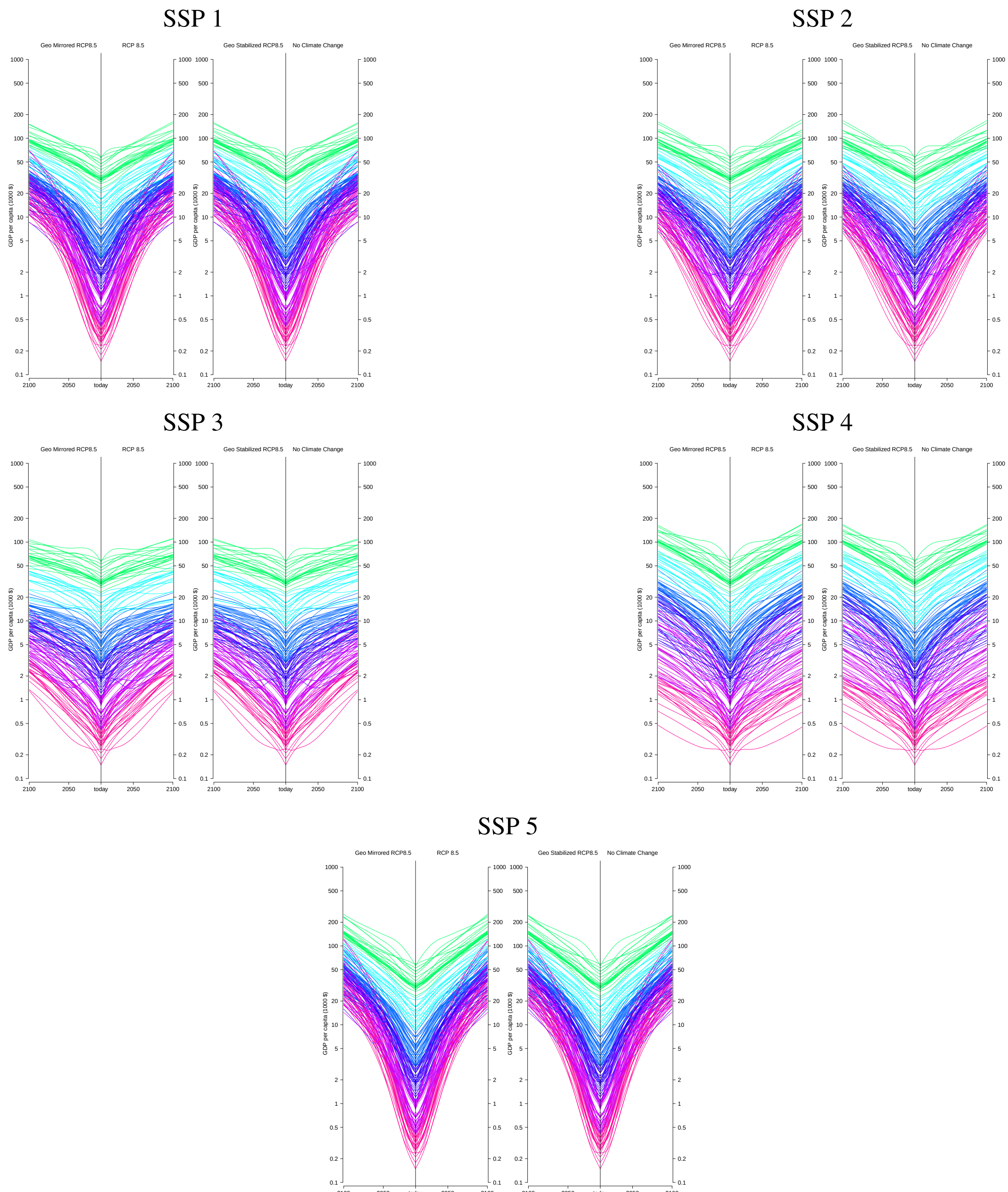
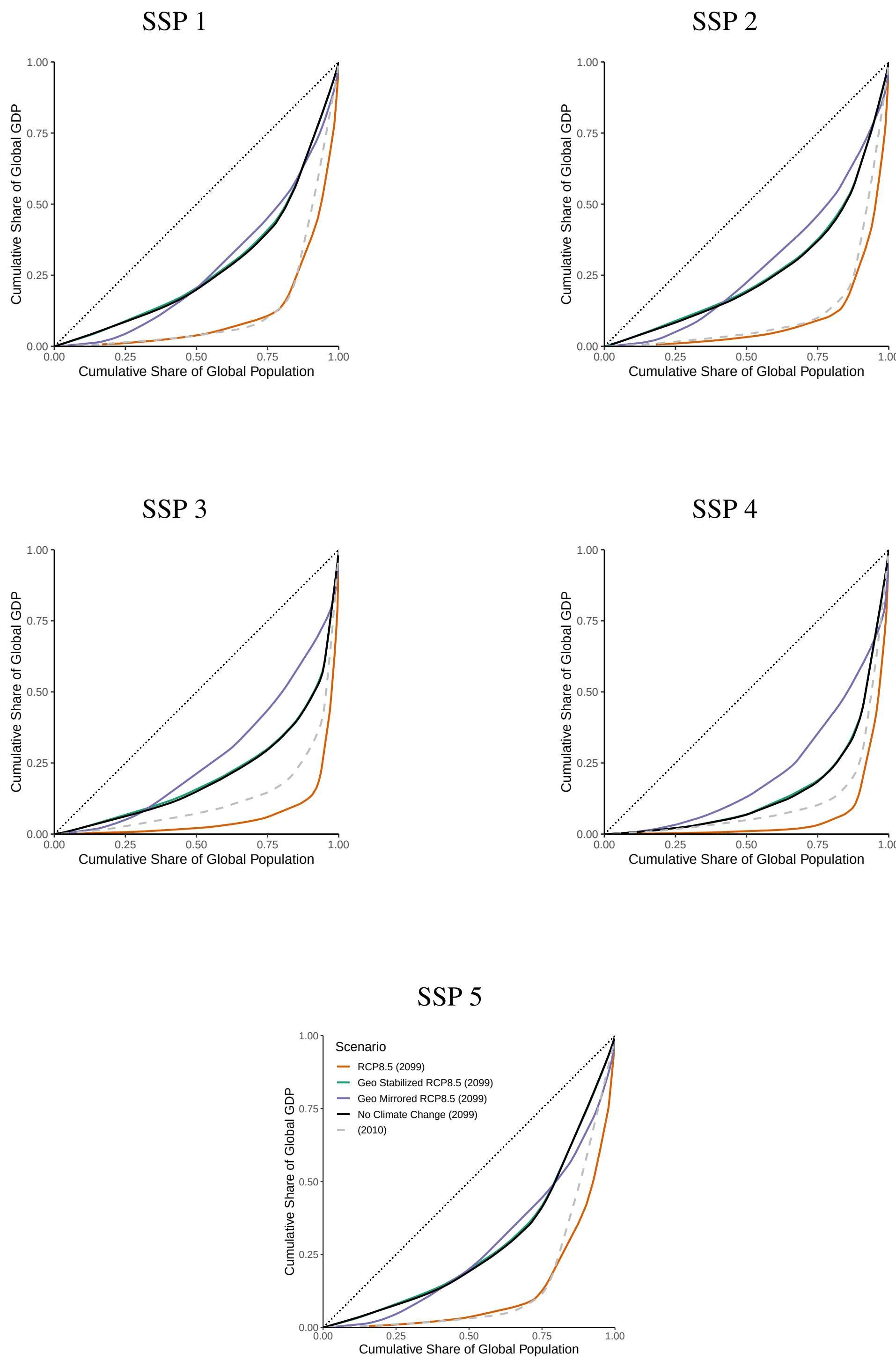
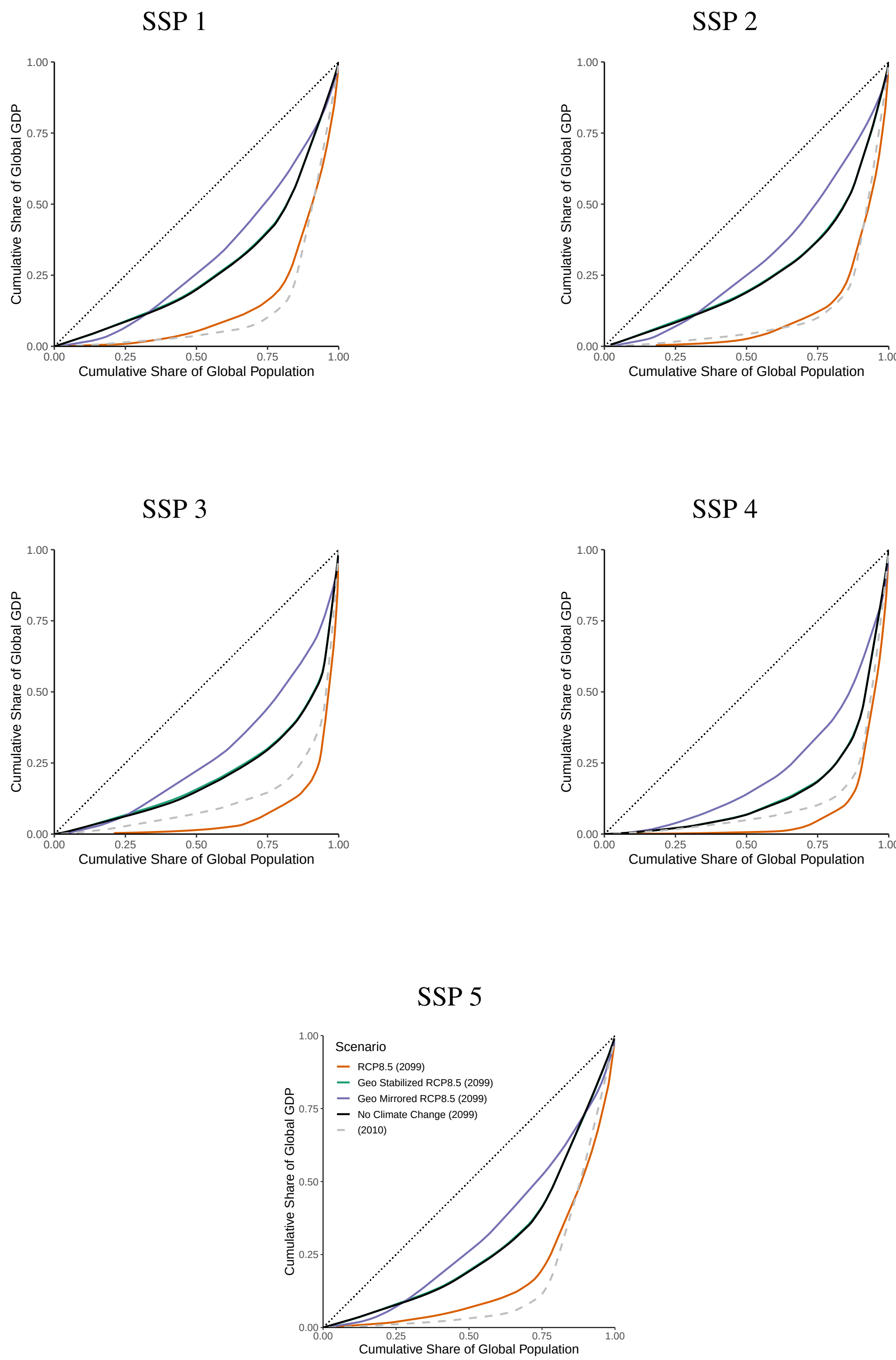


Figure A.36: **Country GDP per capita over time.** Each line represents a single country. The color of each line represents the country's initial GDP per capita in 2010. Each panel shows a different SSP. Each subfigure shows a different climate impacts model. **a** uses the model from column (1) in Table Table A.1; **b** uses column (2); **c** uses column (3); **d** uses column (4); **e** uses column (5); **f** uses column (6); **g** uses column (7); **h** uses column (8); **i** uses column (9); **j** uses column (10); **k** uses column (11).

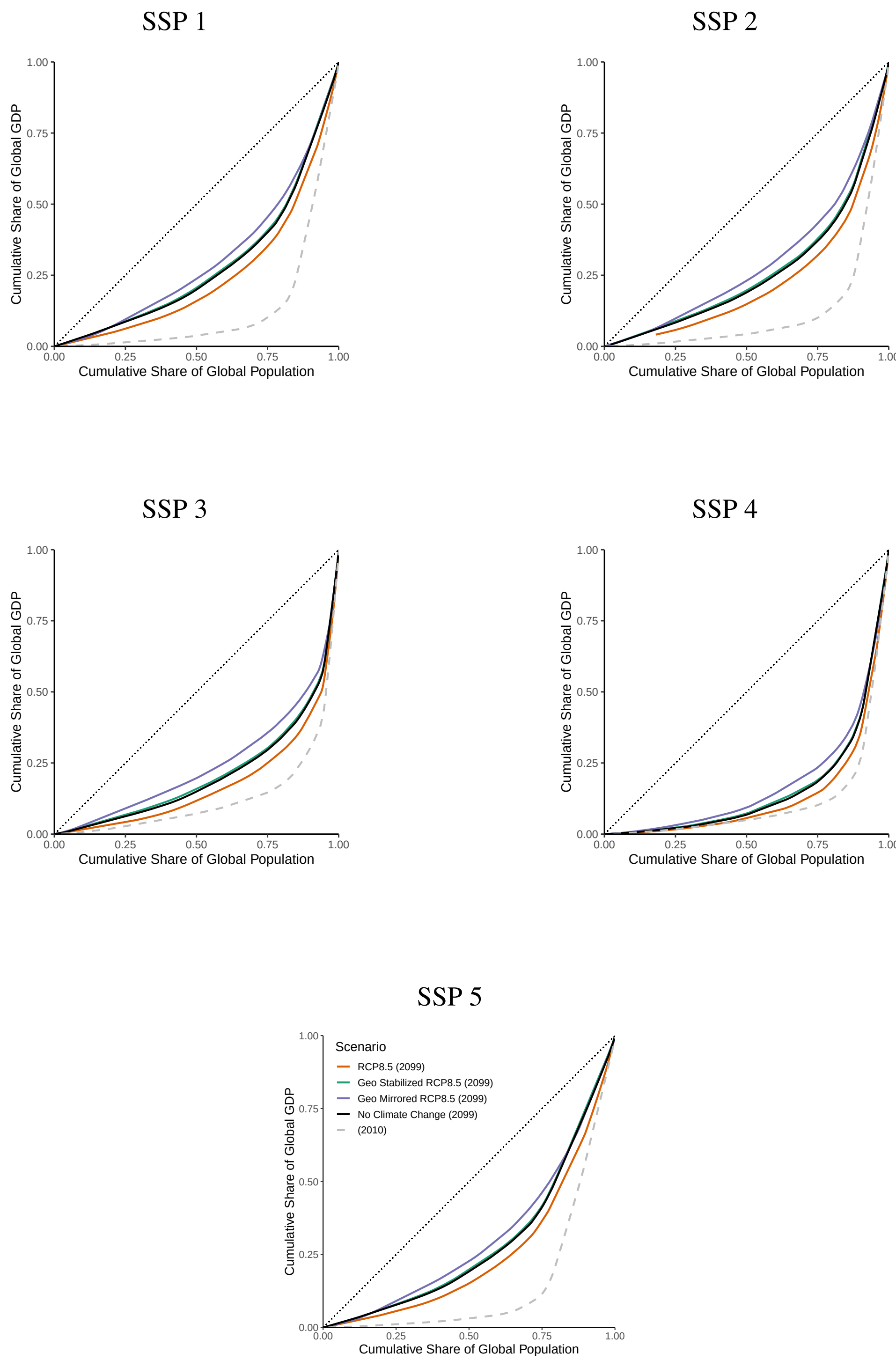
a.


SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Cumulative Share of Global GDP
Cumulative Share of Global Population
0.00
0.25
0.50
0.75
1.00
Scenario
RCP8.5 (2099)
Geo Stabilized RCP8.5 (2099)
Geo Mirrored RCP8.5 (2099)
No Climate Change (2099)
(2010)

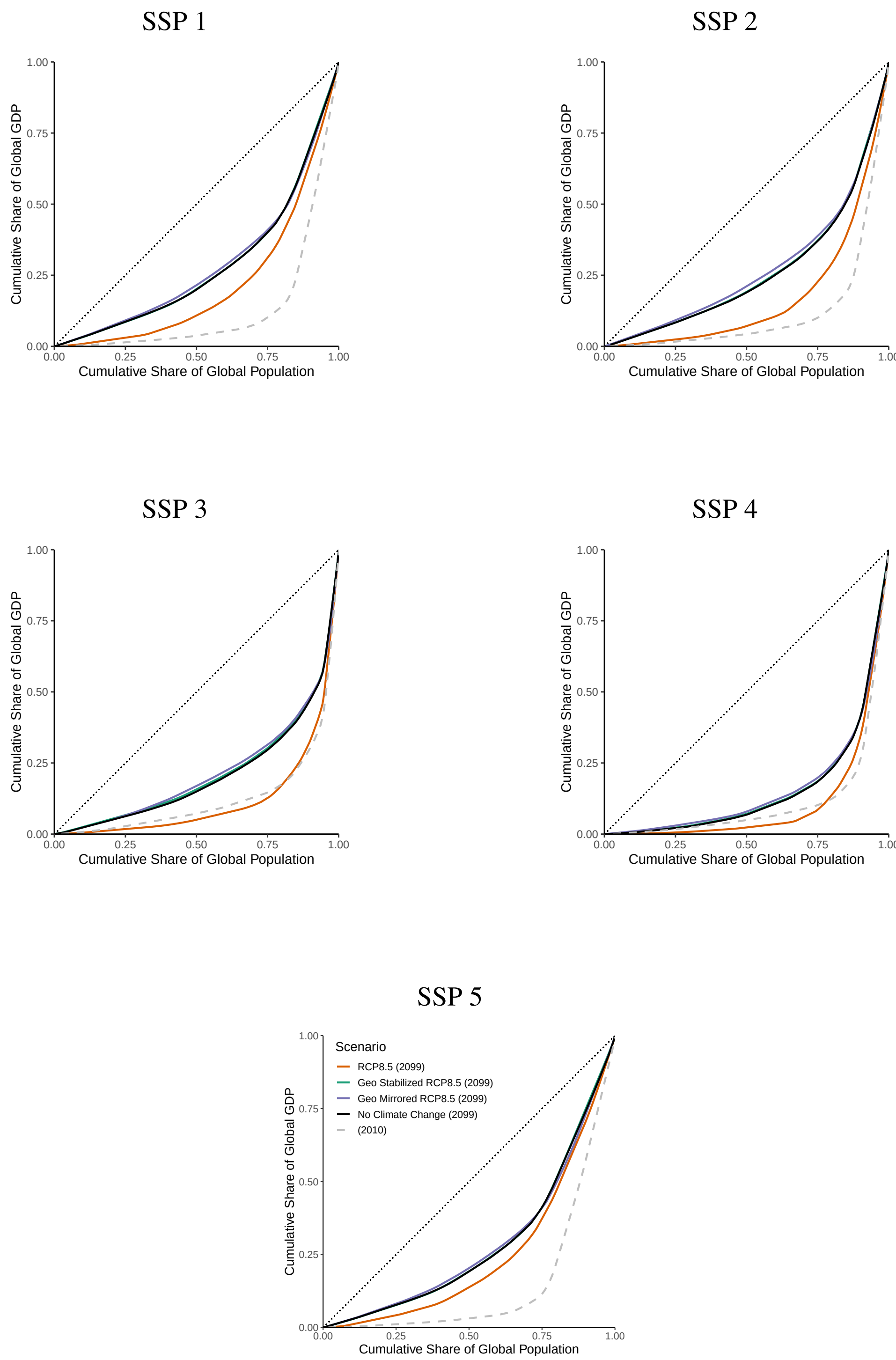
b.


SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Cumulative Share of Global GDP
Cumulative Share of Global Population
0.00
0.25
0.50
0.75
1.00
Scenario
RCP8.5 (2099)
Geo Stabilized RCP8.5 (2099)
Geo Mirrored RCP8.5 (2099)
No Climate Change (2099)
(2010)

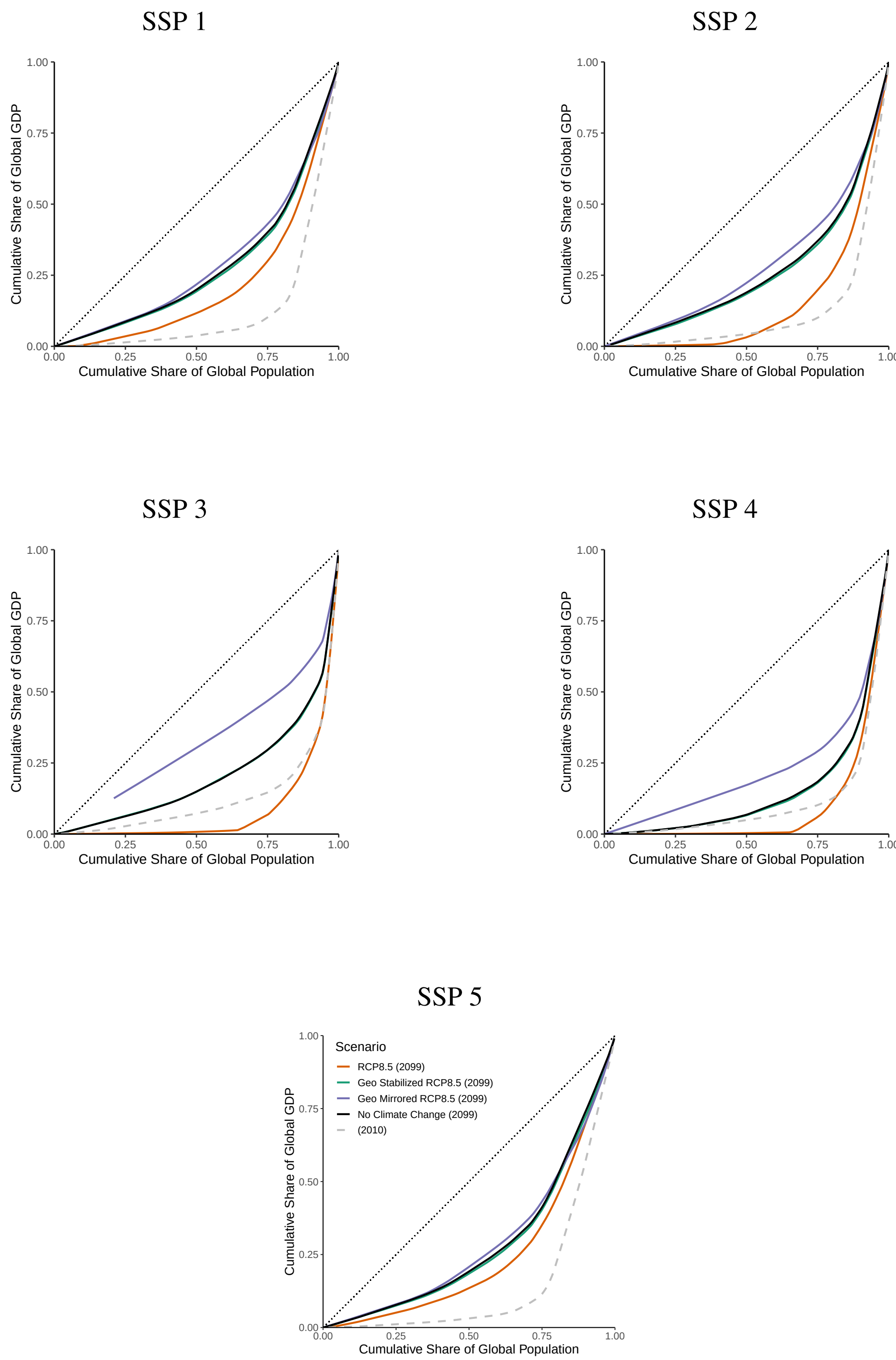
c.


SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Cumulative Share of Global GDP
Cumulative Share of Global Population
0.00
0.25
0.50
0.75
1.00
Scenario
RCP8.5 (2099)
Geo Stabilized RCP8.5 (2099)
Geo Mirrored RCP8.5 (2099)
No Climate Change (2099)
(2010)

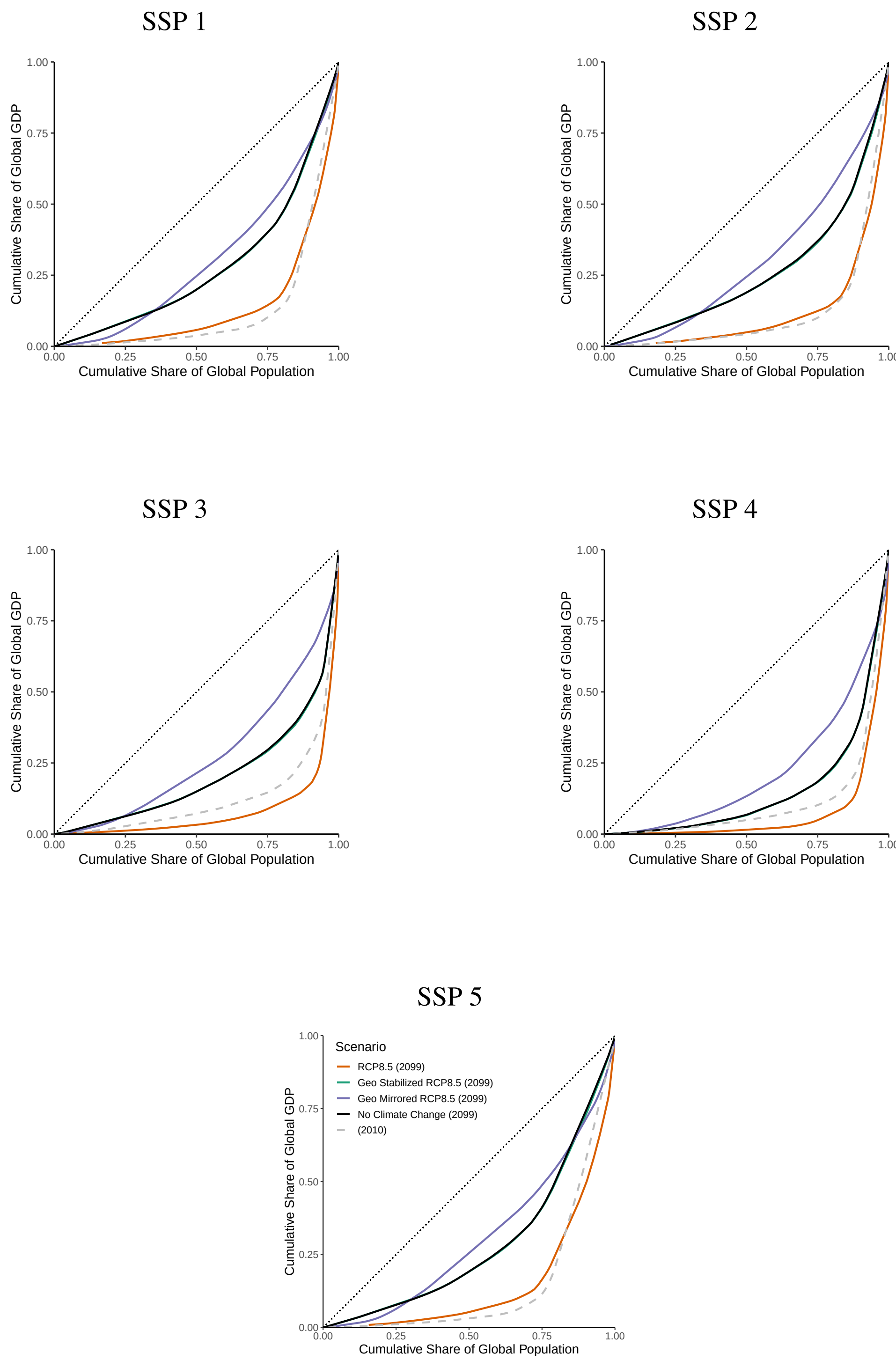
d.


SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Cumulative Share of Global GDP
Cumulative Share of Global Population
0.00
0.25
0.50
0.75
1.00
Scenario
RCP8.5 (2099)
Geo Stabilized RCP8.5 (2099)
Geo Mirrored RCP8.5 (2099)
No Climate Change (2099)
(2010)

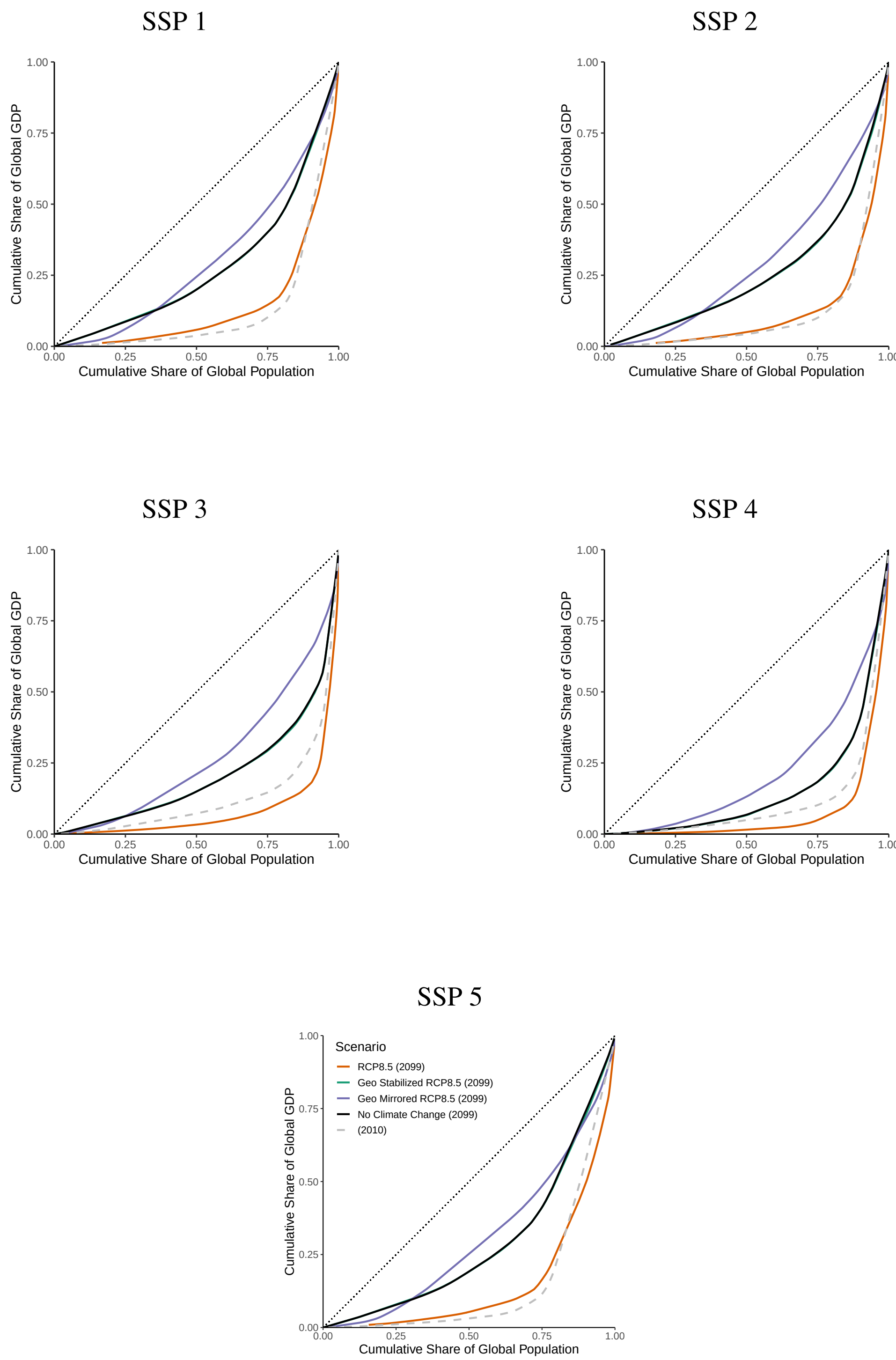
e.


SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Cumulative Share of Global GDP
Cumulative Share of Global Population
0.00
0.25
0.50
0.75
1.00
Scenario
RCP8.5 (2099)
Geo Stabilized RCP8.5 (2099)
Geo Mirrored RCP8.5 (2099)
No Climate Change (2099)
(2010)

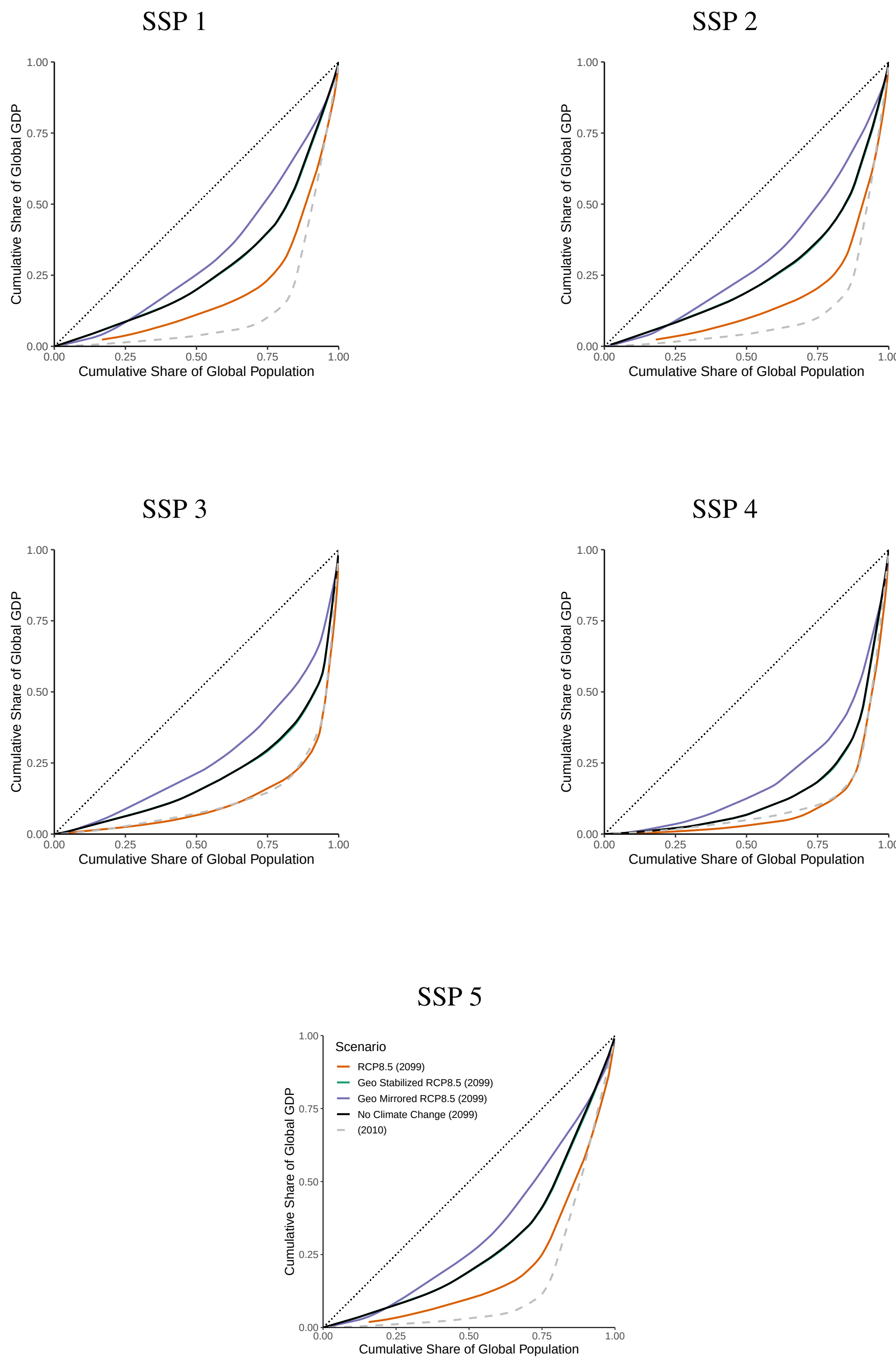
f.


SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Cumulative Share of Global GDP
Cumulative Share of Global Population
0.00
0.25
0.50
0.75
1.00
Scenario
RCP8.5 (2099)
Geo Stabilized RCP8.5 (2099)
Geo Mirrored RCP8.5 (2099)
No Climate Change (2099)
(2010)

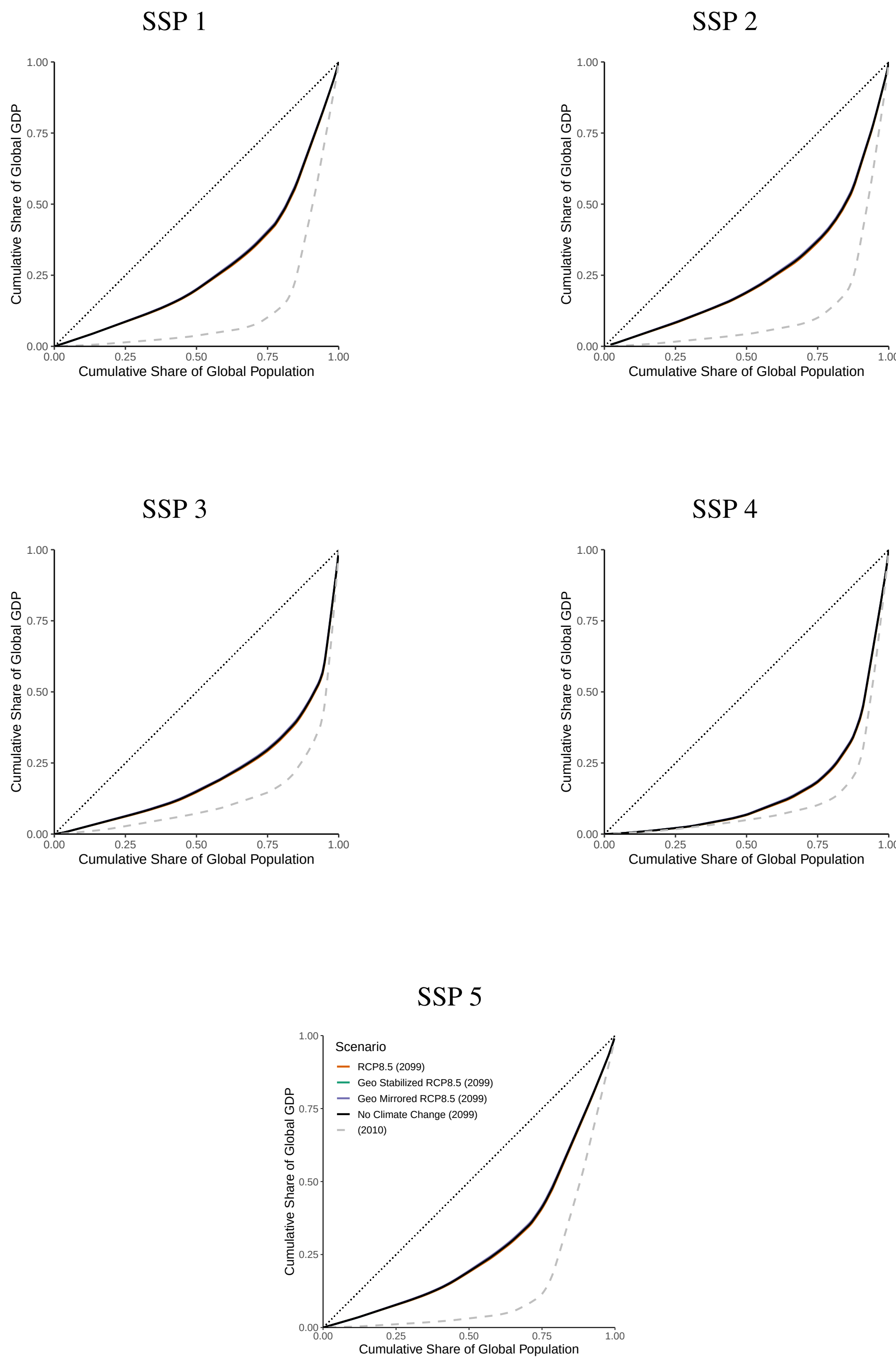
g.


SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Cumulative Share of Global GDP
Cumulative Share of Global Population
0.00
0.25
0.50
0.75
1.00
Scenario
RCP8.5 (2099)
Geo Stabilized RCP8.5 (2099)
Geo Mirrored RCP8.5 (2099)
No Climate Change (2099)
(2010)

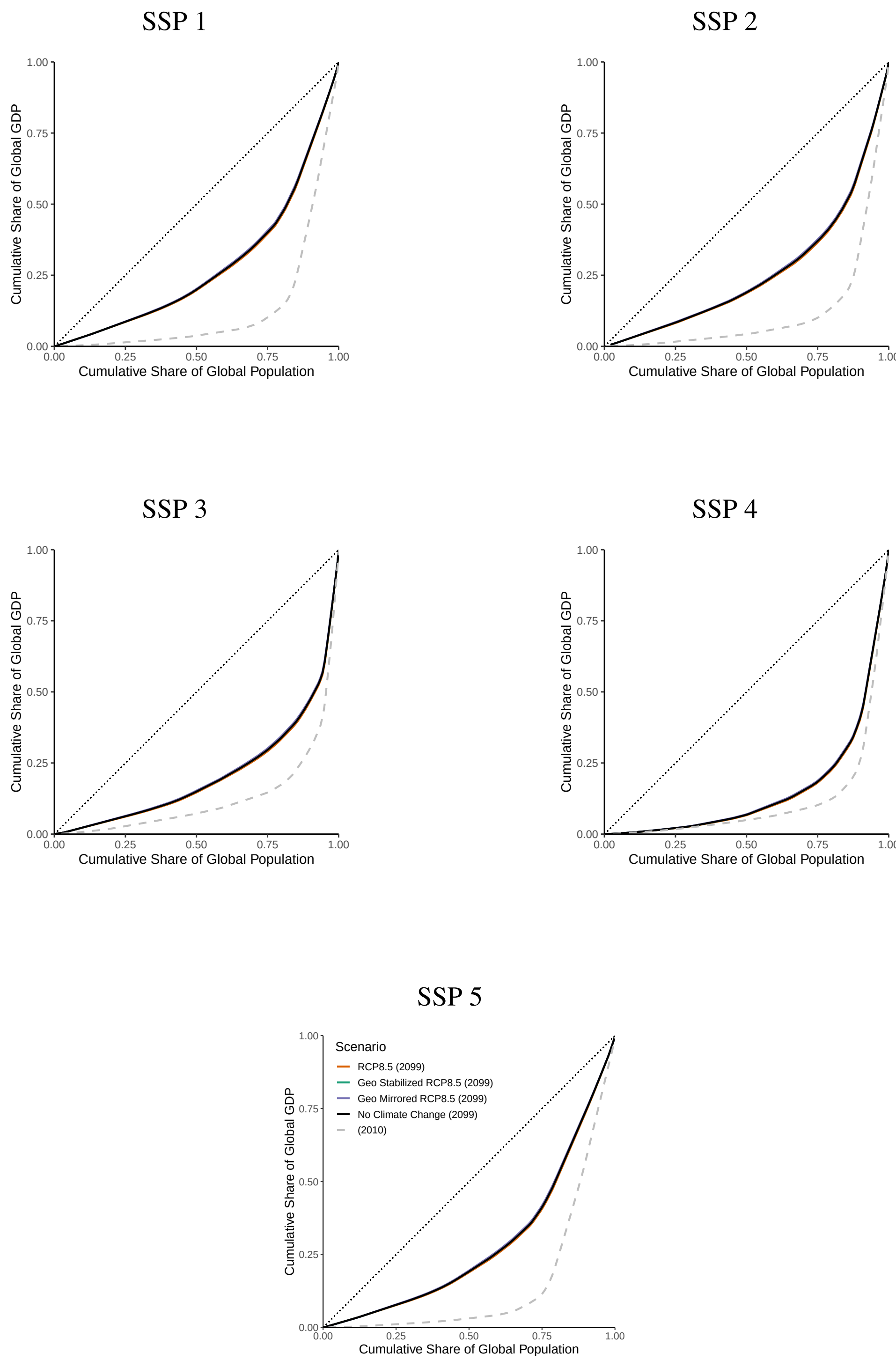
h.


SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Cumulative Share of Global GDP
Cumulative Share of Global Population
0.00
0.25
0.50
0.75
1.00
Scenario
RCP8.5 (2099)
Geo Stabilized RCP8.5 (2099)
Geo Mirrored RCP8.5 (2099)
No Climate Change (2099)
(2010)

i.


SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Cumulative Share of Global GDP
Cumulative Share of Global Population
0.00
0.25
0.50
0.75
1.00
Scenario
RCP8.5 (2099)
Geo Stabilized RCP8.5 (2099)
Geo Mirrored RCP8.5 (2099)
No Climate Change (2099)
(2010)

j.


SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Cumulative Share of Global GDP
Cumulative Share of Global Population
0.00
0.25
0.50
0.75
1.00
Scenario
RCP8.5 (2099)
Geo Stabilized RCP8.5 (2099)
Geo Mirrored RCP8.5 (2099)
No Climate Change (2099)
(2010)

k.

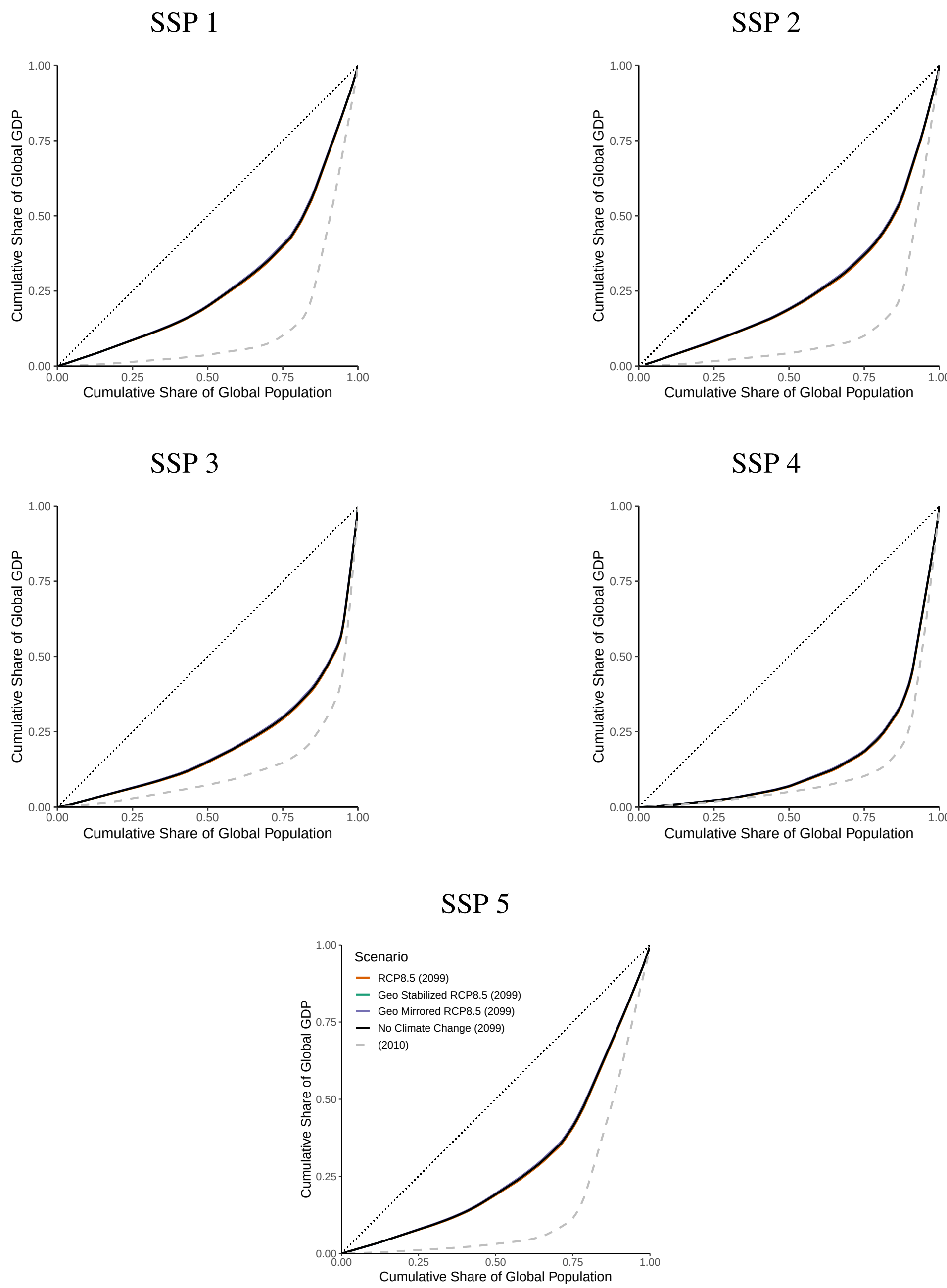
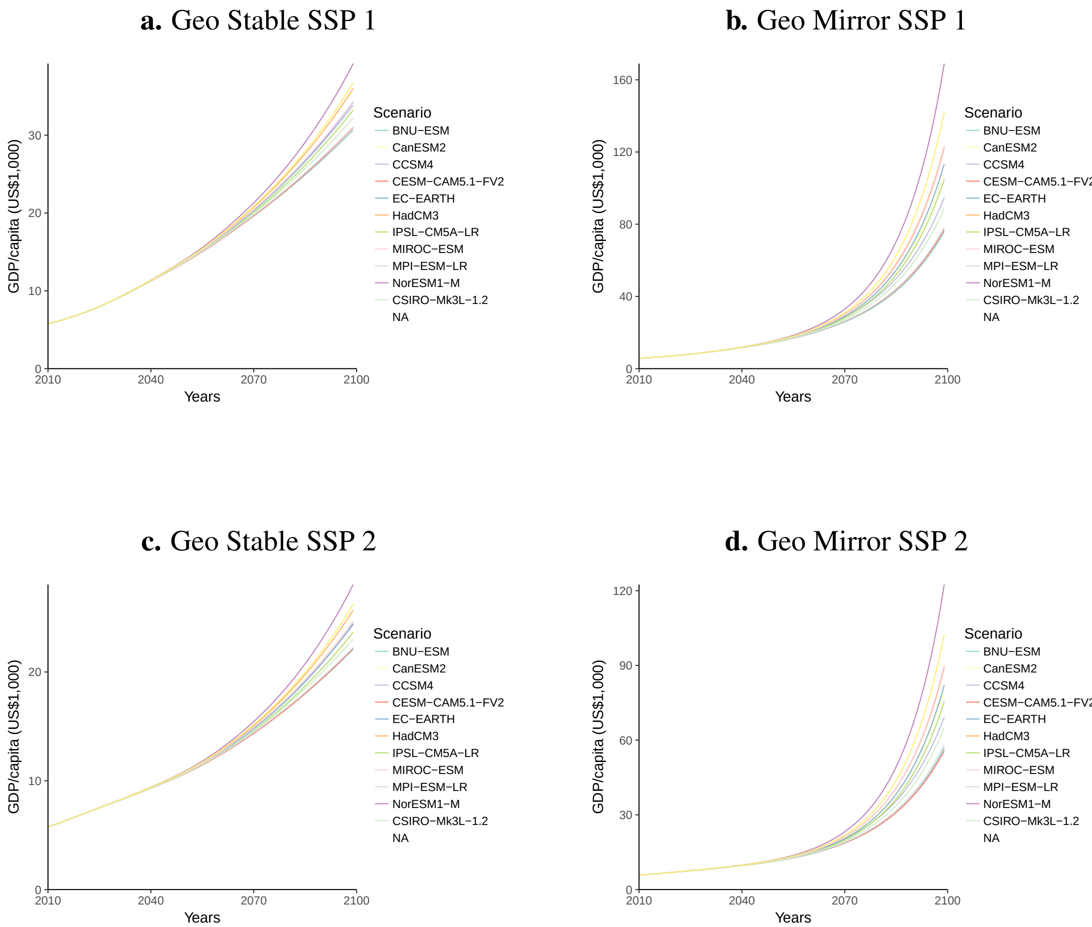
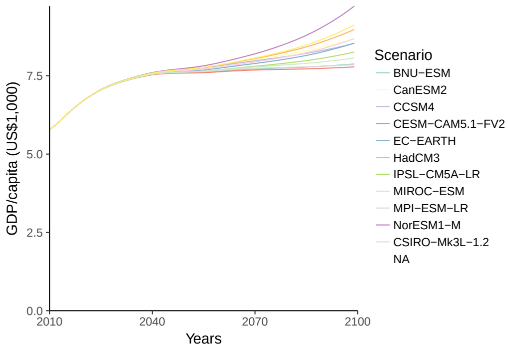


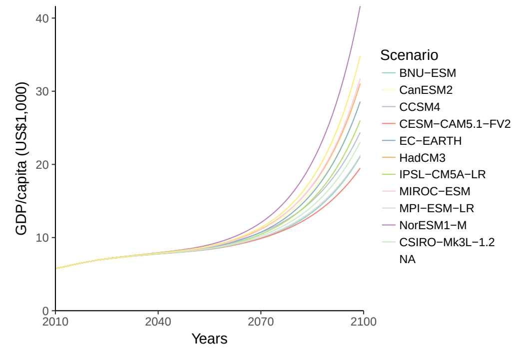
Figure A.47: **Lorenz Curve for share of global GDP.** Each line represents the distribution of the projected share of global GDP in 2099 for a different climate scenario in addition to the initial distribution in 2010. Each panel displays a different SSP. Each subfigure displays a different climate impacts model. **a** uses the model from column (1) in Table Table A.1; **b** uses column (2); **c** uses column (3); **d** uses column (4); **e** uses column (5); **f** uses column (6); **g** uses column (7); **h** uses column (8); **i** uses column (9); **j** uses column (10); **k** uses column (11).


a. Geo Stable SSP 1
b. Geo Mirror SSP 1
c. Geo Stable SSP 2
d. Geo Mirror SSP 2
GDP/capita (US$1,000)
Years
Scenario
BNU−ESM
CanESM2
CCSM4
CESM−CAM5.1−FV2
EC−EARTH
HadCM3
IPSL−CM5A−LR
MIROC−ESM
MPI−ESM−LR
NorESM1−M
CSIRO−Mk3L−1.2
NA

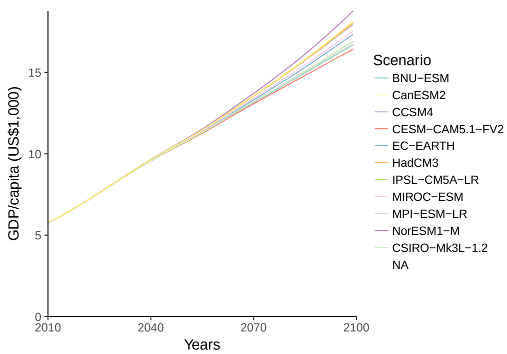
e. Geo Stable SSP 3



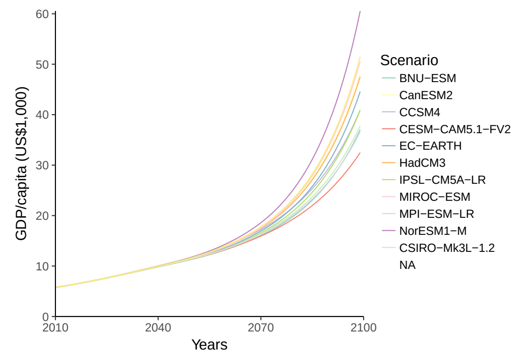
f. Geo Mirror SSP 3



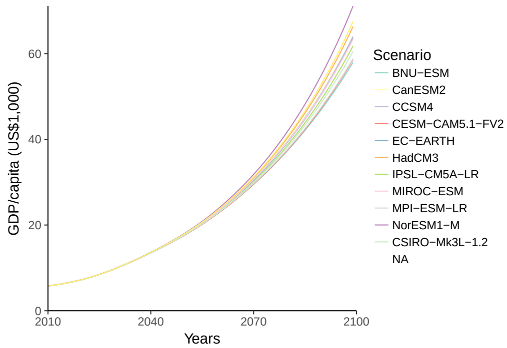
g. Geo Stable SSP 4



h. Geo Mirror SSP 4



i. Geo Stable SSP 5



j. Geo Mirror SSP 5

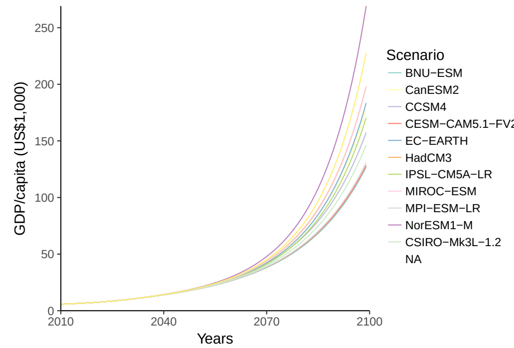
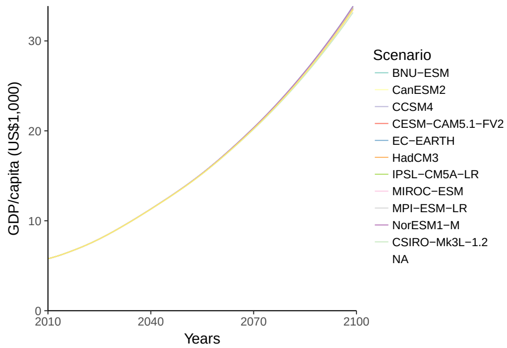
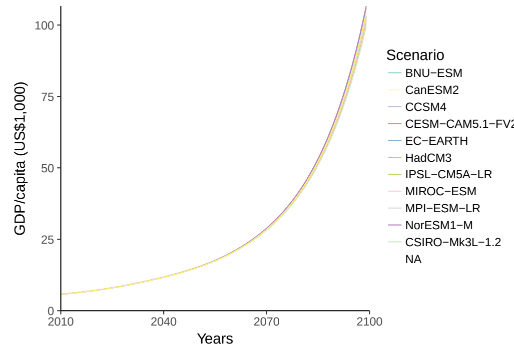


Figure A.50: **Projected global GDP per capita over the 21st Century across precipitation and temperature response to solar geoengineering.** Economic projections for Geoengineering Stabilized (a) SSP 1, (c) SSP2, (e) SSP3, (g) SSP4, (i) SSP5 and Geoengineering Mirrored (b) SSP1, (d) SSP2, (f) SSP3, (h) SSP4, (j) SSP5. Each line represents the median economic projection for temperature and precipitation response for each GeoMIP climate model individually. Results are for the model in column 1 of Table Table A.1.

