Dissertation

Directed International Technological Change and Climate Policy

New Methods for Identifying Robust Policies Under Conditions of Deep Uncertainty

Edmundo Molina-Perez

This document was submitted as a dissertation in February 2016 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of Steven Popper (Chair), David Groves, and Constantine Samaras.

RAND PARDEE RAND GRADUATE SCHOOL

For more information on this publication, visit http://www.rand.org/pubs/rgs_dissertations/RGSD369.html

Published by the RAND Corporation, Santa Monica, Calif.

Preface

The landmark climate agreement reached at the 2015 Paris Conference of the Parties has signaled an important shift in international mitigation and adaptation efforts. This agreement establishes the foundations of a new institutional arrangement for adaptive cooperation based on flexible participation and common aspirations for substantially reducing greenhouse gas emissions.

The Paris climate agreement is by any measure a historical step in climate change negotiations. However, after the initial excitement for the agreement, the international community is beginning to realize that in order to meet its aspirations it will be necessary to direct vast amount of resources towards efforts that can successfully triggered international decarbonization. In this context, climate financing institutions such as the Green Climate Fund have emerged as key enablers of the Paris aspirations.

The challenges faced by these institutions are exacerbated by the complex technological and economic environment prevailing today. The rapid rate of improvement of solar and wind energy technologies over the last decade support optimism about the future of renewable energy. Yet, the substantial decline in oil prices and the strong technological capabilities of the American fracking industry create serious doubts about the feasibility of decarbonization.

The research reported here explores how Robust Decision Making (RDM) methods can be integrated with Integrated Assessment Models (IAMs) to systematically study which forms of international technological cooperation are more robust to technological, economic and climate uncertainties. This is an initial attempt at developing the decision support tools and analysis framework that can support the work of climate financing institutions such as the Green Climate Fund.

An interactive decision support tool accompanies this dissertation. This tool provides an example of the modeling and analytical tools developed for this research project. The tool is available online at https://public.tableau.com/profile/edmundo.molina#!/

Abstract

It is widely recognized that international environmental technological change is key to reduce the rapidly rising greenhouse gas emissions of emerging nations. In 2010, the United Nations Framework Convention on Climate Change (UNFCCC) Conference of the Parties (COP) agreed to the creation of the Green Climate Fund (GCF). This new multilateral organization has been created with the collective contributions of COP members, and has been tasked with directing over USD 100 billion per year towards investments that can enhance the development and diffusion of clean energy technologies in both advanced and emerging nations (Helm and Pichler, 2015). The landmark agreement arrived at the COP 21 has reaffirmed the key role that the GCF plays in enabling climate mitigation as it is now necessary to align large scale climate financing efforts with the long-term goals agreed at Paris 2015.

This study argues that because of the incomplete understanding of the mechanics of international technological change, the multiplicity of policy options and ultimately the presence of climate and technological change deep uncertainty, climate financing institutions such as the GCF, require new analytical methods for designing long-term robust investment plans. Motivated by these challenges, this dissertation shows that the application of new analytical methods, such as Robust Decision Making (RDM) and Exploratory Modeling (Lempert, Popper and Bankes, 2003) to the study of international technological change and climate policy provides useful insights that can be used for designing a robust architecture of international technological cooperation for climate change mitigation.

For this study I developed an exploratory dynamic integrated assessment model (EDIAM) which is used as the scenario generator in a large computational experiment. The scope of the experimental design considers an ample set of climate and technological scenarios. These scenarios combine five sources of uncertainty: climate change, elasticity of substitution between renewable and fossil energy and three different sources of technological uncertainty (i.e. R&D returns, innovation propensity and technological transferability). The performance of eight different GCF and non-GCF based policy regimes is evaluated in light of various end-of-century climate policy targets. Then I combine traditional scenario discovery data mining methods (Bryant and Lempert, 2010) with high dimensional stacking methods (Suzuki, Stern and Manzocchi, 2015; Taylor et al., 2006; LeBlanc, Ward and Wittels, 1990) to quantitatively characterize the conditions under which it is possible to stabilize greenhouse gas emissions and keep temperature rise below 2˚C before the end of the century.

Finally, I describe a method by which it is possible to combine the results of scenario discovery with high-dimensional stacking to construct a dynamic architecture of low cost technological cooperation. This dynamic architecture consists of adaptive pathways (Kwakkel,

Haasnoot and Walker, 2014; Haasnoot et al., 2013) which begin with carbon taxation across both regions as a critical near term action. Then in subsequent phases different forms of cooperation are triggered depending on the unfolding climate and technological conditions.

I show that there is no single policy regime that dominates over the entire uncertainty space. Instead I find that it is possible to combine these different architectures into a dynamic framework for technological cooperation across regions that can be adapted to unfolding climate and technological conditions which can lead to a greater rate of success and to lower costs in meeting the end-of-century climate change objectives agreed at the 2015 Paris Conference of the Parties.

Keywords: international technological change, emerging nations, climate change, technological uncertainties, Green Climate Fund.

Acknowledgments

First I want to thank my dissertation committee-Steven Popper, David Groves and Costa Samaras. My chair -Steven Popper- has been immensely generous and supportive throughout the entire dissertation process. He has been a role model, a mentor and a good friend. I am in huge debt for the many meetings in which he provided me with feedback and direction over the dissertation, without his commitment to this project it would have been impossible to complete this undertaking. David Groves was an important influence in the development of this work. His talent, drive and discipline were extremely motivating to improve the analysis presented in these pages, every single project opportunity with David translated into new additions to this dissertation. I was incredible lucky to have had the opportunity to work with and learn from such a talented researcher. Costa Samaras has been equally supportive in the development of this dissertation, more importantly his perspective on how best use the tools developed for this research and his knowledge of climate financing and sustainable energy technologies were critical inputs to increase the usefulness and appeal of the analysis. Finally, Valentina Bosetti's recommendations as an outside reader provided much needed advice about how to improve the analysis presented in these pages and ultimately how to translate the products of the dissertation into academic journals. It was truly an honor and a humbling experience to have had the opportunity to develop this dissertation under their guidance.

The RAND Corporation and Pardee RAND have become a second home to me. Both institutions provided me with the opportunity of engaging with extremely talented and incredibly hardworking individuals. It was a privilege to be part of these communities. I would especially like to thank the leadership of the Robust Decision Making Laboratory-Robert Lempert, Steven Popper, Jordan Fischbach and David Groves. It was truly an honor to collaborate and learn from such a capable group of individuals. Robert Lempert is an extraordinary researcher and a kind person who provided me with the unique opportunity to learn and apply in real policy settings the RDM methods. Jordan Fischbach is a superb principal investigator, collaborating in projects with him has been a unique experience which provided me with many professional lessons and challenges. Equally important was the opportunity to learn from the talented pool of graduate students working in the RDM laboratory: Benjamin Bryant, Evan Bloom, Chris Sharon and David Johnson. All of them were kind in welcoming into their research group and generous in supporting my learning of the methodology. Their careers at RAND and Pardee RAND were by any measure exemplary.

While at RAND, I was also lucky to collaborate in several projects of the Engineering and Applied Sciences department. In this group, Aimee Curtright and Henry Willis provided me with many interesting and challenging project opportunities. I am very thankful for their words of encouragement for developing the EDIAM model.

Pardee RAND is extremely lucky to have strong leadership. During my tenure as a graduate student I witnessed the rapid evolution of the school and of the student body. I have no doubt that the Dean, Susan L. Marquis will continue leading the school into a direction that will make us all proud. My sincere thanks to Rachel Swanger and Mary Parker who are among the most efficient and agile professionals I have ever encountered.

This dissertation has been sponsored by various sources of funding which were fundamental for completing this project. My sincere thanks for the financial support of the Mexican Science and Technology Council (CONACyT), the John M. Cazier endowed dissertation award, the Nancy and Dana Mead dissertation award and the Carlos Slim Helú fellowship.

I was fortunate to have found good friends at RAND and Pardee RAND with whom I shared many great experiences. Ben and Roxana Colaiaco were supportive and caring friends with whom I shared many lovely moments. Matt Hoover was an excellent student mentor who offered his sincere friendship and sound guidance. Abdul Tariq and Prodyumna Goutam were energetic colleagues who made many bright suggestions about my dissertation and with whom I had many enjoyable discussions. My dear friends Alfonso Rivera and Eduardo Marquez have been excellent companions all these years, their intelligence, maturity and joy for life have certainly made an enduring impression in my own. I am certain that without the many social meetings of the "Mexican Mafia" I would have lost my sanity very early into the program. I am in huge debt to both of them for welcoming me into their life.

I would also like to thank my family. I have been away from my family for many years now. These pages describe the project that has kept me away. They have always encouraged me to do more and work harder. I hope they find this research worthy of the sacrifice. I am incredibly grateful to my parents-Edmundo and Eugenia- for always supporting me in every journey I have embarked into. Their life has been the inspiration of mine. My brothers Isaac, Daniel and Carlos are simply the best friends once could ask for, their love and support are fundamental drivers in my life. I deeply admire their character; they are outstanding individuals who I have always aspired to emulate.

Lastly, and more importantly, I want to thank and dedicate this work to my wife Hilda. Without her passion, courage and discipline this work would not have been possible. She ventured with me into unchartered territory; without her intelligence, we would have certainly got lost. She has inspired me in every possible way. I am blessed every day to share my life with such a beautiful human being. Te amo.

Contents

List of Figures

List of Tables

CHAPTER I

International Technological Change and Climate Policy in the Presence of Deep Uncertainty

I.1 Introduction

At Cancun 2010, the United Nations Framework Convention on Climate Change (UNFCCC) Conference of the Parties (COP) agreed to the creation of the Green Climate Fund (GCF). This new multilateral organization has been created with the collective contributions of COP members, and has been tasked with directing over USD 100 billion per year towards investments that can enhance the development and diffusion of clean energy technologies[1] in both advanced and emerging nations[2] (Helm and Pichler, 2015). The stakes could not be higher: if clean energy technologies fail to be diffused in emerging nations, then global greenhouse gas emissions will continue rising, regardless of the mitigation efforts of advanced nations. In fact, it is estimated that if current trends persist in emerging nations by 2030 the historical cumulative greenhouse gas (GHG) emissions of this block of countries will exceed the cumulative historical emissions of advanced nations (Wheeler and Ummel, 2007).

The landmark agreement arrived at the COP 21 has reaffirmed the key role that the GCF plays in enabling climate mitigation as it is now necessary to align large scale climate financing efforts with the long-term goals agreed at Paris 2015. Looking beyond the COP 21, the GCF is confronted with enormous challenges and critical decisions regarding how to best structure its investments such that these can effectively act as a catalyst of clean technological transitions in emerging nations. In the last few years, the GCF has made clear progress in achieving the investment goals agreed at Cancun 2010. Yet after the Paris agreement it is clear that the GCF needs to focus on two intertwined objectives: 1) demonstrate that it is capable of mobilizing effectively and intelligently climate financing and 2) attract bigger and sustained contributions from both advanced and emerging nations.

International environmental technological change has the potential to play a fundamental role in stabilizing greenhouse gas emissions and preventing the negative environmental consequences of climate change. However, the mechanisms by which international technological change occurs as well as the speed at which such transitions can be achieved are still ill understood (Popp, 2006a). Moreover, both climate and technological change are phenomena

[1] The term *clean technologies* in this monograph encompasses energy technologies used for primary energy production which harness energy resources that do not yield greenhouse gases to the atmosphere. Examples include: wind, solar, nuclear and biomass energy technologies.
[2] The term *"advanced nations"* refers to highly industrialized nations, such as the U.S., Germany, France or the U.K. The term *"emerging nations"* considers rapidly developing countries, such as the BRICS, as well as other less vigorously developing nations.

with many uncertainties. This exacerbates the difficulties of designing policies that can successfully enable international environmental technological change to stabilize greenhouse gas emissions.

In addition to these inherent complexities, the Green Climate Fund has at its disposal a wide range of policy options for achieving international environmental technological change. This multiplicity of policy options exacerbates the challenges of the GCF and other similar multilateral institutions. Therefore, for these institutions it is fundamental to understand the long-term tradeoffs of the proposed policy mechanisms such that portfolios that are economically feasible and that meet the objective of stabilizing greenhouse gas concentrations at sustainable levels may be designed and implemented systematically. Understanding how the combination of these policy instruments can address the uncertainties and long time frames associated with climate change policy and international technological change is a major challenge for policy makers and technological change scholars.

This dissertation argues that because of the incomplete understanding of the mechanics of international technological change, the multiplicity of policy options and ultimately the presence of climate and technological change deep uncertainty, institutions such as the Green Climate Fund, require new analytical methods for designing long-term robust investment plans.

Motivated by these challenges, this dissertation shows that the application of Robust Decision Making (RDM) and Exploratory Modeling (Lempert, Popper and Bankes, 2003) to the study of international technological change and climate policy provides useful insights that can be used to design a robust architecture of international technological cooperation for climate change mitigation. In particular, this monograph investigates the following research questions:

I. How do the Green Climate Fund's investments influence the structure of optimal climate policy[3] across regions?
II. Under which conditions (i.e. economic, technological and climate) would optimal GCF-climate policy achieves the objective of stabilizing CO_2 emissions before the end of the century?

[3] This study follows the standard approach of integrated assessment models and studies. Thus optimal climate policy is the policy response that best balances the economic cost and environmental benefits of climate policy intervention. Moreover, this optimal policy response weights equally the costs and benefits across regions, thus it should be viewed as the policy that seeks to maximize the benefits of climate policy in the entire system. In this monograph, this optimal policy is a mathematical abstraction that is used to analyze the tradeoffs of climate policy and the changes in the structure of climate policy across the uncertainty space. This mathematical abstraction relies on basic rationality and perfect information assumptions. Evidently, these assumptions are made to simplify this complex system and make it feasible and scientifically useful to focus only on parts of this complexity (i.e. climate change uncertainty and technological uncertainty). Thus, the optimal policy response should not be viewed as a normative fixed reference for climate policy design; rather, in this study, the optimal policy response should be discussed in the context of multilateral decision making process and viewed as an analytical reference for illuminating the challenges and opportunities of climate change policy across different climate and technological scenarios.

III. How do climate and technological uncertainties change the structure of the optimal policy response?
IV. How could the GCF's investments become more robust to technological and climate uncertainty?
V. What are the long-term economic and environmental tradeoffs of participating in the GCF for advanced and emerging nations?

The rest of this chapter is structured as follows: in section I.2, I argue that the multiplicity of available policy options complicates enormously the mandate of the GCF. Thus, for this type of multilateral institutions it is fundamental to understand the long-term tradeoffs of the different alternatives proposed by the climate policy community such that they can design and implement investment portfolios that are economically feasible and that meet the objective of stabilizing GHG concentrations at sustainable levels. Understanding how these policy instruments and institutions can address the uncertainties associated with climate change policy and international technological change is a major challenge for policy makers and technological change scholars.

In section I.3, I describe the aspects of climate and technological change that are deeply uncertain. This has important policy implications for directing international technological change towards clean technologies. First, different technological scenarios describing the performance, cost and the extent of usage of clean technologies lead to different levels of GHG emissions that could be reached by the end of this century. Second, different scenarios of climate change determine different feasible temperature rise scenarios by the end of this century for any particular level of GHG emissions. Thus both elements of uncertainty are important to determine what constitutes a sustainable level of GHG concentrations and to determine the economic cost of achieving such level. Not considering the interplay of climate and technological uncertainty is likely to result in biased results when evaluating policy options for directing international technological change towards clean technologies.

Finally, in section I.4, I argue that given the inherent deep uncertainty associated with climate and technological change and the multiplicity of policy options it is then necessary to use new analytical approaches for policy analysis. In the context of the international environmental technological change, RDM (Lempert, Popper and Bankes, 2003) and exploratory modeling (Bankes, 1993) provide a suitable methodological framework that can be used to design robust policy portfolios which can help the GCF meet the objective of enabling the international diffusion of clean energy technologies and contribute to the stabilization of GHG concentrations. I conclude this chapter by summarizing key elements of this policy context using the RDM *"XLRM"* framework.

I.2 Directed International Technological Change, Climate Policy and the Green Climate Fund

The Green Climate Fund is predicated on the belief that directing international technological change towards clean energy technologies can play a significant role in achieving the stabilization of GHG emissions through improvements in the performance and cost of clean energy technologies. This expands the available cost-effective technological options for energy production, ultimately reducing the usage of incumbent fossil energy technologies (Newell, 2008; Fischer and Sterner, 2012; Grübler, Nakićenović and Victor, 1999; Mercure et al., 2014). However, successful international environmental technological change is costly. According to Marangoni and Tavoni (2014) and Newell (2008) and between USD 5 and 22 trillion of investments are necessary over the next decades for achieving a transition from fossil energy technologies to clean energy technologies. For emerging nations, supporting the development and diffusion of clean energy technologies seems to be at odds with their economic development objectives. Evidently, this increases even more the relevance of the investments made by the Green Climate Fund.

This technological orientation of climate change policy is not new. In fact, the policy literature is rich with proposals of how to best direct international technological change towards clean energy technologies. Furthermore, proponents of climate technology policy argue that while these policies are costly in the short term, these can also yield economic benefits in the long term, making this approach more appealing than emission quotas or carbon trading (Newell, 2008).

In Table 1.1, I list several of these policy studies, along with the proposed policy instruments to achieve international environmental technological change. Based on the insights provided by these studies, I describe the need for policy intervention in this context, and the general structure of proposed policies for directing technological change towards clean energy technologies.

Table 1.1
Proposed Policies for International Environmental Technological Change

Author(s)	Policies for Directing International Technological Change
Rosendahl, 2004	• Higher carbon tax in developed nations than in developing nations
Barret, 2006	Two treaty system: • Promoting cooperative R&D • Encouraging collective adoption of a breakthrough technology emerging from this R&D

Table 1.1-Continued
Proposed Policies for International Environmental Technological Change

Author(s)	Policies for Directing International Technological Change
Dechezlepretre, Glachant and Meniere, 2008	• Clean Development Mechanism (CDM) in Kyoto Protocol • Allowing industrialized countries to develop projects that reduce greenhouse gas (GHG) emissions in developing nations in exchange for emission reduction credits
Newell, 2008	• Technology-specific mandates and incentives • International technology-oriented agreements • Cost sharing in R&D • Technology transfer • Emissions pricing and carbon taxes
Fischer and Newell, 2008	• Emissions pricing • Emissions performance standard • Fossil power tax • Renewables share requirements • Technology and R&D subsidies
De Coninck et al., 2008	• Knowledge sharing and coordination of RD&D • Technology-transfer agreements • Technology-specific mandates • Technology subsidies, mandates and performance standards • Loan guarantees for investments
Popp, Newell and Jaffe, 2010	• Policies addressing knowledge market failures include: 1) Patent protection 2) R&D tax credits 3) Funding generic research • Policies with environmental focus on the direction of innovation: 1) R&D subsidies and targeted investments 2) Technology subsidies
Fischer, 2008	• Tax credits • Technology forcing regulation • Price or market share guarantees for the use of particular technologies
Nordhaus, 2011	• International Carbon Tax
Acemoglu et al., 2012	Optimal environmental regulation should always use: • Carbon tax to control current emissions • Research subsidies or profit taxes to influence the direction of research
Helm and Pichler, 2015	• Tradable emission endowments • Technology transfer

NOTES: Policy proposals as listed for each study. Proposals include R&D investments, technology transfer mechanisms, emissions trading, carbon taxes, technology subsidies and tax credits.

The rationale behind the policies proposed by the studies listed in Table 1.1 consists of three main elements. First, Grübler, Nakićenović and Victor (1999) note that normal technological dynamics are decarbonizing the energy sector: continuous improvements of energy technologies make the use of energy resources more efficient. Yet, the rate at which this decarbonization is occurring is slower than the rise in the demand for fossil fuels so overall GHG emissions continue rising. As a result, policy intervention is needed to accelerate this process. In fact, Fischer and Sterner (2012) argue that in order to be able to stabilize GHG concentrations within this century, this technological transition needs to occur at a speed that has never been seen before in any other technological revolution in the historic record. Second, there are market failures that need to be corrected to incentivize entrepreneurs to focus on the development of clean energy technologies, and to incentivize consumer and energy producers to use more environmentally friendly technologies. First, policy intervention is required to correct the environmental externalities of fossil energy technologies. Nordhaus (2011) argues that by correcting this externality consumers and energy producers will be able to make better decisions regarding which technologies to use for meeting their energy needs in an sustainable way. In the same vein, entrepreneurs will be able to identify the most attractive technological sector for their investments. Second, policy is needed to correct the knowledge market failures associated with innovation systems. The economic rationale is that without policy intervention, private R&D investment on clean energy technologies is less than the social optimum because the lack of incentives and/or of knowledge protection scale back innovative activity in this sector (Popp, Newell and Jaffe, 2010). Finally, since most of the environmentally focused innovative activity in the world occurs in a handful of advanced nations (i.e. U.S., Germany and Japan), policy intervention is then needed to facilitate the transfer of clean energy technologies from advanced to emerging nations (Dechezleprêtre et al., 2011).

Table 1.1 lists a rich variety of policy options that have been proposed to direct international technological change towards clean energy technologies. However, three general policy types can be identified from these studies. First, there are policies that focus on increasing innovative activity in clean energy technologies. The objective of these policies is to increase the flow of public and private investments into clean energy technologies' R&D. Policies of this kind generally include: R&D subsidies, co-funding of R&D programs, patent protection treaties and technology transfer treaties (Newell, 2008; Popp, Newell and Jaffe, 2010; Acemoglu et al., 2012) . Second, there are policies that are aimed at creating a market niche for clean energy technologies. These generally include: carbon pricing, technology subsidies, emission performance standards, renewable share commitments and clean energy subsidies (Fischer, 2008; Fischer and Newell, 2008; Nordhaus, 2011). Finally, there are various other policy proposals aimed at facilitating the transfer of clean energy technologies from advanced to emerging nations: co-funding of clean energy technologies' R&D, knowledge sharing and coordination, emissions' credits for technology investments in emerging nations and facilitating direct importation of clean energy technologies (De Coninck et al., 2008; Popp, Newell and Jaffe, 2010). The studies listed in Table 1.1 note that individually these policies are expected to have little or no effect. However, when combined into portfolios that simultaneously incentivize R&D investments for clean energy technologies, create market niches for these technologies in advanced and emerging nations, and facilitate their transfer from advanced nations to emerging nations the effect of such portfolios in enabling international environmental technological change can be much stronger (Acemoglu et al., 2012; Fischer and Sterner, 2012; Fischer and Newell, 2008).

This multiplicity of policy options complicates enormously the mandate of the Green Climate Fund and of other similar multilateral organizations. The policy studies described in the previous paragraphs indicate that it is necessary to implement policy portfolios that both "push" clean technologies more quickly through R&D processes and that "pull" clean technologies more strongly into the energy sector through the creation of market niches. However, policy intervention is costly and subject to strict budget restrictions which makes it necessary to prioritize across areas in order to create a feasible policy mix. In addition, in this international context, it is also imperative to consider how to best distribute costs across regions. Thus, for institutions such as the GCF, it is fundamental to understand under which conditions the "push" component of the policy portfolio should be prioritized over the "pull" component and how each block of countries (i.e. advanced and emerging) should exploit their comparative advantages in the long-term to support these policy efforts.

Understanding how these policy instruments and institutions can address the uncertainties and long time frames associated with climate change policy and international technological change is a major challenge for policy makers and technological change scholars. As stated by Popp, Newell and Jaffe (2010) this is *"perhaps the greatest challenge of climate change policy"*.

I.3 Climate and Technological Deep Uncertainty: Challenges and the Need for New Analytical Methods

The objective of international environmental technological change is to enable the stabilization of global GHG concentrations at levels that are sustainable for the environment and at an economic cost that is feasible for both advanced and emerging nations. However, the uncertainty associated with the behavior of the global climate system and with the future development of energy technologies increases the difficulties of deciding which policies can be used to meet this objective (Fischer and Sterner, 2012). In this section, I argue that in both climate change and technological change policy makers face deep uncertainty. Further, I argue that not considering the interplay of these two sources of deep uncertainty is likely to lead to bias results of the benefits and costs of different policies.

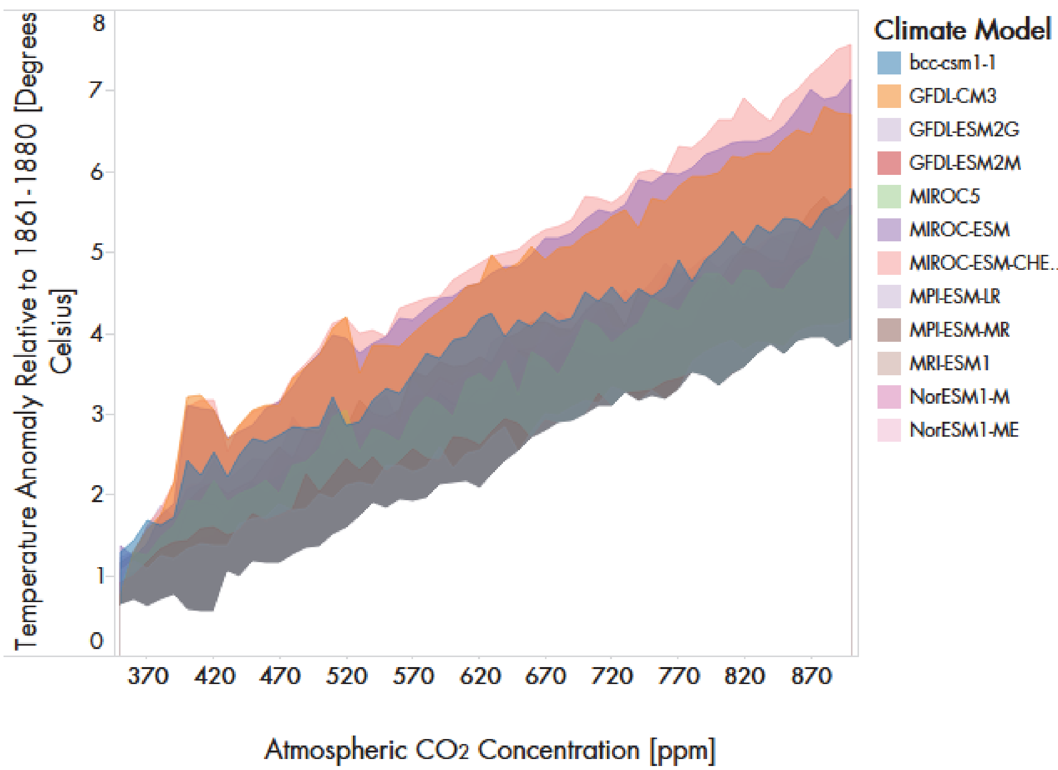
Deep uncertainty exists when the scientists, the analysts or the parties to a decision cannot agree on a) the appropriate causal representation of a system (i.e. structural uncertainty), b) the probability distributions used to represent uncertainty about the relevant parameters in the system (i.e. parametric deep uncertainty), and/or c) how to value the desirability of different outcomes (Lempert, Popper and Bankes, 2003; Lempert et al., 2006).