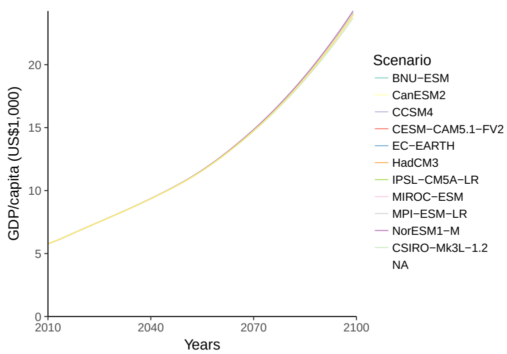
a. Geo Stable SSP 1



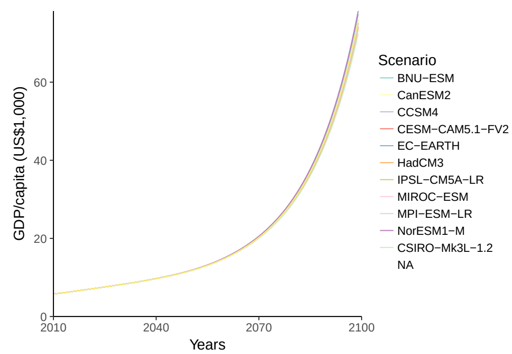
b. Geo Mirror SSP 1



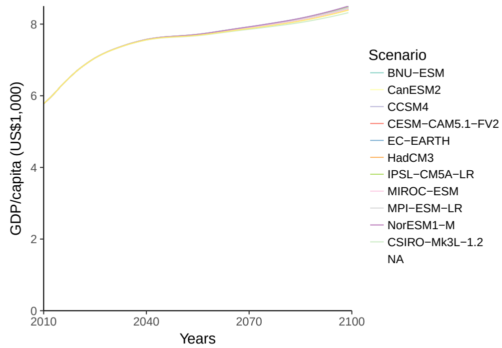
c. Geo Stable SSP 2



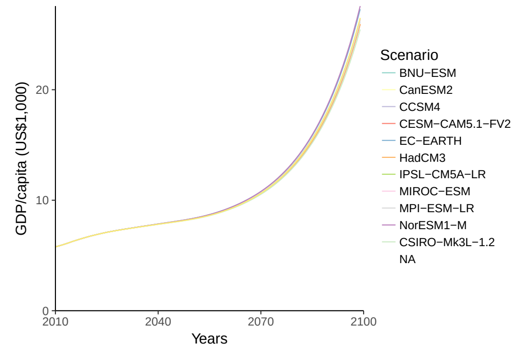
d. Geo Mirror SSP 2



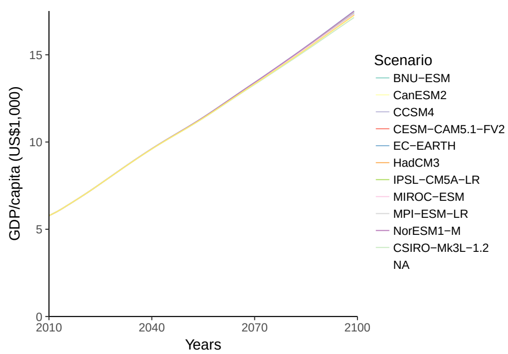
e. Geo Stable SSP 3



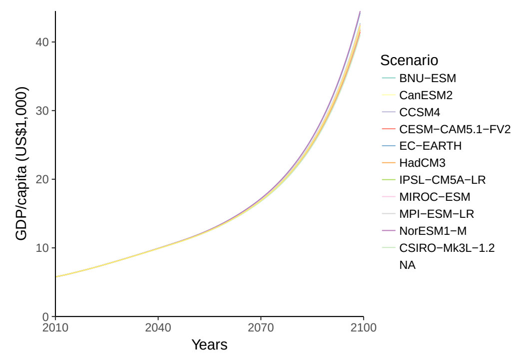
f. Geo Mirror SSP 3



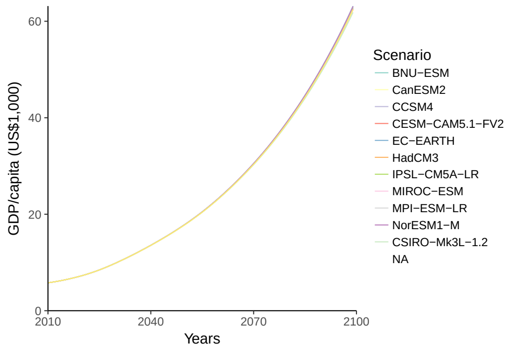
g. Geo Stable SSP 4



h. Geo Mirror SSP 4



i. Geo Stable SSP 5



j. Geo Mirror SSP 5

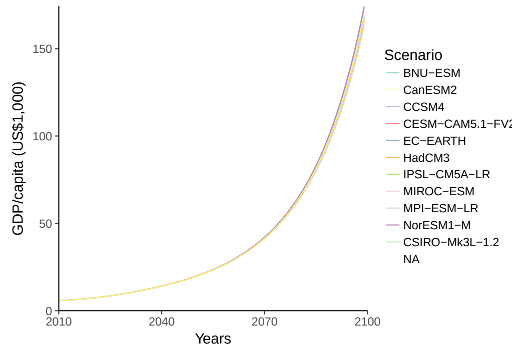


Figure A.53: **Projected global GDP per capita over the 21st Century across precipitation response to solar geoengineering.** Economic projections for Geoengineering Stabilized (a) SSP 1, (c) SSP2, (e) SSP3, (g) SSP4, (i) SSP5 and Geoengineering Mirrored (b) SSP1, (d) SSP2, (f) SSP3, (h) SSP4, (j) SSP5. Each line represents the median economic projection for GeoMIP mean ensemble temperature response and precipitation response for each GeoMIP climate model individually. Results are for the model in column 1 of Table Table A.1.

Supplementary Tables

Table A.1: **Regression Results.** Summary of regression results for the econometrically estimated historical climate-economy relationship. Estimated using fixed-effects models of 165 countries from 1960-2010.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Temp	0.0127***	0.00890*	0.00978**	0.0104*	0.00606	0.0132***	0.0133***	0.0111***			
	(0.00325)	(0.00421)	(0.00355)	(0.00454)	(0.00350)	(0.00369)	(0.00370)	(0.00314)			
Temp Sq.	-0.000487***	-0.000316	-0.000466***	-0.000454**		-0.000385***	-0.000381***	-0.000442***			
	(0.000103)	(0.000162)	(0.000110)	(0.000172)		(0.000104)	(0.000105)	(0.000126)			
Precip	0.0000145	0.00000672	0.00000992	-0.00000791			0.00000838	0.00000734			
	(0.0000102)	(0.0000141)	(0.0000105)	(0.0000144)			(0.0000105)	(0.0000116)			
Precip Sq.	-4.75e-09	-2.69e-09	-3.23e-09	4.75e-10			-2.08e-09	-2.62e-09			
	(2.50e-09)	(3.52e-09)	(2.55e-09)	(3.57e-09)			(2.41e-09)	(2.63e-09)			
Temp*Poor		0.0165		-0.00752	-0.0111*						
		(0.00932)		(0.0106)	(0.00527)						
Temp Sq.*Poor		-0.000456		0.000161							
		(0.000250)		(0.000275)							
Precip*Poor		0.0000191		0.0000342							
		(0.0000207)		(0.0000212)							
Precip Sq.*Poor		-4.75e-09		-7.42e-09							
		(5.07e-09)		(5.19e-09)							
Change Temp									0.00923*	0.0103*	0.00945*
									(0.00363)	(0.00399)	(0.00368)
Change Temp Sq.									-0.000333*	-0.000382*	-0.000337**
									(0.000147)	(0.000157)	(0.000103)
Change Precip									0.00000334	0.00000384	0.00000340
									(0.0000151)	(0.0000125)	(0.00000877)
Change Precip Sq.									-1.12e-09	-1.16e-09	-1.21e-09
									(4.83e-09)	(1.00e-08)	(2.22e-09)
Temperature Function	Quadratic	Quadratic	Quadratic	Quadratic	Linear	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
GDP Growth or Levels	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Levels	Levels	Levels
Time Fixed Effects	Year	Year	Year	Year	Region-Year	Region-Year	Region-Year	Region-Year	Region-Year	Year	Region-Year
Country-Specific Time Trend	Quadratic	Quadratic	Quadratic	Quadratic	None	None	None	None	Quadratic	Quadratic	None
Short or Long Run	Short Run	Short Run	Long Run	Long Run	Short Run	Short Run	Short Run	Long Run			
Obs.	6584	6452	5754	5637	6452	6584	6584	5754	6518	6519	6518
R sq.	0.286	0.291	0.321	0.330	0.278	0.267	0.267	0.295	0.371	0.294	0.266
Adj. R sq.	0.221	0.225	0.247	0.253	0.209	0.211	0.211	0.234	0.285	0.229	0.209

Notes: Standard errors in parentheses. Significance stars correspond to * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All models include country fixed effects. Temperature is measured in C. Precipitation is measured in mm/year. Columns represent models specified as follows. (1) Estimates a pooled growth model with quadratic temperature and precipitation, year fixed effects, and a quadratic country time trend. (2) Estimates a growth model with quadratic temperature and precipitation and lags up to 5 years, year fixed effects, and a quadratic country time trend. (3) Estimates a growth model with quadratic temperature and precipitation for rich and poor countries separately, year fixed effects, and a quadratic country time trend. (4) Estimates a growth model with quadratic temperature and precipitation for rich and poor countries separately lagged up to 5 years, year fixed effects, and a quadratic country time trend. (5) Estimates a growth with linear temperature separately for rich and poor countries, region-year fixed effects, and no country time trend. (6) Estimates a pooled growth model with quadratic temperature, region-year fixed effects, and no country time trend. (7) Estimates a pooled growth model with quadratic temperature and precipitation, region-year fixed effects, and no country time trend. (8) Estimates a pooled growth model with quadratic temperature and precipitation lagged up to 5 years, region-year fixed effects, and no country time trend. (9) Estimates a pooled levels model with quadratic temperature and precipitation, region-year fixed effects, and a quadratic country time trend. (10) Estimates a pooled levels model with quadratic temperature and precipitation, year fixed effects, and a quadratic country time trend. (11) Estimates a pooled levels model with quadratic temperature and precipitation, region-year fixed effects, and no country time trend.

Table A.2: **GeoMIP G1 Experiment Models.** Models used to construct mean ensemble for climate variable changes from solar geoengineering.

Temperature	**Precipitation**
BNU-ESM	BNU-ESM
CanESM2	CanESM2
CCSM4	CCSM4
CESM-CAM5.1-FV2	CESM-CAM5.1-FV2
EC-EARTH	EC-EARTH
HadCM3	HadCM3
HadGEM2-ES	HadGEM2-ES
IPSL-CM5A-LR	IPSL-CM5A-LR
MIROC-ESM	MIROC-ESM
MPI-ESM-LR	MPI-ESM-LR
NorESM1-M	NorESM1-M
CSIRO-Mk3L-1.2	CSIRO-Mk3L-1.2

Table A.3: **Percentage of countries with an absolute loss in 2099 compared to 2010.** Values represent median projections for SSP3. Columns represent models specified as follows. (1) Estimates a pooled growth model with quadratic temperature and precipitation, year fixed effects, and a quadratic country time trend. (2) Estimates a growth model with quadratic temperature and precipitation and lags up to 5 years, year fixed effects, and a quadratic country time trend. (3) Estimates a growth model with quadratic temperature and precipitation for rich and poor countries separately, year fixed effects, and a quadratic country time trend. (4) Estimates a growth model with quadratic temperature and precipitation for rich and poor countries separately lagged up to 5 years, year fixed effects, and a quadratic country time trend. (5) Estimates a growth with linear temperature separately for rich and poor countries, region-year fixed effects, and no country time trend. (6) Estimates a pooled growth model with quadratic temperature, region-year fixed effects, and no country time trend. (7) Estimates a pooled growth model with quadratic temperature and precipitation, region-year fixed effects, and no country time trend. (8) Estimates a pooled growth model with quadratic temperature and precipitation lagged up to 5 years, region-year fixed effects, and no country time trend. (9) Estimates a pooled levels model with quadratic temperature and precipitation, region-year fixed effects, and a quadratic country time trend. (10) Estimates a pooled levels model with quadratic temperature and precipitation, year fixed effects, and a quadratic country time trend. (11) Estimates a pooled levels model with quadratic temperature and precipitation, region-year fixed effects, and no country time trend.

Scenario	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
RCP8.5 (2099)	43.03	46.67	36.97	21.21	16.36	10.91	10.3	6.06	0	0	0
Geo Stabilized RCP8.5 (2099)	0	0	0	0	0	0	0	0	0	0	0
Geo Mirrored RCP8.5 (2099)	10.91	0	8.48	0	28.48	18.79	20	5.45	0	0	0
No Climate Change (2099)	0	0	0	0	0	0	0	0	0	0	0

Table A.4: **Percentage of countries with a relative loss compared with no climate change in 2099.** Values represent median projections for SSP3. Columns as in Table S3.

Scenario	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
RCP8.5 (2099)	76.36	100	72.73	100	35.76	64.24	63.64	66.06	76.97	76.97	75.76
Geo Stabilized RCP8.5 (2099)	32.73	53.33	32.12	57.58	39.39	24.24	29.7	24.24	32.73	32.73	32.12
Geo Mirrored RCP8.5 (2099)	32.12	0	35.76	0	92.73	41.82	41.82	39.39	36.36	36.36	36.36
No Climate Change (2099)	0	0	0	0	0	0	0	0	0	0	0

Table A.5: **Projected country-level Gini Coefficients.** Values represent median projections for SSP3. Columns as in Table S3.