Previous studies have shown that climate change is indeed a deeply uncertain phenomenon (IPCC, 2013a; Deser et al., 2012; Maurer, 2007). For instance, climate scientists have provided strong evidence that shows that rising GHG emissions are causing a global rise in the average surface temperature and that this rise in GHG emissions is caused by human societies' growing consumption of fossil fuels (IPCC, 2013a). Moreover, climate scientists argue that keeping global temperature rise within two degrees Celsius above pre-industrial levels is likely to help human societies prevent irreversible negative environmental consequences that will endanger our survival as a species (IPCC, 2013a; Solomon et al., 2009). However, climate scientists do not yet agree on what level of GHG concentrations will actually maintain global average temperature below the two degrees Celsius ceiling. In fact, different global climate models developed by different groups of climate scientists lead to very different outcomes (IPCC, 2013a). For instance, Figure 1.1 describes the relation between CO_2 atmospheric concentrations and temperature rise for different General Circulation Models (GCMs) developed by different modeling groups under the World Climate Research Program and used by the IPCC (2013b) in its most recent assessment report.

Figure 1.1 shows that for a given level of CO_2 emissions there is a wide range of possible global temperature rise scenarios based on analysis prepared for the latest IPCC assessment report. These projections show that for CO_2 concentration levels between 400 ppm and 700 ppm; temperature rise could be anywhere between 0.8 and 6.0 degrees Celsius. These temperature changes would represent very different environmental outcomes. On the lower end, global temperature would be within sustainable environmental limits. On the upper end, global temperature would likely cause catastrophic environmental damage (Solomon et al., 2009; IPCC, 2013a). As a result, deep uncertainty associated with climate change makes it difficult and controversial to determine at which level of CO_2 concentrations climate policy should be designed for (Lempert, 2015).

Deep uncertainty is also associated with technological change; perhaps it is the case that technological change deep uncertainty is more profound than climate change deep uncertainty. Similarly to the case of climate change, and despite tremendous progress in the field, technological change scholars do not agree yet entirely on the determinants of international technological change and point to various open questions in the field (Popp, Newell and Jaffe, 2010; Keller, 2004; Acemoglu et al., 2012; Dechezleprêtre et al., 2011; Di Maria and Smulders, 2004; Grübler, Nakićenović and Victor, 1999). Open questions remain with respect to the role of emerging nations' technological absorptive capacity (Popp, Newell and Jaffe, 2010), to the role of international trade in facilitating technology diffusion (Keller, 2004; Keller, 2010) and to the role of technologies' properties in technological change (Dechezleprêtre et al., 2011; Fischer and Sterner, 2012). Evidently, this uncertainty associated with the science and evidence of international technological change generates competing views about how direct international technological change towards clean energy technologies.

Figure 1.1
Increase in Global Mean Surface Temperature as a Function of Atmospheric CO2 Concentrations for CMIP5 GMC Ensemble



SOURCE: (IPCC, 2013b; Taylor, Stouffer and Meehl, 2012; Working Group on Coupled Modelling, 2015)
NOTES: The colored legend indicates the multi-model spread over different RCP scenarios for the period 2010-2100 for different GCM models. Each colored area represents the spread of temperature rise for a fixed level of CO_2 concentration. It shows that any given level of CO_2 concentrations is associated with a wide range of plausible temperature rise scenarios within a particular GCM model, and across different GCM models. Temperature values are given relative to the 1861-1880 base period.

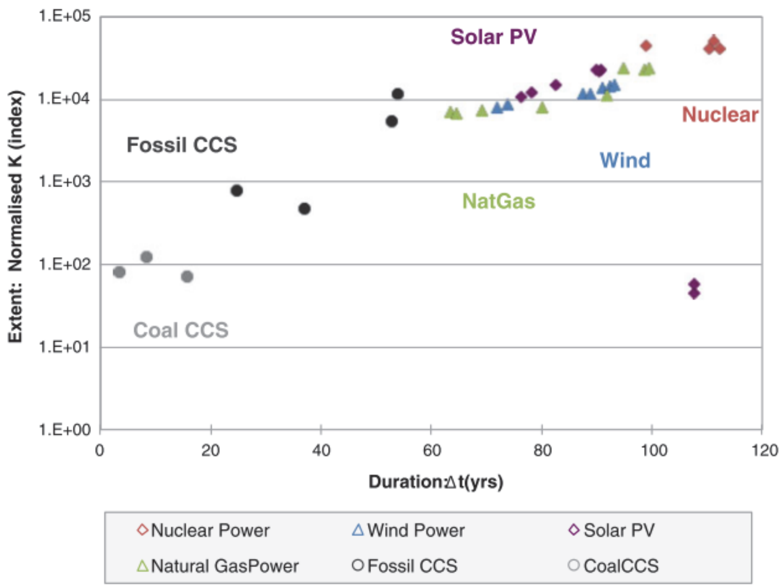
Other aspects of technological change are well understood. Progress in the field has made it possible to conceptualize coherently technological change as an endogenous chain of processes that begins with entrepreneurs' R&D investments and continues with consumers' adoption decisions and firms' learning-by-doing in the market place. Moreover, this progress has also provided useful frameworks for understanding the implications of technological change for the environment and for economic growth (Acemoglu et al., 2012; Di Maria and Smulders, 2004; Rosendahl, 2004; Aghion and Howitt, 1998). Yet, even these well understood processes of technological change are shrouded with uncertainty. In the context of climate change, technological change scientists do not agree on the value of key parameters such as the elasticity of substitution between clean energy and fossil energy technologies (Acemoglu et al., 2012; Di Maria and Smulders, 2004; Pottier, Hourcade and Espagne, 2014; Papageorgiou, Saam and Schulte, 2013). In addition, other important parameters, such as the returns to R&D investments and the technology learning coefficients have been estimated differently across studies (Grübler, Nakićenović and Victor, 1999; Wilson et al., 2013; Baker and Adu-Bonnah, 2008). It is also difficult to choose an appropriate probability distribution to represent these parameters. In some cases, the lack of available data makes it unfeasible to determine the bounds and shape of the probability distributions. In other cases, the nature of technological change (i.e. incremental change or radical change) creates controversies with respect to how best describe the probability distribution of key parameters.

Similarly to climate change uncertainty, the combination of structural and parametric uncertainty in technological change studies results in a wide range of projections about the diffusion of clean energy technologies. Figure 1.2 compares eight climate stabilization scenarios describing the extent of diffusion of key energy technologies(Wilson et al., 2013). The index in the vertical axis indicates for each scenario the importance of each technology in the global energy system: the higher the value, the higher the extent to which that technology is used for energy production. The horizontal axis indicates the number of years that it takes for each technology to achieve that extent of use.

Figure 1.2 shows that projections can vary widely across these stabilization scenarios. For instance, the time needed for achieving meaningful usage of wind energy technologies ranges from 70 to 100 years(Wilson et al., 2013). This uncertainty about our technological future (i.e. performance, costs and extent of use of clean energy technologies) contributes significantly to the difficulties of forecasting future GHG concentrations by the end of the century and ultimately the cost and the time needed for stabilizing GHG concentrations at sustainable levels (Fischer and Sterner, 2012).

There is one important difference between climate and technological change and their association with deep uncertainty. For climate change deep uncertainty, there is the expectation that in the future, as climate science continues to improve and more information is collected, uncertainty about the range of possible global temperature rise scenarios will be reduced. This does not mean that this will happen within a time frame that has any policy relevance. In fact, it may take centuries before climate scientists are able to meaningfully reduce the uncertainty associated with our understanding of the global climate system. Thus, without question, relevant policy decisions will need to be made in the face of deep climate change uncertainty. What about technological change deep uncertainty? Will more science and more accurate data help scientists provide a narrower set of scenarios about our energy technological future? I believe this will not be the case because in technological systems, the inherent uncertainty of any natural system is exacerbated by the unpredictable nature of human behavior and social systems.

Figure 1.2
Example of Energy Technologies' Diffusion Scenarios for the 21st century
SOURCE: (Wilson et al., 2013)



NOTES: The index in the vertical axis indicates for each scenario the importance of each technology in the global energy system: the higher the value, the higher the extent by which that technology is used for energy production. The horizontal axis indicates the number of years that it takes for each technology to achieve that extent of use. It is possible to see that these projections vary widely. For instance, across these stabilization scenarios, the time needed for achieving meaningful usage of wind energy technologies ranges from 70 to 100 years.

Human societies create technologies, but the impact of these technologies on pre-existing technological systems and on society itself is frequently unpredictable. The technological progress experienced during the industrial revolution laid down the foundations for the advent of modern energy and mobility technologies, such as the steam turbine and the internal combustion engine. These technologies have had a profound impact on society and on the economy, but their massive usage has dramatically raised GHG emissions. In response, governments all over the globe are discussing how to best respond to mitigate this negative externality caused by technological change. The size of the policy response is unpredictable at this point. Moreover, even if all the right policies are in placed to support the development and the international diffusion of clean technologies, there still remains the fact that it is not feasible to anticipate accurately the degree of success of R&D programs in clean technologies or the extent to which these technologies will change the scheme of energy production (Baker and Adu-Bonnah, 2008; Golombek and Hoel, 2004; Bosetti and Tavoni, 2009). I argue that because of the interdependent adaptive nature of society and technology, future technological change is an inherently deeply uncertain phenomenon.

Considering both climate and technological change deep uncertainty has important policy implications for directing international technological change towards clean technologies. On the one hand, different technological scenarios describing the performance and the extent of usage of clean technologies determine different levels of GHG concentrations levels that could be reached by the end of this century. On the other hand, different climate change scenarios determine ranges of temperature rise that could materialize by the end of this century. In terms of policy evaluation, both elements of uncertainty are important to determine what constitutes a sustainable level of GHG concentrations and to determine the economic cost of achieving such level. Not considering the interplay of climate and technological uncertainty is likely to result in biased results when evaluating policy options for directing international technological change towards clean technologies.

Since climate and technological change are deeply uncertain phenomena, it is necessary to study the policy response needed for enabling international environmental technological change from a perspective that is different from the traditional predict-then-act planning approach. For instance, the interplay and inherent deep uncertainty of climate and technological change make it impossible to project future GHG concentrations and environmental consequences. It would be unthinkable to choose one or a subset of the many possible projections to design the optimal policy response. Lempert, Popper and Bankes (2003) argue that new analytical methods enabled by modern computing can profoundly transform our ability to reason systematically about the long-term future and help us face the challenges pose by deep uncertainty. The authors propose that in contexts associated with deep uncertainty, instead of attempting to predict the future it is necessary to consider multiple alternative futures simultaneously and to analyze the performance of different policies across this multiplicity of futures. This analytical exercise is enabled by the usage of simulation models in an exploratory modeling setting (Bankes, 1993) and by the application of data mining techniques that support the identification of multi-dimensional conditions under which proposed polices meet their goals (Lempert et al., 2006). This framework, commonly known as Robust Decision Making (RDM)(Lempert, Popper and Bankes, 2003), has been already successfully implemented in policy context for climate mitigation and climate adaptation (Groves, Yates and Tebaldi, 2008; Lempert and Groves, 2010; Groves et al., 2013; Groves et al., 2014; Fischbach et al., 2015).

Technological change scholars have long argued that new methods are needed for studying technological change (Grübler, Nakićenović and Victor, 1999). I believe that given the inherent deep uncertainty associated with climate and technological change RDM provides a suitable methodological framework that can be used for designing robust policy portfolios that can help the Green Climate Fund meet the objective of enabling the international diffusion of clean energy technologies and contribute to the stabilization of GHG concentrations.

I.4 Summary

In this chapter, I argue that because of the incomplete understanding of international technological change, the multiplicity of policy options and ultimately the presence of climate and technological change deep uncertainty, multilateral institutions, such as the Green Climate Fund, require new analytical methods for designing long-term robust investment plans.

In this context, Robust Decision Making (Lempert, Popper and Bankes, 2003) and exploratory modeling (Bankes, 1993) can be used to enable our ability to reason systematically about the long-term future, despite of the challenges pose by deep climate and technological uncertainty. Thus these approaches provide a suitable methodological framework to understand under which conditions the GCF's investments and climate policy enable the international diffusion of clean energy technologies and the stabilization of GHG concentrations.

Table 1.2 summarizes the discussion presented in this chapter using the XLRM framework (Lempert, Popper and Bankes, 2003). Each cell describes the central themes that have been discussed in this chapter. It describes four important metrics **(M)** to evaluate and compare the performance of different policy portfolios, these are: 1) the economic cost of policy intervention, 2) the distribution of costs across regions, 3) the temperature rise level resulting after implementing these investments and 4) ultimately if the stabilization of GHG emissions is achieved before the end of the century.

It also shows that policy levers **(L)** can be comprised of three elements: 1) "push" technology policies that accelerate the RD&D process of clean energy technologies, 2) "pull" technology policies that create market niches to accelerate the commercialization of these technologies, and 3) "transfer" policies that accelerate the diffusion of clean technologies towards emerging nations.

Table 1.2 describes climate and technological change as uncertain **(X)** phenomena. This has important policy implications for analyzing the performance of the different policy options across the key metrics considered. First, different technological scenarios describing the performance and the extent of usage of clean technologies determine different levels of GHG concentrations levels that could be reached by the end of this century. Second, different climate change scenarios determine ranges of temperature rise that are feasible for any given level of GHG concentrations. Both elements of uncertainty are important to determine what constitutes a sustainable level of GHG concentrations and to determine the economic cost of achieving such level. Not considering the interplay of climate and technological uncertainty is likely to result in biased results when evaluating policy options for directing international technological change towards clean technologies.

Finally, several system relationships **(R)** are important to investigate the effectiveness of these policies in meeting the objectives aforementioned. For instance, it is important in this policy context to understand the competition processes between clean energy technologies and fossil energy technologies. It is also fundamental to consider the processes that lead to the development, commercialization and international diffusion of clean energy technologies. As well as the potential response of the climate system to growing GHG emissions and the potential adverse effects of growing temperatures on advanced and emerging nations. The following chapters provide a detailed discussion and a conceptual framework to link these processes systematically.

Table 1.2
XLRM Framework Summary of Main Research Themes

Uncertainties (X)	**Policy Levers (L)**
Climate Uncertainty: • Speed of Temperature Rise • Extend of Temperature Rise Technological Uncertainty: • Penetration of Clean Energy Technologies • Performance of Clean Energy Technologies • GHG Emissions	Push Policies • R&D investments • R&D tax credits and subsidies Pull Policies • Carbon pricing/taxation • Technology subsidies • Technology mandates Transfer Policies • R&D shared programs • Patent protection • Policy harmonization
System Relationships (R)	**Metrics (M)**
• Technological Change • International Diffusion of Clean Technologies • Global Climate Change	• Temperature Rise • GHG emissions • Cost of Policy Intervention • Distribution of costs

NOTES: The main themes associated with scope of this research study are grouped according to four different categories: 1) the deep uncertainties taken into account, 2) the policy levers that can be used to direct technological change towards clean technologies, 3) the system relationship that links actions to consequences, and 4) the relevant metrics necessary to evaluate the performance of different policies.

CHAPTER II

Framing International Technological Change: Theories, Implications, Evidence and Relevant Knowledge Gaps

II.1 Introduction

The scientific literature of international technological change is as diverse in its scope as it is in its research methods. Scholars of international technological change have focused on understanding how technological change occurs in technologically advanced countries and on how the technologies developed in these regions diffuse to other less technologically advanced regions. There are mainly two types of studies: 1) modeling studies that put forward new theories about how innovation and economic processes lead to technological change within and across regions; and 2) statistical empirical studies that describe the determinants of international technological change using technology adoption rates and patenting data. The results of these two streams of research have shed light into the complex web of forces that shape international technological change patterns, but more importantly, it has also shown that there are still intriguing research gaps.

In this chapter, I first focus on describing international technological change through the theoretical models of previous authors. Second, I present relevant empirical works that confirm or challenge some of these theoretical views. Finally, I discuss key unanswered questions in the field that are relevant for this dissertation.

The discussion presented in section II.2 shows that theoretical studies of international technological change describe a two-phase process. First new technologies are developed in technologically advanced countries (Di Maria and Smulders, 2004; Fisher-Vanden and Ho, 2010). Second, new technologies are diffused internationally to less technologically advanced countries (Keller, 1996; Keller, 2004; Di Maria and Smulders, 2004). Within a region, technological change is a process that results out of the investment decisions of technology entrepreneurs and the adoption decisions of consumers. The process occurs endogenously in a closed feedback loop because the technological environment, as well as the economic and institutional context influence the decision making process of entrepreneurs and consumers. In turn, the decisions of entrepreneurs and consumers change the technological and economic landscape (Acemoglu et al., 2012; Popp, 2004; Howitt, 2000; Rosendahl, 2004). Across regions, technological change is driven by the flow of new technologies through trade, foreign direct investments and R&D spillovers (Di Maria and Smulders, 2004; Keller, 2004).

Some of the key features proposed by theoretical models are in accordance with the findings of empirical studies. For instance, existing data shows that worldwide only a handful of advanced countries (e.g. US, Germany, Japan, United Kingdom) account for the majority of the world's creation of new technologies and environmentally focused innovative activity (Keller, 2004; Lanjouw and Mody, 1996; Coe, Helpman and Hoffmaister, 1997; Helm and Pichler, 2015; Rizzi, van Eck and Frey, 2014). These studies also indicate that emerging nations' local capacities, policies and endowments influence the rate at which they can absorb advanced foreign technologies (Blackman and Kildegaard, 2010; Coe, Helpman and Hoffmaister, 1997; Coe, Helpman and Hoffmaister, 2009; Popp, 2006b; Popp, 2006a; Comin and Hobijn, 2004). Also evidence shows that technological convergence across regions is possible, but only under very specific circumstances of R&D intensity and local capacities. Comin and Hobijn (2010) show that technology convergence across countries is common, but this can take a considerable amount of time. In the sample of technologies studied by the authors, they find that it takes on average 45 years for one technology to be fully diffused internationally. However, there is ample variation across countries and technologies. The empirical evidence also suggests that the time required for full international technological diffusion ranges widely across technological sectors which may be an indication that not only country specific institutional and economic factors play a role in facilitating diffusion but also the technical characteristic inherent to each technological sector. In fact, they find that the average speed of convergence is 3.7 percent per year. Importantly, their study suggests that the speed of technological convergence across countries has accelerated over time, and that newer technologies tend to diffuse faster than older technologies

Despite the remarkable progress in the field there are other aspects of international technological change that remain ill-understood. In particular, I emphasize the importance of continuing improving our understanding of technological change in emerging nations and the relevance of developing theoretical frameworks and empirical tools that incorporate deep uncertainty into studies of future international technological change.

II.2 Theories of International Technological Change

Table 2.1 summarizes the main theoretical studies of international technological change. I use this table to describe the main elements of these theoretical models. First, I list the relevant endogenous processes that lead to technological change within a region. Second, I note the processes that lead to the international diffusion of new technologies. Third, I specify whether or not these theories consider economic and institutional differences across nations. Fourth, I note whether or not these theories consider specific technological properties. Finally, I list the main implications of these theories with regards to international technological change.

This review of theoretical studies focuses on studies that have had the highest impact in recent years (i.e. measured by the number of citations). This strategy prioritizes older studies over more recent theoretical studies. To circumvent this limitation I have also included in this review some recent theoretical studies which are still being scrutinized by the research

Table 2.1
Properties of International Technological Change Theories

Author(s)	Change Mechanisms	International Diffusion	Regional Differences	Technical Properties	Implications
Rosendahl, 2004	-Endogenous R&D -LBD (Learning by doing)	None	None	None	- Learning-by-doing leads to better environmental outcomes in climate change studies
Golombek and Hoel, 2004	-Endogenous R&D	-Trade -Local R&D	-Environmental consciousness	-Shape of the environmental damage function	-Unilateral policy can avoid carbon leakage
Fisher-Vanden and Ho, 2010	-Endogenous R&D	-Local S&T capabilities -Local R&D	-S&T Capabilities	None	-Rapid growth in S&T capabilities can lead to higher GHG emissions
Barrett, 2006	-Collective R&D	-Collective commitments to adopt technologies	-Incentive structures	-Increasing returns to adoption	-Increasing returns can facilitate global cooperation
Keller, 2004	-Endogenous R&D	-Technology imports -Learning by exporting -Foreign Direct Investment spillovers -Foreign R&D spillovers -Local R&D -Local S&T capabilities	-Absorptive capacities of foreign technologies	None	-Differences in countries local absorptive capacities determine reliance of local vs foreign innovations
Rivera-Batiz and Romer, 1991 Grossman and Helpman, 1991	-Endogenous R&D	-Free international trade	-Different local technological endowments	None	-Given free international trade, the technological gap between advanced and emerging nations tends to close
Popp, 2004	-Endogenous R&D -Crowding out of R&D	-Instant global diffusion	None	-R&D decay rate -R&D elasticity	-Policy is needed to signal entrepreneurs -Endogenous technological change reduces cost of mitigation but has little effect of climate change outcomes

Table 2.1-Continued
Properties of International Technological Change Theories

Author(s)	Change Mechanisms	International Diffusion	Regional Differences	Technical Properties	Implications
Di Maria and Smulders, 2004	-Endogenous R&D in advanced nations -Competing technological sectors -Multiple markets	-Importation of technologies -Technology imitation	Capacities for endogenous R&D	-Degree of substitutability among sectors -Potential for imitation -Varying returns to R&D -Difficulty of R&D	-The more difficult to substitute technologies the more likely carbon technologies are used in emerging nations, leading to worse environmental outcomes
Di Maria and Van der Werf, 2008	-Endogenous R&D -Competing technological sector -Multiple markets	-Terms-of-trade effect -Trade price effect	-Environmental policy context	-Elasticity of substitution -Varying returns to R&D -Difficulty of R&D	-Unilateral climate policy can induce technologies change in trade partner. Technological diffusion depends on the elasticity of substitution.
Howitt, 2000	-Endogenous R&D	-Trade -Technology transfer	-R&D Intensity	None	-Countries that engage in R&D will converge to similar productivity levels
Acemoglu et al., 2012	-Endogenous R&D -Competing technological sectors -Market size effect -Price effect	-Instant global diffusion	None	-Different maturity levels across technology sectors	-Elasticity of substitution determines ease of transition towards clean technologies -The greater gap in development across technology sector, the more difficult this transition
Mercure et al., 2014	-Endogenous R&D	-Agent based adoption decisions	21 regions	None	-Policy diversification needed for successful mitigation

NOTES: Each theoretical framework is described across four dimensions: 1) the technological change process considered, 2) the international diffusion processes considered, 3) the regional differences taken into account and 4) the technological properties considered. In addition, implications for international technological change are noted for each theoretical framework.

community. Other studies have been recently published in the field, for example Cabo, Martin-Herran and Martinez-Garcia (2014), Engwerda (2014) and Greiner (2014). However, these other studies are not reviewed in detail in this chapter.

Economic and institutional differences among nations are fundamental to understand more comprehensively international technological change. The theoretical models listed in Table 2.1 find that the science and technology capabilities (i.e. human capital development, R&D capacities, and existing technologies) of emerging nations are essential to facilitate the diffusion of new technologies developed in advanced nations (Keller, 2004; Fisher-Vanden and Ho, 2010; Howitt, 2000). These studies argue that local science and technology endowments help emerging nations adopt, adapt and imitate foreign technologies which enhances their local diffusion. In addition, these studies find that while technological change in advanced nations pushes indirectly technological change in emerging nations. In the former, without a favorable institutional environment (i.e. R&D subsidies, technology subsidies and price incentives), it is not possible to guarantee complete diffusion of advanced clean technologies in emerging nations (Golombek and Hoel, 2004; Di Maria and Van der Werf, 2008; Di Maria and Smulders, 2004; Barrett, 2006).

Recent studies consider in more detail the role of technological properties in understanding international technological change. In these more recent models, technological properties, such as: increasing returns to adoption, R&D investments diminishing returns, elasticity of substitution, and difficulty of finding new innovations have been formally included in theoretical models. Initial findings suggest that these technological properties can significantly drive technological change outcomes. As a result, it seems crucial to consider technological properties in technological change studies (Di Maria and Smulders, 2004; Popp, 2004; Barrett, 2006; Acemoglu et al., 2012).

The implications of these theoretical models for international technological change and climate policy are important. These studies show that by seeing international technological change as an endogenous process occurring within nations, the cost of climate change mitigation is less than the cost estimated without considering endogenous technological change. This also implies that, when considering endogenous technological change, it is possible to find slightly more optimistic scenarios of technology diffusion and climate change mitigation (Rosendahl, 2004; Popp, 2004; Di Maria and Smulders, 2004; Acemoglu et al., 2012). However, these conclusions depend primarily on emerging nations' ability to catch-up technologically with advanced nations. These studies also show that this process of catching-up is possible, but it depends heavily on the science and technology capabilities of emerging nations, the policies in place in these nations and the inherent technological properties of the technologies considered (Golombek and Hoel, 2004; Keller, 2004; Di Maria and Van der Werf, 2008). In terms of climate change, this implies that even though clean technologies continue to be developed in advanced nations, the success of these technologies in emerging nations can still follow many different paths, from successful adoption to continuing dominance of fossil energy technologies. In the following paragraphs I discuss in more detail the elements of the theoretical models listed in Table 2.1.

Several of these theoretical works center on understanding the role of endogenous technological change in the context of directed international technological change towards clean technologies. Acemoglu et al. (2012) suggest that by directing international technological change towards clean technologies, it is possible to maintain GHG concentrations at a sustainable level for the environment. The policy mix required for directing technological change consists of both carbon taxes and research subsidies to influence the direction of research towards clean technologies. Their findings suggest that with the optimal policy mix, such costly policies only need to be in place temporarily to guarantee a sustained international transition towards clean technologies. Their framework considers a world model with endogenous technological change, competing technological sectors (i.e. clean and carbon sectors) and multiple markets, including markets for innovations, for intermediary inputs and for final consumption. Two mechanisms are particularly important in shaping the pattern of technological change: 1) the market size effect which incentivizes entrepreneurs to work on the technologies that support the larger intermediary input sector, and 2) the price effect which incentivizes entrepreneurs to work on the sector with the greater intermediary input prices. The lessons derived from their analysis suggest that there are three fundamental factors for ensuring the success of the optimal policy mix of carbon taxes and research subsidies: 1) the elasticity of substitution between the two competing sectors, 2) the relative levels of development of the technologies of the two sectors and 3) and whether the carbon inputs are produced using an exhaustible resource. The more substitutable the technologies of competing sectors are, the easier the transition towards clean technologies. Also, the greater the gap in productivity between clean and carbon technologies, the longer the transition towards clean technologies. Thus, delays in implementing the optimal mix result in higher costs. Rosendahl (2004) argues that learning by doing and R&D activities are two of the most important sources of induced technological change. He shows that taking into consideration the effect of learning-by-doing (LBD) leads to less disastrous environmental scenarios and to more cost savings of environmental policy. He argues that the processes that lead to induced technological change (i.e. LBD and R&D) are often complementary and thus using models or theories that do not consider the interplay of these processes together may lead to biased conclusions.