Scenario	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
RCP8.5 (2099)	0.8740	0.6452	0.8572	0.7626	0.8335	0.8382	0.8372	0.7544	0.5875	0.5882	0.5876
Geo Stabilized RCP8.5 (2099)	0.5735	0.5703	0.5736	0.5727	0.5834	0.5849	0.5840	0.5842	0.5823	0.5823	0.5823
Geo Mirrored RCP8.5 (2099)	0.4595	0.5063	0.4379	0.5621	0.3488	0.4499	0.4538	0.4568	0.5772	0.5764	0.5771
No Climate Change (2099)	0.5824	0.5824	0.5824	0.5824	0.5824	0.5824	0.5824	0.5824	0.5824	0.5824	0.5824
(2010)	0.7482	0.7482	0.7482	0.7482	0.7482	0.7482	0.7482	0.7482	0.7482	0.7482	0.7482

APPENDIX B

SUPPLEMENTARY MATERIALS FOR "FROM MICRO-LEVEL WEATHER SHOCKS TO MACROECONOMIC IMPACTS"

B.1 Data Description

Table B.1: List of Industries

NAICS Code	Industry Description
11	Agriculture, forestry, fishing, and hunting
21	Mining
22	Utilities
23	Construction
31-33	Manufacturing
42	Wholesale trade
44-45	Retail trade
48-49	Transportation and warehousing
51	Information
52-53	Finance, insurance, real estate, rental, and leasing
54-56	Professional and business services
61-62	Educational services, health care, and social assistance
71-72	Arts, entertainment, recreation, accommodation, and food services
81	Other services, except government
G	Government

B.2 Proofs

B.2.1 Comparative Statics

Price Effect

$$
\begin{aligned}
\frac{\partial \mathbf{P}}{\partial W_r} &= \frac{\partial\Big(\boldsymbol{\mathcal{L}}'\boldsymbol{\gamma}^*\Big)^{\frac{1}{1-\sigma}} w}{\partial W_r} \\
&= \frac{1}{1-\sigma}\Big(\boldsymbol{\mathcal{L}}'\boldsymbol{\gamma}^*\Big)^{\frac{\sigma}{1-\sigma}} w\boldsymbol{\mathcal{L}}'\frac{\partial\Big(\boldsymbol{\gamma}\odot\mathbf{A}(\mathbf{W})^{\sigma-1}\Big)}{\partial W_r} + \Big(\boldsymbol{\mathcal{L}}'\boldsymbol{\gamma}^*\Big)^{\frac{1}{1-\sigma}}\frac{\partial\Big(\boldsymbol{\Upsilon}'\boldsymbol{\gamma}^*\Big)^{\frac{1}{\sigma-1}}}{\partial W_r} \\
&= \begin{cases} P_{js}\lambda_{ir}\frac{\partial \log\Big(A_{ir}(W_r)\Big)}{\partial W_r}, & \text{if } j,s \neq i,r \\ P_{js}(\lambda_{ir}-1)\frac{\partial \log\Big(A_{ir}(W_r)\Big)}{\partial W_r}, & \text{if } j,s = i,r \end{cases}
\end{aligned}
\tag{B.1}
$$

Wage Effect

$$
\begin{aligned}
\frac{\partial w}{\partial W_r} &= \frac{\partial\Big(\boldsymbol{\Upsilon}'\boldsymbol{\gamma}^*\Big)^{\frac{1}{\sigma-1}}}{\partial W_r} \\
&= \frac{1}{\sigma-1} w\Big(\boldsymbol{\Upsilon}'\boldsymbol{\gamma}^*\Big)^{-1}\frac{\boldsymbol{\Upsilon}'\partial\Big(\boldsymbol{\gamma}\odot\mathbf{A}(\mathbf{W})^{\sigma-1}\Big)}{\partial W_r} \\
&= \frac{1}{\sigma-1} w\Big(\boldsymbol{\Upsilon}'\boldsymbol{\gamma}^*\Big)^{-1}\boldsymbol{\Upsilon}_{ir}\gamma^*_{ir}\frac{\sigma-1}{A_{ir}(W_r)}\frac{\partial A_{ir}(W_r)}{\partial W_r} \\
&= w\left(\frac{wL_{ir}}{M}\right)\frac{\partial \log\Big(A_{ir}(W_r)\Big)}{\partial W_r} \\
&= w\lambda_{ir}\frac{\partial \log\Big(A_{ir}(W_r)\Big)}{\partial W_r}
\end{aligned}
\tag{B.2}
$$

Labor Share Effect

$$
\begin{aligned}
\frac{\partial \gamma^*_{js}}{\partial W_r} &= \frac{\partial \gamma_{js}A_{js}(W_r)}{\partial W_r} \\
&= \begin{cases} 0, & \text{if } j,s \neq i,r \\ (\sigma-1)\gamma^*_{js}\frac{\partial \log\Big(A_{js}(W_r)\Big)}{\partial W_r}, & \text{if } j,s = i,r \end{cases}
\end{aligned}
\tag{B.3}
$$

Sales Effect

$$\begin{aligned}
\frac{\partial p_{js}^{\sigma} y_{js}}{\partial W_r} &= \frac{\partial \Upsilon_{js} M}{\partial W_r} \\
&= \Upsilon_{js} \frac{\partial M}{\partial W_r} \\
&= \Upsilon_{js} \frac{\partial w \bar{L}}{\partial W_r} \\
&= \Upsilon_{js} \bar{L} \frac{\partial w}{\partial W_r} \\
&= \Upsilon_{js} \bar{L} w \lambda_{ir} \frac{\partial \log \Big(A_{ir}(W_r) \Big)}{\partial W_r} \\
&= p_{js}^{\sigma} y_{js} \lambda_{ir} \frac{\partial \log \Big(A_{ir}(W_r) \Big)}{\partial W_r}
\end{aligned} \tag{B.4}$$

B.2.2 Own Value Added Effect

Labor Demand Effect

$$\begin{aligned}
\frac{\partial L_{ir}}{\partial W_r} &= \frac{\partial (\gamma_{ir}^{*} w^{-\sigma} p_{ir}^{\sigma} y_{ir})}{\partial W_r} \\
&= \frac{\partial \gamma_{ir}^{*}}{\partial W_r} w^{-\sigma} p_{ir}^{\sigma} y_{ir} + \gamma_{ir}^{*} \frac{\partial w^{-\sigma}}{\partial W_r} p_{ir}^{\sigma} y_{ir} + \gamma_{ir}^{*} w^{-\sigma} \frac{\partial p_{ir}^{\sigma} y_{ir}}{\partial W_r} \\
&= \left((\sigma - 1) \gamma_{ir}^{*} \frac{\partial \log \big(A_{ir}(W_r) \big)}{\partial W_r} \right) w^{-\sigma} p_{ir}^{\sigma} y_{ir} \\
&\qquad + \gamma_{ir}^{*} \left(- \sigma w^{-\sigma} \lambda_{ir} \frac{\partial \log \big(A_{ir}(W_r) \big)}{\partial W_r} \right) p_{ir}^{\sigma} y_{ir} \\
&\qquad + \gamma_{ir}^{*} w^{-\sigma} \left(p_{ir}^{\sigma} y_{ir} \lambda_{ir} \frac{\partial \log \big(A_{ir}(W_r) \big)}{\partial W_r} \right) \\
&= (\sigma - 1) L_{ir} \frac{\partial \log \big(A_{ir}(W_r) \big)}{\partial W_r} - \sigma L_{ir} \lambda_{ir} \frac{\partial \log \big(A_{ir}(W_r) \big)}{\partial W_r} + L_{ir} \lambda_{ir} \frac{\partial \log \big(A_{ir}(W_r) \big)}{\partial W_r} \\
&= L_{ir} \frac{\partial \log \big(A_{ir}(W_r) \big)}{\partial W_r} \Big[(\sigma - 1) + \lambda_{ir} (1 - \sigma) \Big]
\end{aligned} \tag{B.5}$$

Value Added Effect

$$
\begin{aligned}
\frac{\partial(wL_{ir})}{\partial W_r} &= \frac{\partial w}{\partial W_r}L_{ir} + w\frac{\partial L_{ir}}{\partial W_r} \\
&= wL_{ir}\lambda_{ir}\frac{\partial \log\Big(A_{ir}(W_r)\Big)}{\partial W_r} + wL_{ir}\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r}\Big[(\sigma-1)+\lambda_{ir}(1-\sigma)\Big] \\
&= wL_{ir}\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r}\Big[(\sigma-1)+\lambda_{ir}(2-\sigma)\Big]
\end{aligned}
\tag{B.6}
$$

B.2.3 Indirect Value Added Effect

Labor Demand Effect

$$
\begin{aligned}
\frac{\partial L_{js}}{\partial W_r} &= \frac{\partial(\gamma_{js}^* w^{-\sigma} p_{js}^{\sigma} y_{js})}{\partial W_r} \\
&= 0 + \gamma_{js}^*\frac{\partial w^{-\sigma}}{\partial W_r}p_{js}^{\sigma}y_{js} + \gamma_{js}^* w^{-\sigma}\frac{\partial p_{js}^{\sigma}y_{js}}{\partial W_r} \\
&= \gamma_{js}^*\Bigg(-\sigma w^{-\sigma}\lambda_{ir}\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r}\Bigg)p_{js}^{\sigma}y_{js} \\
&\qquad + \gamma_{js}^* w^{-\sigma}\Bigg(p_{js}^{\sigma}y_{js}\lambda_{ir}\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r}\Bigg) \\
&= -\sigma L_{js}\lambda_{ir}\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r} + L_{js}\lambda_{ir}\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r} \\
&= L_{js}\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r}\Big[\lambda_{ir}(1-\sigma)\Big]
\end{aligned}
\tag{B.7}
$$

Value Added Effect

$$
\begin{aligned}
\frac{\partial(wL_{js})}{\partial W_r} &= \frac{\partial w}{\partial W_r}L_{js} + w\frac{\partial L_{js}}{\partial W_r} \\
&= wL_{js}\lambda_{ir}\frac{\partial \log\Big(A_{ir}(W_r)\Big)}{\partial W_r} + wL_{js}\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r}\Big[\lambda_{ir}(1-\sigma)\Big] \\
&= wL_{js}\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r}\Big[\lambda_{ir}(2-\sigma)\Big]
\end{aligned}
\tag{B.8}
$$

B.2.4 Aggregate Value Added Effect

Value Added Effect

$$
\begin{aligned}
\frac{\partial M}{\partial W_r} &= \frac{\partial w \sum\limits_{j=1}^{N}\sum\limits_{r=1}^{R} L_{js}}{\partial W_r} \\
&= \frac{\partial w}{\partial W_r}\sum_{j=1}^{N}\sum_{r=1}^{R} L_{js} + w\sum_{j=1}^{N}\sum_{s=1}^{R}\frac{\partial L_{js}}{\partial W_r} \\
&= \frac{\partial w}{\partial W_r}\bar{L} + w\frac{\partial L_{ir}}{\partial W_r} + \sum_{j=1}^{N}\sum_{s\neq r}^{R}\frac{\partial L_{js}}{\partial W_r} \\
&= w\bar{L}\lambda_{ir}\frac{\partial \log\Big(A_{ir}(W_r)\Big)}{\partial W_r} \\
&\qquad + wL_{ir}\frac{\partial \log\big(A_{ir}(W_r)\big)}{\partial W_r}\Big[(\sigma-1)+\lambda_{ir}(1-\sigma)\Big] \\
&\qquad + \sum_{j=1}^{N}\sum_{s\neq r}^{R} L_{js}\frac{\partial \log\big(A_{js}(W_r)\big)}{\partial W_r}\Big[\lambda_{js}(1-\sigma)\Big] \\
&= \left[w\bar{L}\lambda_{ir}[1+(1-\sigma)] + M\frac{wL_{ir}}{M}(\sigma-1)\right]\frac{\partial \log\big(A_{js}(W_r)\big)}{\partial W_r} \\
&= M\big[\lambda_{ir}\big(1+(1-\sigma)\big)+\lambda_{ir}(\sigma-1)\big]\frac{\partial \log\big(A_{js}(W_r)\big)}{\partial W_r} \\
&= M\lambda_{ir}\frac{\partial \log\big(A_{js}(W_r)\big)}{\partial W_r}
\end{aligned} \tag{B.9}
$$

B.2.5 Labor Productivity

Bias for value added per unit labor

Here I show that using value added per unit labor as a measure of labor productivity growth can lead to biased empirical estimates in the relationship between labor productivity growth and weather shocks when weather shocks are correlated across an economy.

I begin with the growth of labor productivity for an industry i in region r at time t, measured as the log difference of the ratio of value-added to employment.

$$\Delta \log(A_{irt}) = \log\left(\frac{VA_{irt}}{L_{irt}}\right) - \log\left(\frac{VA_{irt-1}}{L_{irt-1}}\right) \tag{B.10}$$

Differentiating this measure of labor productivity growth for an industry i in region r at time t with respect to a weather shock to some different industry j in region s at time t gives

$$\begin{aligned}
\frac{\partial \Delta \log(A_{irt})}{\partial W_{st}} &= \frac{\partial}{\partial W_{st}}\left[\log\left(\frac{VA_{irt}}{L_{irt}}\right) - \log\left(\frac{VA_{irt-1}}{L_{irt-1}}\right)\right] \\
&= \frac{\partial}{\partial W_{st}}\left[\log\left(\frac{w_t L_{irt}}{L_{irt}}\right) - \log\left(\frac{w_{t-1} L_{irt-1}}{L_{irt-1}}\right)\right] \\
&= \frac{\partial}{\partial W_{st}}\left[\log(w_t) - \log(w_{t-1})\right] \\
&= \lambda_{jst}\frac{\partial \log\Big(A_{jst}(W_{st})\Big)}{\partial W_{st}}
\end{aligned} \tag{B.11}$$

Thus, labor productivity growth for an industry i in region r at time t is not independent of weather shocks in other industries j in regions s at time t.

Derivation of unbiased labor productivity measure

According to classic labor theory, wages should be reflective of (equal to) the marginal revenue product of labor (MRP_L). This gives an expression for wages as

$$w = \frac{\partial p_{irt} y_{irt}}{\partial L_{irt}}$$

Multiplying each side by labor input L_{irt} and dividing by revenues $p_{irt}y_{irt}$ gives

$$\phi_{irt} = \frac{wL_{irt}}{p_{irt}y_{irt}} = \frac{\partial p_{irt}y_{irt}}{\partial L_{irt}}\frac{L_{irt}}{p_{irt}y_{irt}}$$

This gives the following expression for MRP_L where firms take price as given.

$$\frac{\partial p_{irt} y_{irt}}{\partial L_{irt}} = \gamma_{ir}^{\frac{1}{\sigma}} A_{irt}(W_{rt})^{\frac{\sigma-1}{\sigma}} L_{irt}^{-\frac{1}{\sigma}} p_{irt} y_{irt}^{\frac{1}{\sigma}}$$

Plugging this back in, I find the following expression for the share of total revenues that go to labor compensation.

$$\begin{aligned}
\phi_{irt} &= \frac{\partial p_{irt} y_{irt}}{\partial L_{irt}} \frac{L_{irt}}{p_{irt} y_{irt}} \\
&= \gamma_{ir}^{\frac{1}{\sigma}} A_{irt}(W_{rt})^{\frac{\sigma-1}{\sigma}} L_{irt}^{-\frac{1}{\sigma}} p_{irt} y_{irt}^{\frac{1}{\sigma}} \frac{L_{irt}}{p_{irt} y_{irt}} \\
&= \gamma_{ir}^{\frac{1}{\sigma}} \left[\frac{A_{irt}(W_{rt}) L_{irt}}{y_{irt}} \right]^{\frac{\sigma-1}{\sigma}}
\end{aligned}$$

Rearranging this equation, I solve for labor productivity as

$$\begin{aligned}
A_{irt}(W_{rt}) &= \phi_{irt}^{\frac{\sigma}{\sigma-1}} \gamma; \frac{1}{1-\sigma} \frac{y_{irt}}{L_{irt}} \\
&= \gamma^{\frac{1}{1-\sigma}} \left(\frac{w_{irt}^{\sigma} L_{irt}}{p_{irt}^{\sigma} y_{irt}} \right)^{\frac{\sigma}{\sigma-1}}
\end{aligned} \tag{B.12}$$

I now find an equation for growth in labor productivity measured as the difference of logs over periods. I begin by taking the log of labor productivity in period t.

$$\Delta \log(A_{irt}(W_{rt})) = \frac{\sigma}{\sigma-1} \Delta \log \Big(\phi_{irt} \Big) + \Delta \log \left(\frac{p_{irt} y_{irt}}{L_{irt}} \right) - \Delta \log \Big(p_{irt} \Big)$$

Bias for new labor productivity measure

Here I show that labor productivity growth measure derived from theory leads to unbiased empirical estimates in the relationship between labor productivity growth and weather shocks when weather shocks are correlated across an economy.