Other theoretical models have focused on understanding how country differences and endogenous technological change processes can result in technological convergence or divergence across countries. Howitt (2000) uses a multi-country endogenous growth model to analyze to what extent differences in R&D investment levels among countries lead to divergence in income and technological productivity. His findings suggest that because of technology transfer, countries that invest similar levels of R&D converge to similar productivity levels, while countries that do not, diverge. Golombek and Hoel (2004) consider the case of endogenous technological change, cross-country diffusion of clean technologies and differences in environmental consciousness among countries. Their theory suggests that under these conditions, unilateral climate mitigation actions in the country with the highest valuation of the environment will not necessary lead to higher use of fossil technologies in the country with the lowest valuation of the environment. This pattern of technological change will depend on the R&D investment levels in the less environmentally conscious country, and on the shape of the environmental damage function which is shaped by the inherent technological properties of clean technologies. Fisher-Vanden and Ho (2010) argue that rapid growth in science and technology (S&T) capabilities of developing countries does not lead to reduction of GHG emissions. Their study shows that higher S&T intensity (i.e. R&D investments as a share of GDP) leads to using more efficient energy technologies in the economy (i.e. technique effect), but at the same time, this technological revolution leads to lower goods' prices, which increases aggregate demand (i.e. scale effect) and also increases the use of energy in production (i.e. composition effect). These last two effects offset the environmental benefits of the technique effect.

International technology diffusion and the importance of local endowments for adoption of new technologies have also been the focus of the models described in Table 2.1. Keller (2004) argues that international technological change is mainly shaped by processes of international diffusion of technologies from advanced nations to other advanced or emerging nations. He describes the process of international diffusion of technologies as a phenomenon shaped by the interplay of several mechanisms, including: international trade (i.e. direct technology imports, learning by exporting), foreign direct investment (FDI), technological spillovers, foreign R&D spillovers and local R&D and human capital capabilities. He argues that countries have different capacities for absorbing advanced foreign technologies (Keller, 1996). This absorptive capacity is determined by their local human capital development and R&D investments. Differences in countries' absorptive capacities lead to differences in the degree to which countries rely on local and foreign technologies. Under this framework, emerging nations are expected to rely more on local innovations than advanced nations. Similar ideas regarding the need of complementary capacities for technology adoption are proposed by Dechezlepretre, Glachant and Meniere (2008), Evenson and Westphal (1995), Pack (1992), and Dahlman (1992). The same issue is found to be important for the diffusion of clean technologies by Worrell et al. (2001).

Environmental international technological change has also being studied from a trade and environmental regulation perspective. Di Maria and Smulders (2004) framework focuses on the interconnection between trade, technological change and environmental regulation. In their theoretical model, emerging nations are assumed to have no endogenous capacities for R&D so they use technologies developed in advanced nations. They consider two competing technological sectors (i.e. clean sector and carbon sector). The pattern of technological change results from the profit incentives of entrepreneurs in the advanced region. Their analysis suggests that trade between the two regions induces the use of clean technologies in the emerging region; however, this is not an absolute result as it is possible that trade also induces the use of carbon technologies in the emerging region. They conclude that the degree of substitutability between the technologies used in the clean and carbon sectors and the degree of protection of intellectual property rights are key determinants of diffusion patterns. The more difficult it is for the technologies of one sector to substitute the functions of the technologies in the incumbent sector, the more likely it is that the emerging region adopts only carbon technologies, and the less protection to intellectual property rights, then the more likely, too, it is that the emerging region uses carbon rather than clean technologies. Di Maria and Van der Werf (2008) analyze the case in which international diffusion of clean technologies occurs as a result of the unilateral climate policy implementation in one country. In this case, they consider two regions connected by trade that are similar in all aspects (i.e. same R&D capacities, same preferences and same factors endowments). The only difference is that one region sets an emissions' cap while the other does not. Three key lessons are derived from their theoretical model. First, they find that there is a terms-of-trade effect: when the production of carbon-intensive goods is reduced in one region due to the implementation of an emissions cap, then the international prices of such goods increases, incentivizing the non-constrained region to produce more of the carbon intensive goods. Second, a reduction in the use of fossil fuels in one region reduces the prices of fossil fuels, incentivizing the unconstrained region to use more fossil fuels in production. Third, while these two processes lead to carbon leakage[4]at the same time this change in prices increases entrepreneurs' incentives to work on the development of clean technologies, which offsets the degree of carbon leakage. Rivera-Batiz and Romer (1991) and Grossman and Helpman (1993) argue that free international trade facilitates the diffusion of advanced technologies to emerging nations by allowing the latter to gain access to advanced technologies invented abroad. As a result, this theoretical view argues that the technological gap between advanced and emerging nations has a natural tendency to be reduced.

Finally, relatively more recent models have begun focusing on the role of alternative technological properties in shaping the pattern of international technological change. Barrett (2006) argues that in a context in which R&D investments are directed towards breakthrough technologies that exhibit increasing returns to adoption, then both developed and developing countries have sufficient incentives to sustain international diffusion of these technologies and thus mitigating growing GHG emissions. Mercure et al. (2014) framework depicts innovation in energy markets as being driven by innovation, path-dependent technology decisions and

4 Carbon leakage is the case in which the reductions of emissions in one country lead to increase emissions in another, via to three main channels: 1) reduced emissions in one country reduce the marginal costs of abatement in other countries, thus incentivizing higher emissions, 2) a reduction in the demand for fossil fuels in one country, leads to cheaper international prices of fossil fuels, incentivizing other countries to use more fossil fuels, 3) if one country introduces a carbon tax, the local supply of carbon intensive goods reduces, increasing their prices, this in turn incentivizes trade partners to increase their production of carbon intensive goods (Golombek and Hoel, 2004).

diffusion of these technologies across regions. Their framework, in a similar fashion to endogenous growth theory, considers the decisions of technology investors central to understanding technology diffusion from one region to another. Their theory pays particular attention to how differences across all the 21 regions they considered contribute to shaping macro behavior of technology diffusion and temperature rise. Their analysis departs from mainstream general equilibrium modelling in that they do not focus on the equilibrium conditions on the markets they considered. However, their findings are similar to those of Acemoglu et al. (2012) and Di Maria and Van der Werf (2008) in that they estimate that policies such as carbon taxes and R&D investments need to be complementary to achieve the necessary technological progress to stabilize GHG emissions at sustainable levels. In fact, similarly to Acemoglu et al. (2012) they find that policy diversification leads to a smaller carbon tax needed to direct technological change towards clean technologies. Other studies such as Popp (2004) and Di Maria and Smulders (2004) consider parameters that describe the R&D potential of different technologies. Golombek and Hoel (2004) and Fischer and Sterner (2012) note that the shape of the abatement curves is defined by the potential of the technologies considered and how these response to R&D investments. Acemoglu et al. (2012) explicitly considers the role of different maturity levels of competing technological sectors in shaping technological change patterns and increasing the difficulties of transitioning towards cleaner technologies.

II.3 Empirical Evidence on International Technological Change

Table 2.2 lists the main empirical studies that focus on international technological change. These studies use comprehensive datasets and econometric analyses to understand the determinants of technological change patterns across nations. For each study, I list the type of data used for the analysis, its main findings and its implications for the theory of international technological change. I focus primarily on reviewing the studies that have had the highest impact in the scientific literature (i.e. measured by their number of citations) and combine these classic studies with insights from some of the more recent studies. This provides a more comprehensive review of the empirical studies on international technological change available for policy research.

I focus on comparing the findings of these studies against the assumptions and propositions of the theoretical frameworks listed in Table 2.1. The objective of this exercise is understand to which extent the theoretical frameworks described in Table 2.1 are in accordance with empirical evidence that results from conducting econometric analysis on available data that describe innovation and technology diffusion. Thus, these studies offer a complementary view of international technological change that is supported by econometric techniques designed purposefully to disentangle the effect of various forces at play and, more importantly, that is supported by data that attempt to describe accurately how international technological change occurs in specific economic and institutional contexts.

I center this discussion on four main themes. First, I discuss evidence associated with the assumption that new technologies are primarily developed in advanced nations. Second, I describe studies of the role of local institutions and endowments in facilitating the adoption of foreign technologies. Third, I review the issue of technological convergence across nations. Finally, I focus on assessing whether or not empirical evidence shows that technological patterns seen in historical records are technology sector dependent.

Table 2.2
Findings and Implications of Empirical Studies of International Technological Change

Author(s)	Findings	Implications
Keller, 2004	-Foreign sources of technology account for 90 percent or more of domestic productivity growth. -Only a handful of rich countries account for most of the world's creation of new technology.	-Worldwide technical change is determined by international technology diffusion
Coe, Helpman and Hoffmaister, 1997	-The seven largest economies of the OECD account to 92% of all R&D in the world.	-Most technology innovation is done by advanced nations
Lanjouw and Mody, 1996	-Environmental innovation mainly done in United States, Japan, and Germany. -Patents registered in developing countries correspond to inventors from developed nations.	-Most clean technology innovation is done by advanced nations
Blackman and Kildegaard, 2010	-Firms' human capital and stock of technical information influence adoption of advanced technologies	-Local capacities in emerging nations influence adoption
Coe, Helpman and Hoffmaister, 2010	-Institutional differences determine technology factor productivity growth and the impact of R&D spillovers.	-Institutional differences determine adoption rates
Popp, 2006	-Clean technologies from advanced countries are not transferred directly to other nations, but rather indirectly. -Local environmental regulations and local R&D capacities influence adoption of clean technologies in developing nations.	-Local R&D intensities and policies influence the rate of adoption of foreign technologies
Comin and Hobijn, 2004	-Country's per capita income, human capital endowment, type of government, degree of openness to trade, and adoption of predecessor technologies are positively associated with the speed of adoption of foreign technologies.	-Local capacities in emerging nations influence adoption
Rizzi, van Eck and Frey, 2014	-Scientific publication patterns over the last decade suggest that innovative activity in BRICS countries focuses on adaptive technologies developed in advanced countries	- Scientific and innovative activity associated with clean technologies shows specific geographical patterns

Table 2.3-Continued
Findings and Implications of Empirical Studies of International Technological Change

Author(s)	Findings	Implications
David Popp, 2014	- Most innovation is concentrated in a few rich countries. -Innovation in emerging nations focuses on incremental improvement over existing technologies	-Adaptive R&D in emerging nations can improve the fit of new technologies to local market conditions
Comin, Hobijn and Rovito, 2006; Comin and Hobijn, 2010	-On average it takes 45 years for one technology to be fully diffused internationally. -Ample variation across countries and technologies	-Technology convergence across countries

NOTES: Empirical findings and implications are described for each study. Local endowments, R&D intensity rates, institutional differences are listed as important determinants of international technological change.

The studies listed in Table 2.2 report that there are substantial R&D intensity and technology penetration level differences between advanced and emerging nations. For instance, existing data show that only a handful of advanced countries (e.g. US, Germany, Japan, United Kingdom) account for the majority of the world's creation of new technologies measured by number of patents granted to inventors (Keller, 2004; Lanjouw and Mody, 1996; Coe, Helpman and Hoffmaister, 1997; Rizzi, van Eck and Frey, 2014; Popp, 2014).

For most countries, foreign sources of technology account for 90 percent or more of domestic productivity growth (Keller, 2004). Multi-national corporations spent most of their R&D funds in advanced nations (Worrell et al., 2001; Siedschlag et al., 2013). This pattern has remained consistent over the past two decades but recent empirical research also shows that emerging nations are beginning to capture more R&D funds from multinational companies (Siedschlag et al., 2013). R&D investments in advanced nations are found to be important for emerging nations due to R&D spillovers. For instance, a one percent increase in the R&D intensity of the United States raises total factor productivity on average for its trade partners by about 0.03 percent. A similar increase in R&D intensity in Japan, Germany, France and the United Kingdom raises total factor productivity in emerging nations by 0.004 to 0.008 percent. Comin, Hobijn and Rovito (2006) use a database of the diffusion of 155 technologies across 150 countries, covering the last 200 years. Their analysis shows that technologically advanced nations like the U.S. have historically led the usage of modern technologies like telephones, cars, electricity, modern agriculture and aviation. Moreover, the adoption lags between technology leaders and followers tends to be measurably large. For instance, the level of phones per capita in the U.S. in 1910 was reached by France 45 years later, by South Africa 55 years later, by Brazil 65 years later, by China more than 80 years later, and by India 90 years later. In the case of Tanzania, this country has fewer phones per capita today than the U.S. did in 1910. In summary, it appears that these findings provide further backing to the assumption that new technologies are primarily developed by advanced nations and that these are later adopted in emerging countries.

Several of the theoretical frameworks described in Table 2.1 argue that local capacities, policies and endowments influence the rate at which countries can absorb more advanced foreign technologies. The empirical studies listed in Table 2.2 show indications that this assertion is reasonable. For instance, regarding the role of local capacities and endowments, Blackman and Kildegaard (2010), in a survey study on the adoption of environmentally clean leather tanning technologies in Mexico, find that human capital and technical sophistication play an important role in influencing the adoption of clean technologies. Interestingly, they find that firm size and regulatory environments are not strongly correlated with adoption. Coe, Helpman and Hoffmaister (2009) find that institutional factors such as the ease of doing business, the quality of tertiary education systems and the degree of patent protection in emerging nations are important determinants of the degree to which emerging nations can effectively use R&D spillovers from trading with advanced nations with high levels of R&D activity. Coe, Helpman and Hoffmaister (1997) show that emerging nations that engage in trade with advanced nations with intense R&D activity are able to adopt advanced technologies faster if they too invest in R&D. They argue that emerging nations' R&D investments reduce the costs of acquiring useful information for the adoption of advanced technologies. Regarding the role of local policies and institutions,Popp (2006a) studies the diffusion of air pollution control technologies across the U.S., Japan and Germany. He finds that clean technologies from advanced countries are not transferred directly to other nations, but rather indirectly. His results show that other nations adopt clean technologies created in advanced nations through the implementation of similar environmental regulations but also through local R&D investments that help these countries adapt these innovations to their local markets. Coe, Helpman and Hoffmaister (2009) show that institutional differences among countries are important determinants of total factor productivity and of the degree of R&D spillovers across countries. They find that country characteristics such as the ease of doing business, the quality of advanced education and adequate patent protection tend to be positively associated with stronger returns to local R&D and higher R&D spillovers. Comin and Hobijn (2004) find that country's per capita income, human capital endowment, type of government, degree of openness to trade, and adoption of predecessor technologies are positively associated with the speed of adoption of foreign technologies.

The theoretical models listed in Table 2.1 argue that technological convergence across regions is possible, but only under very specific circumstances of R&D intensity and local capacities. Recent empirical work has made the monumental effort of collecting historical technology diffusion datasets that cover long periods of time, multiple countries and multiple technologies. These studies offer evidence that technological convergence occurs across countries. The data shows that this a lengthy process, but it also shows that this process is accelerating (Comin and Hobijn, 2009; Grübler, Nakićenović and Victor, 1999). Using a comprehensive data set of this type, the econometric analysis of Comin, Hobijn and Rovito (2006) and Comin and Hobijn (2010) show that technology convergence across countries is common, but this can take a considerable amount of time. In the sample of technologies studied by the authors, they find that it takes on average 45 years for one technology to be fully diffused internationally. However, there is ample variation across countries and technologies. For example, in the case of steam and motor ships, after 123 years, only 50% of the 150 countries considered in their sample had adopted this technology. The authors assert that there is absolute convergence in 91 percent of the 155 technologies they considered and that the average speed of convergence is 3.7 percent per year. Importantly, they find evidence that the speed of technological convergence across countries has accelerated over time, and that newer technologies tend to diffuse faster than older technologies. Their conjecture is that this process is associated with the convergence of some of the key determinants of technology adoption, such as institutions, science and technology capacities, and adoption of previous technologies. However, they emphasize that more empirical research is needed to corroborate this. Grübler, Nakićenović and Victor (1999) use a similar dataset that focuses specifically on energy technologies. Their analysis also supports the idea that worldwide there are energy technology leaders and followers and that countries eventually converge on the usage of energy technologies. Similarly to Comin, Hobijn and Rovito (2006) they find that laggard countries seem to adopt energy technologies faster than the technology leaders, but the time required for global diffusion of energy technologies is quite considerable, ranging from 50 to 100 years.

Finally, the empirical evidence also suggests that the time required for full international technological diffusion ranges widely across technological sectors. This may be an indication that not only country-specific institutional and economic factors play a role in facilitating diffusion, but also the technological characteristics inherent to each technological sector. In this respect Grübler, Nakićenović and Victor (1999) argue that new technologies co-evolve with other technologies and infrastructures. Some technologies integrate better than others with the existing technological base in a country. Also they find that the degree of substitutability between incumbent and new technologies determines importantly the speed of diffusion. They also present evidence that the rate of improvement of technologies diminishes as technologies become more mature concepts. Comin and Hobijn (2010) also take into account the variation in diffusion rates across technology sectors. They find that 53 percent of the variance in diffusion rates in their sample is explained by variation across technologies, 18 percent by cross-country variation, and 11 percent by the covariance between the two. The fact that such a large share of the variance is explained by technologies themselves may be an indication that the specific technological properties of different technology sectors and its relation with existing infrastructures and policies play an important role in shaping international technological change patterns.

II.4 Open Questions Associated with International Technological Change

It is evident that tremendous progress has been made in the study of international technological change and in understanding its implications for the economy and the environment. However, this progress in the field has also shown that there are many other aspects of this phenomenon that remain ill understood.

Most of the research on technological change has centered on understanding this process in advanced nations; much work seems to remain to understand how technological change occurs in developing nations (Popp, Newell and Jaffe, 2010). The theoretical frameworks and empirical studies discussed previously argue that countries have an absorptive capacity of foreign technologies. Yet, more research is needed to describe more accurately the concept of absorptive capacity. For example, empirical studies consider a wide range of local factors as proxies for countries' absorptive capacity (e.g. regulatory environment, quality of education, R&D intensity) but it seems that a more coherent concept of absorptive capacity is still needed. In the same vein, there is still much work ahead to determine what institutional conditions and policies must be place in developing countries to adopt modern environmental technologies (Popp, Newell and Jaffe, 2010). The variation of diffusion rates across technological sectors may indicate that there is a specific relation between technologies' characteristics and the required absorptive capacity for their adoption. Moreover, it is still necessary to better understand to which extent developing countries need to adapt foreign technologies to their local needs and to which extent imports of advanced technologies improve their environment and create new economic opportunities (Popp, Newell and Jaffe, 2010).

More comprehensive theoretical frameworks to represent technological change in developing countries are also required. Currently, the majority of models assume that developing countries import, adapt or imitate more advanced foreign technologies. Historical data appears to support this assumption, but it is also feasible to assume that in the long run some countries will join the ranks of the advanced technological leaders. Studying under which conditions this can happen will certainly complement the existing frameworks of international technological change.

There is still ample room for discussion in the literature on the mechanisms that can explain different technological patterns and on the identification of the channels by which technologies diffuse internationally. This is relevant for the context of climate change because it creates uncertainty regarding the effectiveness of different policy mechanisms to help diffuse clean technologies globally. For instance, Comin and Hobijn (2010) show that the familiar S-shape logistic diffusion pattern found in micro-focused studies of technological change does not hold in the context of cross-country technology diffusion. Although, this finding is derived in part because they measure diffusion of technologies across countries in their intensive margins (i.e. the intensity by which a technology is used) versus using the traditional extensive margin (i.e. the extent of people using in any level a particular technology), this type of findings suggest that there are still mechanism of technologies diffusion that may be added to the existing theoretical frameworks.

Keller (2004) concludes that empirical data on international technological change is fragmented and inconclusive. Specifically, he argues that although international trade is believed to be an important channel of technology diffusion, the evidence shows that learning by exporting is not an important force in diffusion. With respect to foreign direct investment (FDI) spillovers, the evidence shows that there is important variation across countries. Rosendahl (2004) argues that it is still not known whether knowledge spillovers have an important role in inducing technological change or not. Di Maria and Van der Werf (2008) and Acemoglu et al. (2012) argue that with the available data today it is difficult to estimate accurately the elasticity of substitution between clean and carbon intensive sectors which leads to uncertainty about the difficulty and the cost of successfully directing technological change towards clean technologies. They believe that building models that can be calibrated with such data remains one of the most formidable challenges for future research in the field. Finally, in terms of policy evaluation, Popp, Newell and Jaffe (2010) state that there is still little research that evaluates the effectiveness of policies such as R&D subsidies and technology subsidies in the context of climate change.

Finally, the incorporation of technological uncertainty in studies of international technological change remains an ongoing challenge for the field, especially for those studies concern with future scenarios of technological change (Bosetti and Tavoni, 2009). In technological systems, the inherent uncertainty of any natural system is exacerbated by the unpredictable nature of human behavior and social systems because both systems are intimately intertwined. Societies put in place incentives and institutions that direct innovative activity to particular sectors, which in turn creates new technologies that have profound effects on societies themselves. For instance, in the context of climate change, given the huge uncertainty associated with the impacts of climate change and the difficulties of anticipating the magnitude of the policy response, it is extremely difficult to anticipate the stream of R&D investments towards clean technologies (Popp, Newell and Jaffe, 2010). Moreover, even if all policies are in placed to support the development and the international diffusion of clean energy technologies, there still remains the fact that it is not feasible to anticipate accurately the degree of success of R&D programs in clean technologies, and the links that may develop across futures technologies (Baker and Adu-Bonnah, 2008; Golombek and Hoel, 2004; Bosetti and Tavoni, 2009). Developing the appropriate theoretical frameworks and empirical tools to formally incorporate these sources of uncertainty in studies of future international technological change is an ongoing challenge for the field.

II.5 Summary

The discussion presented in this chapter shows that the theoretical studies of international technological change describe this as a two phase process. First new technologies are developed in technologically advanced countries (Di Maria and Smulders, 2004; Fisher-Vanden and Ho, 2010). Second, new technologies are diffused internationally to less technologically advanced countries (Keller, 1996; Keller, 2004; Di Maria and Smulders, 2004). Within a region, technological change is a process that results out of the investment decisions of technology entrepreneurs and the adoption decisions of consumers. The process occurs endogenously in a closed feedback loop because the technological environment, as well as the economic and institutional context influence the decision making process of entrepreneurs and consumers. In turn, the decisions of entrepreneurs and consumers change the technological and economic landscape (Acemoglu et al., 2012; Popp, 2004; Howitt, 2000; Rosendahl, 2004). Across regions, technological change is driven by the flow of new technologies through trade, foreign direct investments and R&D spillovers (Di Maria and Smulders, 2004; Keller, 2004).

Recent empirical evidence of international technological change shows that some of the key features proposed by theoretical models are in accordance with the findings of empirical studies. For instance, existing data shows that worldwide only a handful of advanced countries (e.g. US, Germany, Japan, United Kingdom) account for the majority of the world's creation of new technologies and environmentally focused innovative activity (Keller, 2004; Lanjouw and Mody, 1996; Coe, Helpman and Hoffmaister, 1997). These studies also indicate that emerging nations' local capacities, policies and endowments influence the rate at which they can absorb more advanced foreign technologies (Blackman and Kildegaard, 2010; Coe, Helpman and Hoffmaister, 1997; Coe, Helpman and Hoffmaister, 2009; Popp, 2006b; Popp, 2006a; Comin and Hobijn, 2004). Also evidence is found that shows that technological convergence across regions is possible, but only under very specific circumstances of R&D intensity and local capacities. Comin and Hobijn (2010) show that technology convergence across countries is common, but this can take a considerable amount of time. In the sample of technologies studied by the authors, they find that it takes on average 45 years for one technology to be fully diffused internationally. However, there is ample variation across countries and technologies. The empirical evidence also suggests that the time required for full international technological diffusion ranges widely across technological sectors, which may be an indication that not only country specific institutional and economic factors play a role in facilitating diffusion, but also the technological characteristic inherent to each technological sector. Yet, despite the remarkable progress in the field, there are many other aspects of international technological change that remain ill understood. In particular, it is important to continue improving our understanding of technological change in emerging nations and the relevance of developing theoretical frameworks and empirical tools that incorporate deep uncertainty in studies of future international technological change.

CHAPTER III

An Exploratory Dynamic Integrated Assessment Model (EDIAM) for Analyzing International Environmental Technological Change and Climate Policy

III.1 Model's Objective

The objective of this model is to support quantitative exploratory analysis of different cooperation schemes associated with the architecture of the GCF. The model focuses primarily on the technological evolution of both advanced and emerging nations and on the effects that policy intervention has on climate change mitigation and on economic growth. Thus, the model is useful as an assessment tool that can be used to study tradeoffs faced by the two regions in supporting the type of policies embodied in the GCF. In the context of an RDM study, the model works as the scenario generator that supports the analytical task of understanding under which conditions different architectures of the GCF meet the objective of inducing international environmental technological change and successfully stabilizing greenhouse gas emissions.

The model's design philosophy follows four principles, namely that: 1) its size and detail result in computational requirements that make it feasible to simulate an ample space of technological, economic and climate scenarios, 2) its structure allows for tractability and reflects insights from previous theoretical and empirical studies, 3) its functionality allows the study of various different policy architectures, and 4) it is calibrated using a full ensemble of Coupled Model Intercomparison Project Phase 5 (CMIP5) climate projections, which are also used in the IPPC's assessment studies.

The model borrows heavily from previous empirical studies, primarily from Acemoglu et al. (2012), and in a smaller degree from Dasgupta and Stiglitz (1980) Keller (1996), Aghion and Howitt (1998) , Di Maria and Smulders (2004) and Bosetti et al. (2006). Therefore, the model's objective is not to put forward new theoretical ideas about international technological change; rather it uses previous well known and peer-reviewed research studies as its structural foundation. The principal innovation lies in its use as an RDM scenario generator.

The model's structure and principles follow closely the insights of endogenous growth theory (Aghion and Howitt, 1998) and directed technological change (Acemoglu, 2002). It differs from traditional modeling studies in this field in the way that policy intervention is considered. In this model, policy intervention is modeled as a perturbation that is active during a limited period of time subject to a budget constraint and to specific policy regime constraints. I attempt also to provide a more detailed description of the technological properties of competing technological systems. Although this characterization is still generic and exploratory, because of the technological focus of my study this model attempts to follow the example set by recent modeling studies in which technological disaggregation is incorporated more seriously into climate assessment studies. A prime example of this type of technological and geographic disaggregation is the model WITCH (World Induced Technical Change Model) developed by Bosetti et al. (2006).