I begin with the growth of labor productivity for an industry i in region r at time t, measured as in Equation Equation 4.19.

$$\Delta \log(A_{irt}) = \frac{\sigma}{\sigma - 1} \Delta \log \left(\phi_{irt} \right) + \Delta \log \left(\frac{y_{irt}}{L_{irt}} \right) \tag{B.13}$$

Differentiating this measure of labor productivity growth for an industry i in region r at time t with respect to a weather shock to some different industry j in region s at time t gives

$$\begin{aligned} \frac{\partial \Delta \log(A_{irt})}{\partial W_{st}} &= \frac{\partial}{\partial W_{st}} \left[\frac{\sigma}{\sigma - 1} \Delta \log \left(\phi_{irt} \right) + \Delta \log \left(\frac{y_{irt}}{L_{irt}} \right) \right] \\ &= \frac{\partial}{\partial W_{st}} \left[\frac{\sigma}{\sigma - 1} \Delta \log \left(\frac{w_{irt}^{\sigma} L_{irt}}{p_{irt}^{\sigma} y_{irt}} \right) \right] \\ &= \frac{\sigma}{\sigma - 1} \left[\sigma \lambda_{jst} + \lambda_{jst}(1 - \sigma) - \lambda_{jst} \right] \\ &= 0 \end{aligned} \tag{B.14}$$

Thus, labor productivity growth for an industry i in region r at time t is are independent of weather shocks in other industries j in regions s at time t.

B.3 Robustness

B.3.1 Microeconomic Impacts

Here I re-estimate the historical relationship between weather shocks and county-industry labor productivity across the US for different values of the elasticity of substitution. In particular, I re-estimate with $\sigma = 0.3$ and $\sigma = 0.9$. I estimate each of the models examined in the text for $\sigma = 0.5$.

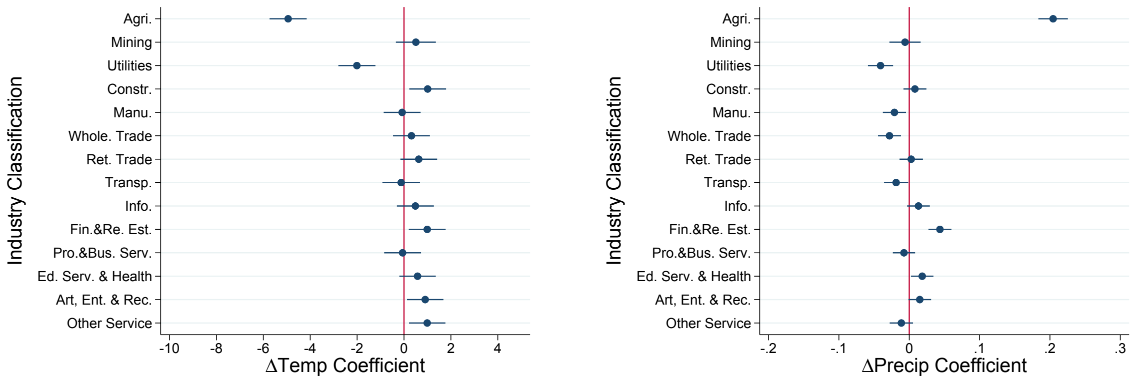
Comparing results across different values for the elasticity of substitution, it is clear that the quantititative estimates change, but the qualitative findings are consistent across values. This is because the elasticity of substitution scales the constructed labor productivity growth rates, as shown in Equation (Equation 4.20).

σ = 0.3

Table B.2: **[Linear Labor Productivity Sensitivity Sigma 0.3**

	Labor Productivity Growth Rate
Δ Temp	0.330
	(0.277)
Δ Precip	0.00642*
	(0.00354)
Obs.	457,625
R sq.	0.0705

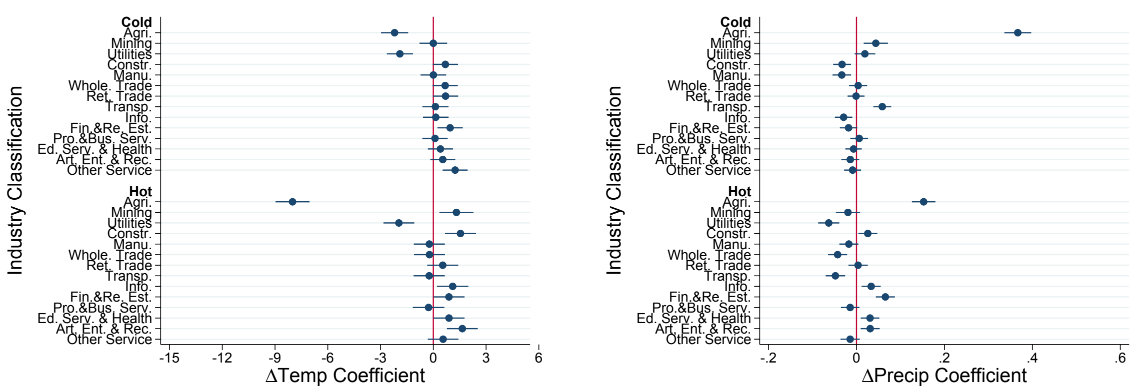
Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Temperature is measured in C. Precipitation is measured in mm/year. The unit of observation is a county-industry in a year. Regression includes county-by-industry fixed effects and state-by-year fixed effects. Standard errors are clustered by county and industry.



(a) Temperature Coefficients.

(b) Precipitation Coefficients.

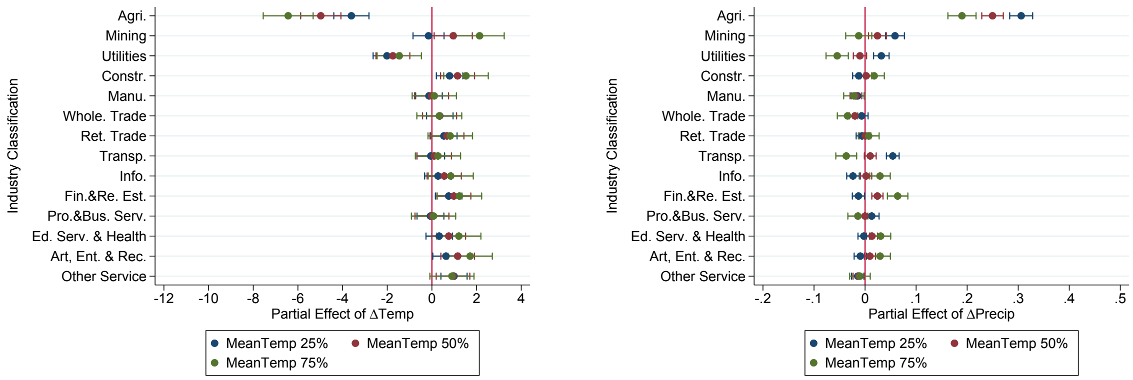
Figure B.1: **Heterogeneous Industry Response** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification with 95% confidence intervals. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0737.



(a) Temperature Coefficients.

(b) Precipitation Coefficients.

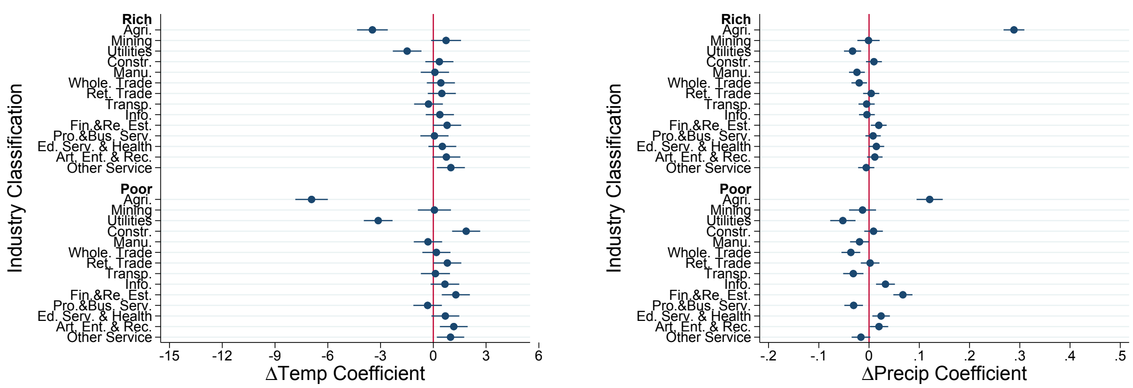
Figure B.2: **Heterogeneous Industry Response by Hot/Cold** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification with 95% confidence intervals. Hot counties are those with mean temperatures above the median. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0747.



(a) Temperature Coefficients.

(b) Precipitation Coefficients.

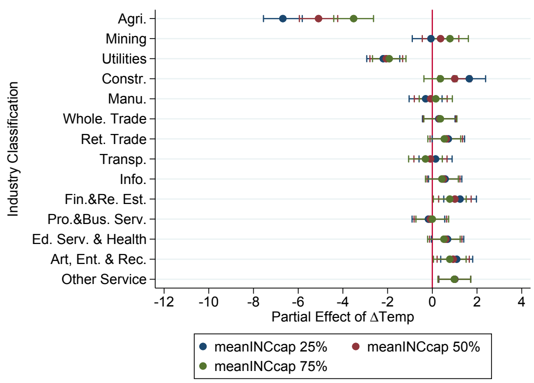
Figure B.3: **Heterogeneous Industry Response by Mean Temperature** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification and county mean temperature with 95% confidence intervals. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0747.



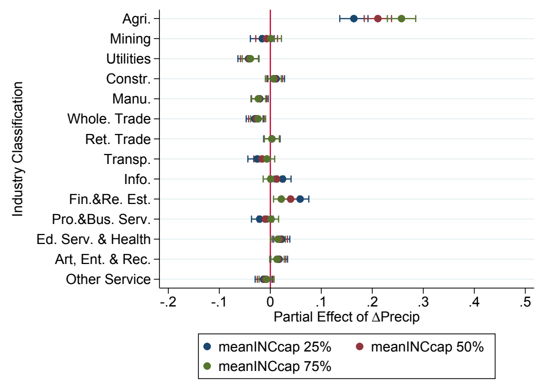
(a) Temperature Coefficients.

(b) Precipitation Coefficients.

Figure B.4: **Heterogeneous Industry Response by Rich/Poor** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification with 95% confidence intervals. Counties are considered poor if the mean income per capita is below the median. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0742.



(a) Temperature Coefficients.



(b) Precipitation Coefficients.

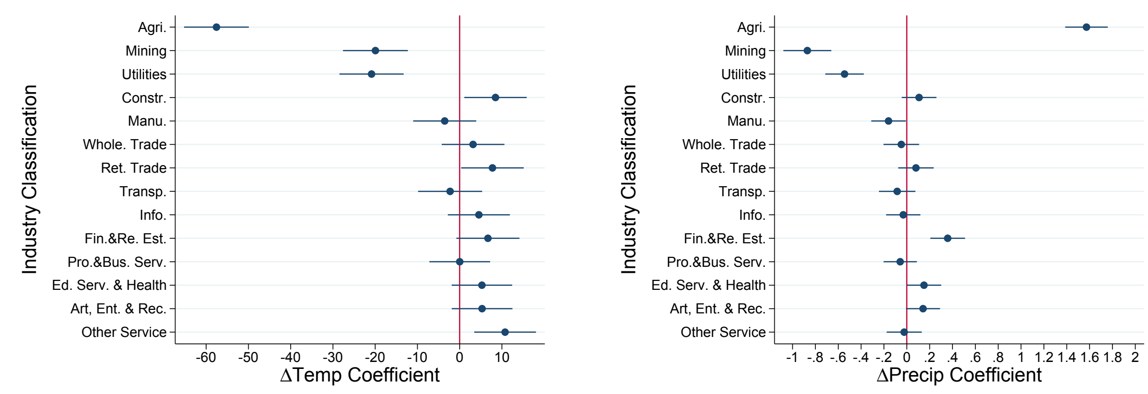
Figure B.5: **Heterogeneous Industry Response by Mean Income/capita** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification and county mean income per capita with 95% confidence intervals. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0743.

σ = 0.9

Table B.3: **[Linear Labor Productivity Sensitivity Sigma 0.9**

	Labor Productivity Growth Rate
Δ Temp	1.17
	(01.81)
Δ Precip	0.0360
	(0.0261)
Obs.	457,625
R sq.	0.0705

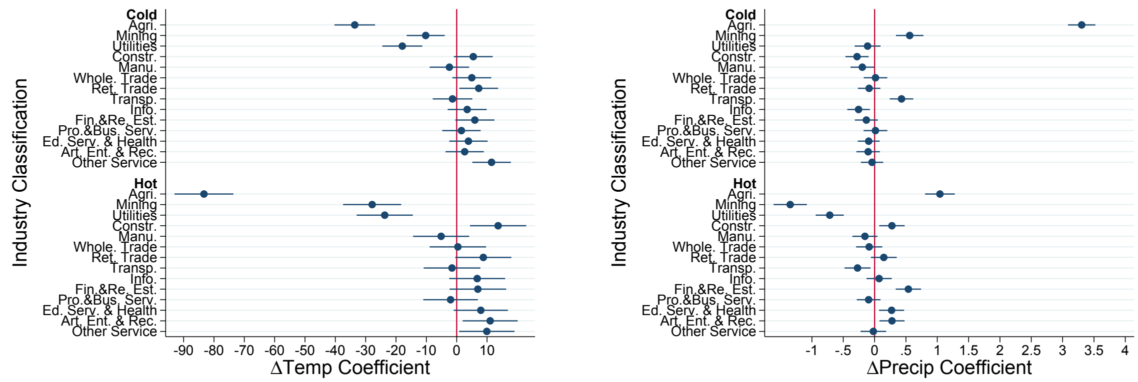
Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Temperature is measured in C. Precipitation is measured in mm/year. The unit of observation is a county-industry in a year. Regression includes county-by-industry fixed effects and state-by-year fixed effects. Standard errors are clustered by county and industry.



(a) Temperature Coefficients.

(b) Precipitation Coefficients.

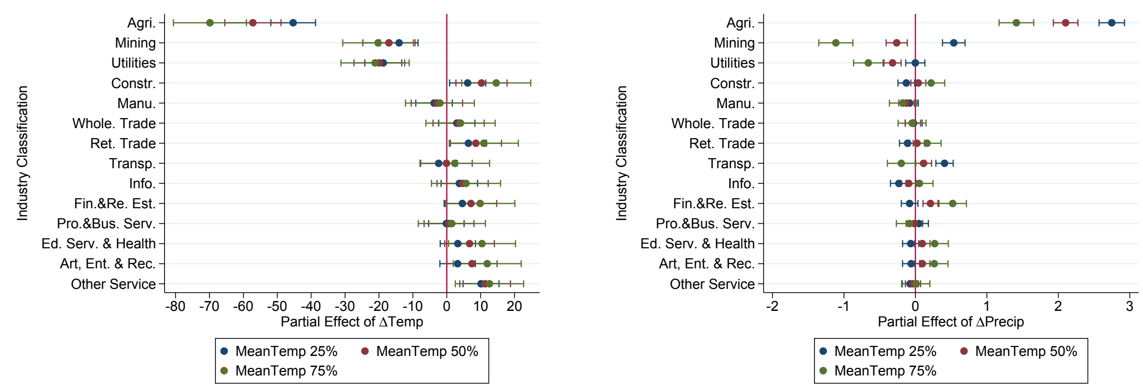
Figure B.6: **Heterogeneous Industry Response** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification with 95% confidence intervals. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0767.