In Section III.2 of this chapter I describe in detail the structure of the model. I focus primarily on describing the decision-making process of the different agents considered in the two regions and on how technological and climate change affect the decisions of economic agents and the desirability of policy intervention. In Section III.3, I conduct a series of empirical validation exercises to test the behavior of the model against historic trends and against previous empirical studies. The results of this validation exercise show that although the model provides a more simple dynamic behavior, it successfully captures historical patterns of energy use in advanced and emerging nations, and reproduces patterns reported by relevant empirical studies in this field.

III.2 Modeling Framework

The model provides an abstract and simplified representation of the multi-county context in which directed international technological change takes place. Therefore, the objective of this model is not to represent specific countries' contexts or to be used for forecasting exercises. Rather, this model has been developed to carry out quantitative exploratory analysis of the long-term diffusion of sustainable energy technologies (SETs)5 and to analyze the performance of different architectures for cooperation between advanced and emerging nations.

The model focuses primarily in three areas: 1) the innovation ties that exist between regions, 2) the regional processes that contribute to shaping the international diffusion paths of SETs and 3) the effectiveness of policy coordination across regions in stabilizing global CO2 emissions. The following sections describe the main elements of the model.

III.2.1 Climate Change Dynamics

The model depicts a global economy consisting of two generic regions: a technologically advanced region and an emerging region that is less technologically advanced. The production of energy in both regions is done using a mix of two different primary energy supplies: fossil

[5] In this study Sustainable Energy Technologies (SETs) group all energy technologies used for primary energy production which exploit energy resources that do not result in greenhouse gas emissions. Examples of these technologies include: photovoltaic solar panels, solar thermal energy systems, wind turbines, marine current turbines, tidal power technologies, nuclear energy technologies, geothermal energy technologies, hydropower technologies and very low life cycle GHG biomass. This group of technologies does not include carbon removal and sequestration technologies from power plant emissions such as carbon capture and storage (CCS).

energy "Y_{fe}" and sustainable energy[6] "Y_{se}". The use of fossil energy in both regions contributes to the degradation of the environment, according to the following expression:

$$\frac{dS}{dt} = -\xi\left(Y(t)_{fe}{}^{A} + Y(t)_{fe}{}^{E}\right) + \delta S(t) \qquad (e1)$$

where S denotes the quality of the environment, ξ represent the marginal environmental damage per unit of fossil energy used in both regions, δ represents the average rate of natural environmental regeneration and the upper index denotes the two different regions: the Advanced Region (A) and the Emerging Region (E).

CO_2 emissions are a function of the quality of the environment, following:

$$CO_2(t) = CO_{2|6.0\,°\mathrm{C}} - S(t) \qquad (e2)$$

In equation *(e2)*, the term $CO_{2|6.0\,°\mathrm{C}}$ denotes the level of CO_2 emissions that will result in temperature rise of 6.0°C with respect to pre-industrial levels. The model is not defined beyond this limit of temperature rise because such level of temperature rise will result in abrupt and irreversible changes to the global climate system, including events such as: the ice sheet collapse, permafrost carbon release and methane hydrate release (IPCC, 2013a).

Temperature rise is modeled using a logarithmic function with the form:

$$\Delta T(t) = \beta * ln\left(\frac{CO_2(t)}{CO_{2,0}}\right) \qquad (e3)$$

Where $CO_{2,0}$ denotes the initial level of CO_2 concentration in the atmosphere at the beginning of the 20th century.

III.2.2 Economic Agents' Decisions

Within each region, the mix used for energy production is the result of the interaction of the decisions of different agents in the economy. The following paragraphs describe in detail the decision-making process of the different economic agents considered in this model.

[6] Sustainable primary energy refers to all energy forms which their conversion does not result in direct GHG emissions to the atmosphere. These includes: solar energy, wind energy, tidal energy, marine currents energy, geothermal energy, hydro energy and nuclear energy (i.e. uranium). Note each of these energy sources is associated to other specific environmental impacts besides GHG emissions. Then the concept "Sustainable Energy" used in this monograph considers only GHG emissions and no other environmental impacts which are also important. However, in this study their consideration is outside of the research scope.

Secondary energy producers

It is assumed that within each region, there are numerous agents that produce secondary energy with free entry and exist into this market. Therefore, I assume secondary energy is produced competitively.

Secondary energy producers use two types of primary energy for the production of secondary energy "Y": fossil energy "Y_{fe}" and sustainable energy "Y_{se}". These agents decide how much of these two sources they require in order to meet their production constraints and also maximize profits. This decision problem is described by the following maximization problem:

$$Max_{Y^k(t),Y_r^k(t),Y_f^k(t)} \; p^k(t)Y^k(t) - p_{se}^k(t)Y_{se}^k(t) - p_{fe}^k(t)Y_{fe}^k(t) \qquad (e4)$$

s.t.

$$Y^k(t) = \left(Y_{se}^k(t)^{\frac{\varepsilon-1}{\varepsilon}} + Y_{fe}^k(t)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} \qquad (e5)$$

$$Y^k, Y_{se}^k, Y_{fe}^k, \; p^k, p_{se}^k, p_{fe}^k \geq 0$$

$$\varepsilon > 0$$

where ε is the elasticity of substitution between the two sectors and k is an index denoting each region, such that k ϵ [A,E][7]. $\mathrm{Y^k(t)}$, $\mathrm{Y_{se}^k(t)}$ and $\mathrm{Y_{fe}^k(t)}$ denote the level of production of secondary energy, primary sustainable energy and primary fossil energy, in region k, at time t, respectively. Similarly, $\mathrm{p^k}$, $\mathrm{p_{se}^k}$ and $\mathrm{p_{fe}^k}$ denote the price of secondary energy, sustainable energy and fossil energy, in region k, at time t, respectively. For the remainder of the discussion the time notation will be omitted, but it should be understood that all variables are a function of time, unless otherwise indicated.

Note that equation (e5) assumes secondary energy production in both regions can be modelled as a CES aggregate of the two primary energy sources: fossil energy and sustainable energy. This is a common representation of aggregate production in endogenous technological change models; see for example Di Maria and Smulders (2004), Bosetti et al. (2006) and

7 A: Advanced Region, E: Emerging Region

Acemoglu et al. (2012) for technological change studies using the same specification in the context of climate change.

Primary energy producers

There are two types of primary energy suppliers: producers of sustainable energy and producers of fossil energy. These agents use labor and an infinite number of sector-specific technologies for energy production according to the aggregate production function (Acemoglu, 2002):

$$Y_j^k = {L_j^k}^{1-\alpha} \int_0^1 {A_{ji}^k}^{1-\alpha} {x_{ji}^k}^{\alpha} di \quad (e6)$$

Where L_j^k represents the labor used in sector "j" ϵ {renewable energy, fossil energy}, A_{ji}^k is the productivity of technology of type "i" used in sector "j", and x_{ji}^k is number of units of technology type "i" in sector "j" used in production, for region "k".

In this model, relative labor allocations are a proxy for the relative energy market size of each primary energy sector. Therefore,

$$L_{se}^k + L_{fe}^k = L^k\ (t) \quad (e7)$$

In line with endogenous growth theory and in the same fashion as Aghion and Howitt (1998 ;pp 447), I assume that the stock of labor grows at an exogenous rate r^k, such that:

$$L^k\ (t) = L_0^k e^{r^k t} \quad (e8)$$

where $L^k\ (t)$ denotes labor supply as a function of time, L_0^k represents the initial labor supply and r^k is the rate of growth of the labor supply in region "k". Furthermore, in order to differentiate both regions. I assume that initially labor supply in the emerging region is higher that the available labor supply in the advanced region, such that:

$$L_0^E > L_0^A \quad (e9)$$

Formally, primary energy suppliers decide the combination of labor and technology units needed for production such that these maximize their profits and meet their regional labor and production constraints. Therefore, they face the following maximization problem:

$$Max_{L_j,Y_i}\ p_j^k Y_j^k - w^k L_j^k - \int_0^1 p_{ji}^k x_{ji}^k di \quad (e10)$$

$$s.t.$$

$$L_{se}^k + L_{fe}^k = L^k \ (t)$$

$$Y_j^k = L_j^{k\,1-\alpha} \int_0^1 A_{ji}^{k\,1-\alpha} x_{ji}^{k\,\alpha} di$$

where p_j^k represents the price of input "j", Y_j^k represents the production level of input "j", "w^k" denotes wages, p_{ji}^k denotes the price of technology "i" in sector "j", all in region "k". In the following sections the region notation will be omitted, unless differences among the two regions need to be explained in more detail. However, it should be understood that all variables are associated with one of the two regions.

Producers and distributors of technologies

In line with the framework of endogenous technical change, technologies for both sectors are supplied by monopolistically competitive firms. Once technology entrepreneurs successfully develop a new technology, they obtain monopoly rights over their invention for a fixed period of time. These agents decide the number of technology units they need to manufacture in order to maximize profits. Formally:

$$max_{p_{ji},x_{ji}} \ \pi_{ji}^m = (p_{ji} - \psi_{ji})x_{ji} \tag{e11}$$

where ψ_{ji} denotes the unitary cost of production for technology type "i" in sector "j".

Technology entrepreneurs

Technology entrepreneurs work on improving the technologies used for primary energy production by making R&D investments. They decide which sector to target by comparing the expected profits of investing R&D funds in the development and improvement of energy technologies in both sectors. Technology entrepreneurs work on either one of the technology sectors, supporting primary energy production, such that:

$$\theta_{se} + \theta_{fe} = 1 \tag{e12}$$

where θ_{se} and θ_{fe} denote the share of entrepreneurs working in R&D of technologies in the sustainable energy sector and in the fossil energy sector, respectively. Each entrepreneur decides first whether to work on the sustainable energy sector "θ_{se}" or in the fossil energy sector "θ_{fe}", then she targets a single technological innovation in the chosen sector. Thus, no more than one entrepreneur (i.e. firm or start-up company) works in the same technological innovation (Acemoglu et al., 2012).

I model this decision making process using a nominal logic model. Under this framework, I assume that the utility of working in sector "j" for each entrepreneur "z" is given by:

$$U_{jz}(t) = V(x_j) + \varepsilon_{jz} \tag{e13}$$

where $V(x_j)$ is a deterministic utility component, depending on attributes x_j of investing R&D resources in sector "j" and ε_{jz} is an independent and identically distributed unobserved stochastic component associated with the preferences of each entrepreneur "z". Furthermore, for simplicity I assume that:

$$V(x_j) = \Pi_j(t) \tag{e14}$$

such that $\Pi_j(t)$ is the expected profitability of investing in sector "j" at any period in time. Under these assumptions and given utility-maximization behavior (Achtnicht, Bühler and Hermeling, 2012; Train Kenneth, 2003), then $\theta_j(t)$, the share of entrepreneurs deciding to invest in sector "j" at time "t" takes the closed form:

$$\theta_j(t) = \frac{e^{\Pi_j(t)}}{\sum_{k=se}^{fe} e^{\Pi_k(t)}} \tag{e15}$$

Then the average expected profitability of working in each sector is given by:

$$\Pi_j(t) = \eta_j \int_0^1 \pi_{ji}^m(t) di \tag{e16}$$

where η_j denotes the innovation propensity of sector "j". This is the probability of successfully developing and commercializing a new technology in sector "j".

Consumers

Finally, in the same fashion as Di Maria and Smulders (2004) and Acemoglu et al. (2012) I assume a representative consumer, facing the following maximization problem:

$$Max_{C(t)} \sum_{t=0}^{\infty} \frac{1}{(1+\rho)^t} u(C(t), S(t)) \tag{e17}$$

s.t.

$$C(t) + M(t) = Y(t) \tag{e18}$$

where ρ denotes consumers' discount rate, $C(t)$ represents consumption, $M(t)$ investment in technologies and $Y(t)$ is the production of secondary energy. This expression states that consumption and investment in technologies are the only two possible uses of the final good (i.e. secondary energy)

For operationalizing the utility function, I use the same constant relative risk aversion (CRRA) utility function as in Acemoglu et al. (2012), such that:

$$u\big(C(t), S(t)\big) = \frac{(\phi(S(t))C(t))^{1-\sigma}}{1-\sigma} \tag{e19}$$

Equation *(e19)* assumes that consumer's utility is a function of both consumption and the quality of the environment. The parameter σ is the inverse of the intertemporal elasticity of substitution. Using the same functional form as Acemoglu et al. (2012), I also parametrize the quality of the environment as*:*

$$\phi(S) = \phi(\Delta S) = \frac{(\Delta T_{disaster} - \Delta T(S))^{\lambda} - \lambda \Delta T_{disaster}^{\lambda-1}(\Delta T_{disaster} - \Delta T(S))}{(1-\lambda)\Delta T_{disaster}^{\lambda}} \tag{e20}$$

where $\Delta T(S)$ results of combining equations *(e2)* and *(e3)*, representing the increase in average surface global temperature since pre-industrial times for a given level of quality of the environment (i.e. CO_2 emissions), and λ is a parameter that controls how quickly the quality of the environment decreases as CO_2 emissions rise.

III.2.3 Technological Change Dynamics

Technological change is of vital importance for both regions because the continuous improvement of technologies used for primary energy production leads to higher production of secondary energy and to lower energy prices. More importantly, technological changes ripple through the economy affecting the decisions of the different economic agents.

This section describes the form in which technological change takes place and the relevant important technological characteristics that determine its pace across the different sectors. I also discuss the major differences in the model between the advanced and the emerging region.