(a) Temperature Coefficients.

(b) Precipitation Coefficients.

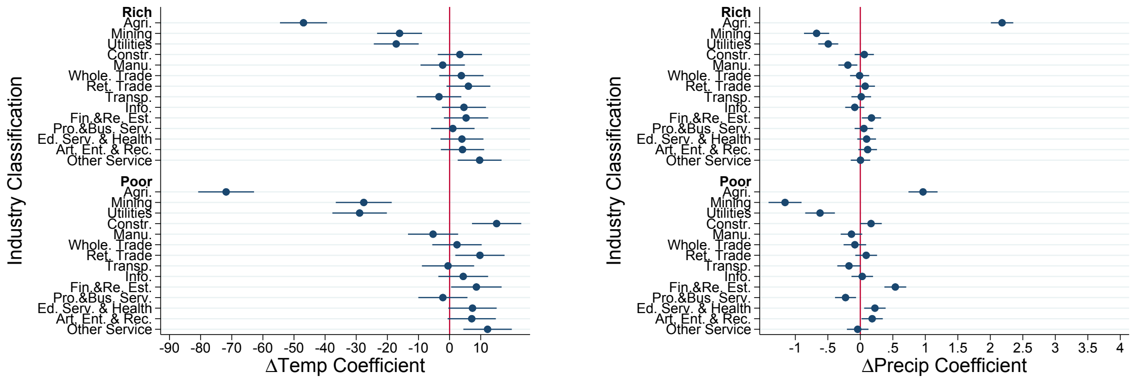
Figure B.7: **Heterogeneous Industry Response by Hot/Cold** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification with 95% confidence intervals. Hot counties are those with mean temperatures above the median. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0783.



(a) Temperature Coefficients.

(b) Precipitation Coefficients.

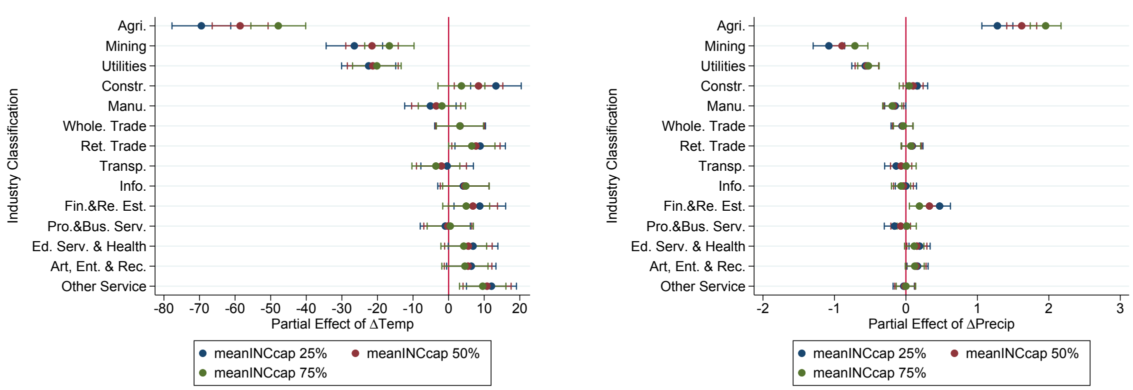
Figure B.8: **Heterogeneous Industry Response by Mean Temperature** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification and county mean temperature with 95% confidence intervals. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0783.



(a) Temperature Coefficients.

(b) Precipitation Coefficients.

Figure B.9: **Heterogeneous Industry Response by Rich/Poor** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification with 95% confidence intervals. Counties are considered poor if the mean income per capita is below the median. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0772.



(a) Temperature Coefficients.

(b) Precipitation Coefficients.

Figure B.10: **Heterogeneous Industry Response by Mean Income/capita** Temperature and precipitation regression coefficients differentiated by NAICS 2-digit industry classification and county mean income per capita with 95% confidence intervals. Regression includes county-by-industry and state-by-year fixed effects. Standard errors are clustered by county and industry. Regression statistics: N_{obs}=457,625; R^2=0.0773.

B.3.2 Macroeconomic Impacts

Non-linear Response by Mean Income/capita

Here I present the macroeconomic impact estimates and decomposition constructed from the microeconomic estimates for elasticity of substitution $\sigma = 0.5$ and for the empirical specification that allows for heterogeneity across industries as well as across counties based on mean income per capita shown in Figure Figure 4.7.

Comparing with the results shown in the text, the quantitative results differ slighly. However, the differences do not change the qualitative results or the key takeaways. The macroeconomic impacts are still statistically insignificant across all the years. Consistent with the results in the text, as the macroeconomic impacts are decomposed in the underlying county, industry, and county-industry contributions, the significance increases with resolution. This suggests that the aggregation masks considerable underlying heterogeneity in weather shock impacts.

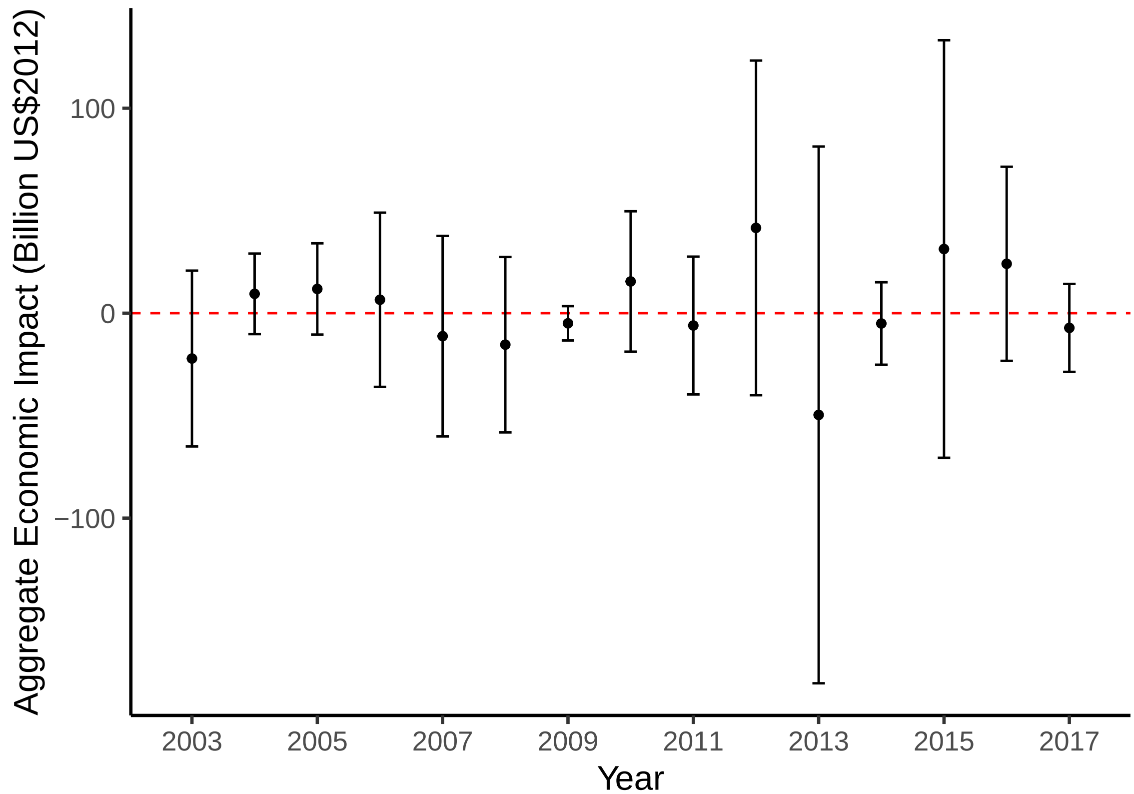
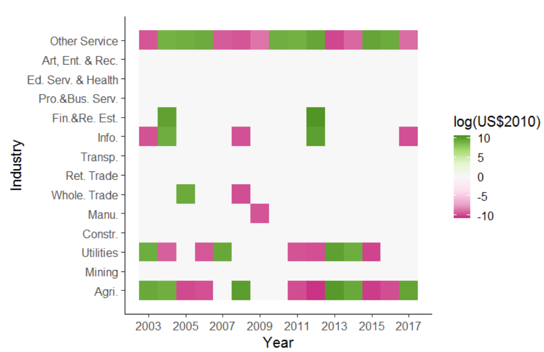
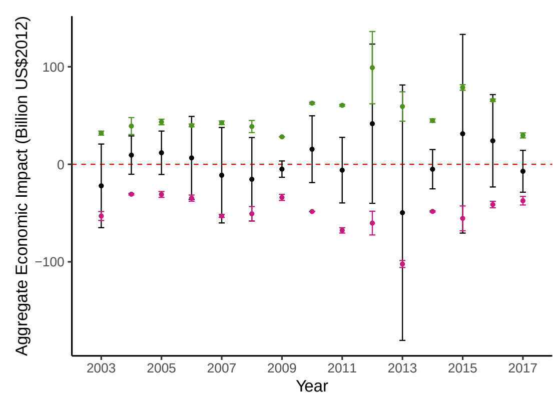


Figure B.11: **Macroeconomic Impact of Weather Shocks by Year.** Macroeconomic impact of weather shocks across the United States in each year year. Points show the mean estimate. Bounds show the 95% confidence interval.

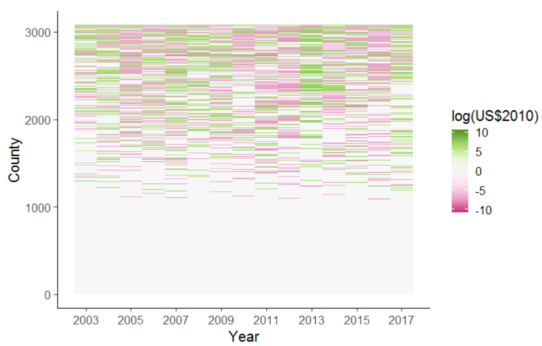


(a)

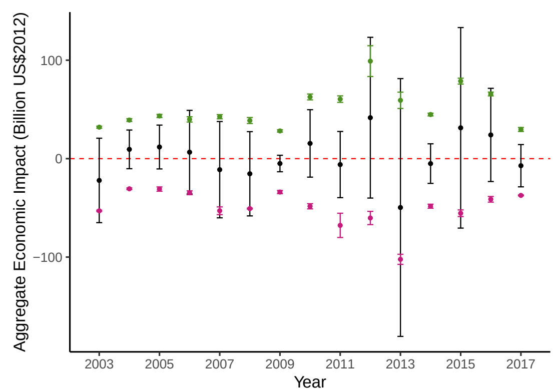


(b)

Figure B.12: **Industry-level Contributions to Macroeconomic Growth** Contribution to macroeconomic growth for statistically significant aggregate industry-level weather impacts by year. Panel **(a)** displays by industry. Panel **(b)** shows the aggregate impacts of the statistically significant positive and negative effects separately.



(a)



(b)

Figure B.13: **County-level Contributions to Macroeconomic Growth** Contribution to macroeconomic growth for statistically significant aggregate county-level weather impacts by year. Panel **(a)** displays by county, sorted by the frequency of significant aggregate county-level impacts. Panel **(b)** shows the aggregate impacts of the statistically significant positive and negative effects separately.

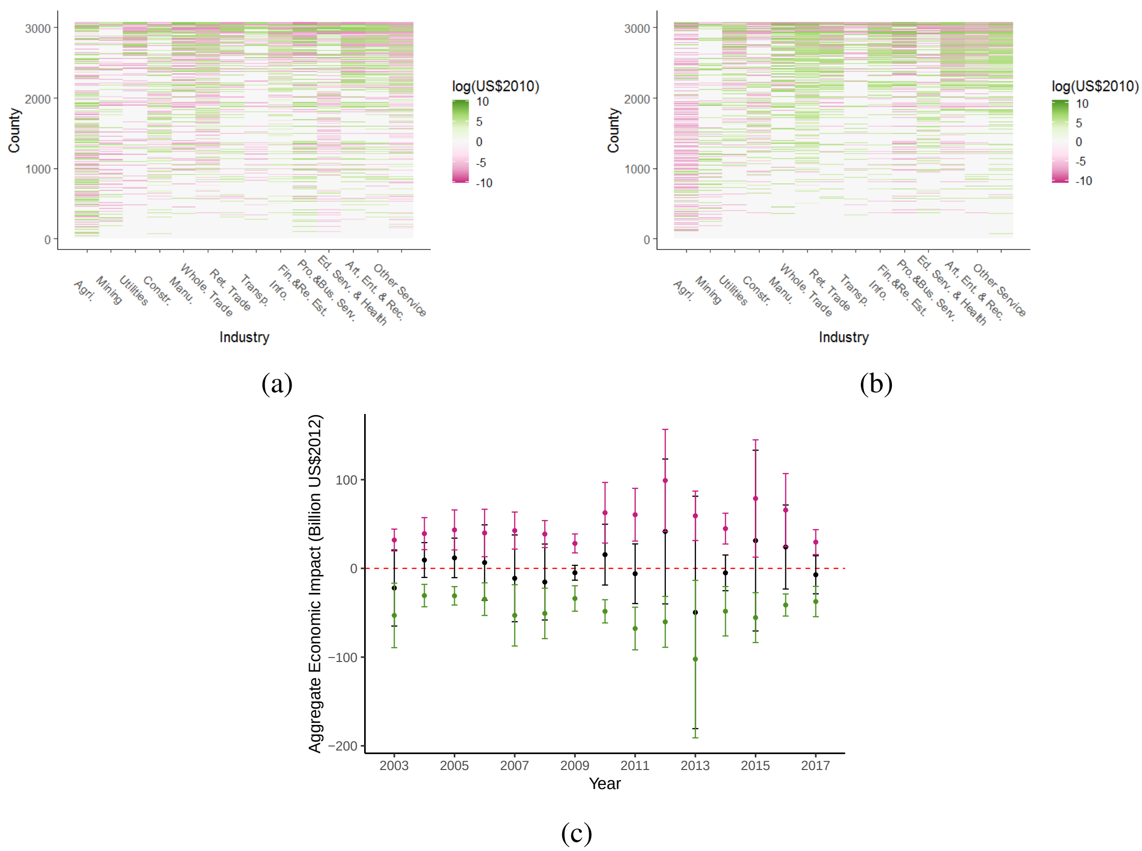


Figure B.14: **County-Industry-level Contributions to Macroeconomic Growth** Contribution to macroeconomic growth for statistically significant county-industry-level weather impacts by year. Panel **(a)** and **(b)** display county-by-industry impacts for 2009 and 2010, respectively. Counties are sorted by the frequency of significant aggregate county-level impacts. Panel **(c)** shows the aggregate impacts of the statistically significant positive and negative effects separately.

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