Technological competition

The model considers two competing technological sectors: sustainable energy technologies (SETs) and fossil energy technologies (FETs). Each technology sector supports one of the two primary energy sectors: SETs support the production of sustainable energy and FETs support the production of fossil energy.

These technological sectors compete against each other in two fields: competition exists in terms of the share of secondary energy that is being produced using one of the two technological sectors; competition also exists in terms of the share of research and development resources that each technological sector receives from technology entrepreneurs.

In the initial state of the system, I assume that FETs are more productive technologies (i.e. higher energy output in MWh per unit of installed capacity in MW) than SETs, such that:

$$A_{fet,0}^{k} \gg A_{set,0}^{k} \tag{e21}$$

As a result, initially, fossil energy technologies are more widely used in the production of secondary energy. This incentivizes a greater share of technology entrepreneurs to work on the research and development of these technologies. In contrast, due to the initial low productivity of sustainable energy technologies, less renewable energy is produced and fewer research and development resources are directed towards improving these technologies.

Technological options

In line with the theory of "Directed Technological Change" (Acemoglu, 2002) each primary energy sector in the model considers an abstract continuum of technological options that can be used to support the production of primary energy. This generality in the model is fundamental for this exploratory study because it centers the analysis on the technological evolution of each primary energy sector as a whole, rather than in the technological evolution of a specific set of technological options. At the same time, it portrays a technological system that conceptually considers innovation not only on key technologies such as photovoltaic cells and wind turbines, but on all technologies that could potentially increase the productivity of sustainable energy technologies. For instance, technological developments in sectors such as: information technologies, remote control technologies and materials sciences can also be fundamental for the future of sustainable energy technologies (Baker, 2008; Jacobsson and Johnson, 2000). In fact, this portrait of technological change resembles recent theoretical development in the field of technological evolution. Arthur (2009) argues that technological evolution is driven not only by incremental improvements within the same technological family, but also by the recombination with other technological fields. For example, during the first part of the 20^{th} century, the internal combustion engine was improved markedly by the introduction of new mechanical designs such as Daimler's two cylinders four-stroke engine. Today, the internal combustion engine continues to be re-designed and improved combining innovations from other technological fields (e.g. engine modeling and reactivity controlled compression ignition)(Reitz, 2013).

Using the same assumption as in Acemoglu et al. (2012), the productivity of each primary energy sector is described by averaging the productivity of all the technologies used for energy production, as described by:

$$A_j^k \equiv \int_0^1 A_{ji}^k di \tag{e22}$$

where, A_j^k is the average productivity of sector "j" in region "k", and A_{ji}^k denotes the productivity of individual technologies "i" in sector "j" in region "k".

Resource driven change and regional differences

In both regions the decisions of technology entrepreneurs are fundamental to push the technological frontier forward. Entrepreneurs invest in the research and development of the two technological sectors, increasing the productivity of technologies.

In the advanced region, entrepreneurs developed new and more productive technologies for production of primary energy. This evolution of productivity through the incorporation of new technologies in the advanced region is described by the following differential equation:

$$\frac{dA_j^A}{dt} = \gamma_j (A_j^A) \eta_j \theta_j^A(t) A_j^A(t) \tag{e23}$$

where $\frac{dA_j^A}{dt}$ is the rate of productivity change in sector "j", θ_j^A denotes the share of entrepreneurs working in sector "j" and A_j^A denotes the current productivity of sector "j" at time "t". Parameters γ_j and η_j describe the technological characteristics of each primary energy sector. The parameter γ_j denotes the average R&D returns to productivity in sector "j"; this is the average positive change in productivity in sector "j" resulting by the development of new technologies. The parameter η_j denotes the innovation propensity of sector "j": this is the probability of developing and successfully commercializing new technologies that increase the overall productivity of sector "j" technologies.

Equation *(e23)* implies that entrepreneurs in the advanced region use previous technologies to develop new technologies, an incremental pattern of change commonly defined in the literature as "building on the shoulders of giants" (Acemoglu, 2002; Arthur, 2009).

In the emerging region, technology entrepreneurs also innovate, but their efforts are targeted towards imitating the existing technologies in advanced region. This process is described by the following expression:

$$\frac{dA_j^E}{dt} = \nu_j \gamma_j (A_j^E) \theta_j^E (A_j^A(t) - A_j^E(t)) \qquad (e24)$$

where ν_j denotes the probability of successfully imitating/adapting (i.e. transferability) the technologies of sector "j" developed in the advanced region. This implies that entrepreneurs in the advanced region push the technological frontier forward, while the innovative activity in the emerging region is focused on closing the technological gap (i.e. $A_j^A(t) - A_j^E(t)$) through imitation and adaptation of foreign technologies.

I also assume that initially the technologies used in the advanced region are more productive than the technologies used in the emerging region, such that:

$$A_{j,0}^A > A_{j,0}^E \qquad (e25)$$

Similarly to the framework of Dasgupta and Stiglitz (1980), the returns to R&D (γ_j) are a function of the existing productivity in each region and they display diminishing returns such that $\gamma_j'(A_j) < 0$ and $\gamma_j''(A_j) > 0$ according to the following expression:

$$\gamma_j = \gamma_{j,0} e^{\omega_j \frac{A_j^D(t)}{A_0^D}} \qquad (e26)$$

This indicates that as the productivity of a given technological sector increases, then the returns to R&D in that sector decrease. This implies that for mature technological sectors, the returns of R&D in productivity gains are smaller compared to immature technological sectors. This captures the notion that in mature technological sectors, innovative activity focuses primarily on achieving incremental improvements over the defined technological standards. In contrast, in immature technological sectors, as technological standards have not yet been well defined, initially innovative activity focuses both in radical and incremental innovations that increase more sharply the productivity of technologies.

This does not imply that the overall productivity of immature technological sectors grows at a faster rate than the productivity of mature technological sectors. As described in equation *(e23)*, the sectorial rate of growth in productivity depends also on the share of entrepreneurs doing R&D. For mature technologies that capture large shares of R&D investments, even though R&D returns might be smaller than the R&D returns from immature technologies, in as much as a bigger share of entrepreneurs work on mature technologies' R&D, then it is possible than the productivity of mature technologies grows at a faster rate than the productivity of immature technologies. In subsequent chapters, this case is reviewed in more detail for the case of sustainable energy technologies (i.e. immature technologies) and fossil energy technologies (i.e. mature technologies).

The parameter $\omega_j \in [0,1]$ in the exponential equation *(e26)* represents R&D returns decay rate of sector "j", which is also an important characteristic of the technological sectors considered in this model. The parameter "ω_j" controls how rapidly the R&D returns decrease as the overall productivity of a sector increases: the higher the value of this parameter, the quicker the decay of the R&D returns. For instance, a low decay rates represents a case in which entrepreneurs are assumed to always be able to developed new technologies that improve markedly the productivity of the sector, which portrays a vibrant technological sector in which there are ample technical problems that need to be solved and in which entrepreneurs are capable of solving them. In contrast, a high decay rate describes a sector in which new technologies quickly stop providing marked improvements in productivity, which is perhaps the result of a lack of major technical problems to be solved or the inability of entrepreneurs to solve these problems.

Initially, I assumed that there are not decay rate differences among the technological sectors considered, and that both technological sectors are equally mature.

$$\omega_{set} = \omega_{fet} = 0 \tag{e27}$$

Experience-driven change

Similar to Bosetti et al. (2006), the model also considers the effect of the accumulation of experience in the two technological sectors. In this case, as more energy technology units are installed in both regions, the average cost of producing these technologies reduces. This is modeled using the following power-law function:

$$\psi_j(t) = \psi_{j,0}\left(X_j^A(t) + X_j^E(t)\right)^{\iota_i} \tag{e28}$$

where $\psi_j(t)$ represents the average production costs of technologies in sector "j" at time "t", $\psi_{j,0}$ stands for the initial costs of producing technologies in sector "j". X_j^A and X_j^E represent the accumulated number of technologies used in each sector "j" in the advanced and emerging regions. The parameter ι_i controls the rate at which experience leads to cost reductions in technologies. Similarly, initially I assume that there are no differences among technological sectors, such that:

$$\iota_{set} = \iota_{fet} = 0 \tag{e29}$$

The expressions described in this section depict an incremental technological change process that depends on the economic decisions and actions of entrepreneurs in each region, and on the inherent technological characteristics of the two competing technological sectors.

Considering separately the technological characteristics of each sector is important for this exploratory analysis because, from a technological perspective, the two sectors are profoundly different. I argue that fossil energy technologies are more mature technologies than sustainable energy technologies. For example, gas turbines were first introduced commercially at the beginning of the 20th century, since then, substantial progress has been made on this technology; not only on defining well established technological paradigms, but also on devising the adequate firm structure needed to develop and commercialize this technology. Although innovation on this technology sector continues to improve the productivity of these technologies, these efforts are well aligned with the already established technological solutions, and therefore technological surprises are less expected.

In contrast, sustainable energy technologies are less mature technological systems in which it is difficult to assess whether or not an established technological paradigm has been reached yet. Although there are already a few firms that have experienced great success in developing sustainable energy technologies, it is still uncertain whether these firms have found the right balance between entrepreneurship and commercial pragmatism. As a result, innovation in sustainable energy technologies is more prone to surprises.

III.2.4 Regional Policy Instruments and International Cooperation

This section describes the policies that can be implemented in each region to incentivize the development of SETs and to increase their use in the production of secondary energy.

From a technological perspective, these policies fall into two categories. Technological push policies increase the rate of innovation in the SETs sector, thus accelerating the introduction of better and more productive SETs into the energy market. Technological pull policies incentivize secondary energy producers to increase the share of sustainable energy being used in secondary energy production, and also incentivize primary energy producers to use more SETs in primary energy production by reducing the costs of these technologies,

International cooperation (i.e. Green Climate Fund) is modeled through mixing elements of these two types of policies in both regions, and by assuming that the international policy portfolio is funded by both regions.

Subsidies for research and development

R&D subsides are part of the "technological push" policies. These subsidies are used to incentivize a greater share of entrepreneurs to work on the sustainable energy technologies sector. Formally, these subsidies are modelled as a markup over the profits of entrepreneurs working in SETs, such that:

$$\pi_{set,i}^{k} = (1 + q_{set})\left(p_{set,i}^{k} - \psi_{se,i}\right)x_{set,i}^{k} \qquad \textit{(e30)}$$

where "q_{set}" $\in [0, \infty)$ denotes the subsidy rate. These subsidies increase the expected profits of conducting research in the SETs sector. This, as described by equation *(e15)*, results into a higher share of entrepreneurs (θ_{se}) working in the development of sustainable energy technologies.

Price subsidies for clean energy technologies

Sustainable energy technologies subsidies reduce the market price of these technologies which increases the demand for SETs in primary energy production. This effectively affects the decision making process of primary energy producers by reducing the costs of using sustainable energy technologies in production, thus increasing the demand for SETs and also decreasing the market price of sustainable energy. Formally, this subsidy is modeled as follows:

$$p_{set,i,s}^{k} = (1 - t_{set})p_{set,i}^{k} \qquad \textit{(e31)}$$

where $t_{set} \in [0,1)$ denotes the price subsidy rate for these technologies.

Taxation on the use of fossil energy

Taxation of fossil energy increases the cost of using fossil energy for secondary energy production, such that:

$$p_{fe,s}^{k} = p_{fe}^{k} * (1 + \tau_{fe}) \qquad \textit{(e32)}$$

where $\tau_{fe} \in [0, \infty)$. As a result this tax incentivizes secondary energy producers to use more sustainable energy for secondary energy production.

Green Climate Fund

The Green Climate Fund (GCF) is a multi-lateral financial institution funded by contributions of both advanced and emerging nations. The GCF will provide financing in the form of grants and concessional lending to implement mitigation and/or adaptation projects in emerging nations (van Kerkhoff et al., 2011). The focus areas and architecture of the GCF remain under heated discussion in part because of disagreements between advanced and emerging nations regarding how to best channel the funds of the GCF into emerging nations(Schalatek, Nakhooda and Bird, 2012; Cui et al., 2014). Funds from the GCF can be directed towards facilitating the implementation of sustainable energy technologies in emerging nations by means of co-funding of technological projects, or by means of facilitating the transfer of advanced energy technologies to emerging nations. I model this policy as a complement to the local technology subsidy in the emerging region, such that in the emerging region, once the GCF is implemented, the price of SETs is given by:

$$p^E_{set,i,s} = \left(1 - (t_{set} + t_{GCF})\right) p^E_{set,i} \qquad (e33)$$

$$t_{GCF} \begin{cases} 0\,;\ t_{set} = 0 \\ > 0;\ \ t_{set} > 0 \end{cases}$$

note that under this specification, for the GCF to work it is necessary that a local technology subsidy exists in the emerging region as well, capturing the fact that this policy is co-funded by both regions.

Another focus area for the GCF is the co-funding of R&D programs and the development of local technical capacities that can facilitate the diffusion, adaptation and implementation of SETs in emerging nations. I model this also as a complement to the local R&D subsidy in the emerging region:

$$\pi^E_{set,i} = (1 + q_{set} + q_{GCF})\left(\, p^E_{set,i} - \psi_{se,i}\right) x^E_{set,i} \qquad (e34)$$

$$q_{GCF} \begin{cases} 0\,;\ q_{set} = 0 \\ > 0;\ \ q_{set} > 0 \end{cases}$$

Similarly to the case of technology subsidies, under this framework, the share of the R&D subsidy funded by the GCF is only implemented when the emerging region participates to some degree in the financing of this policy, which mimics the financial architecture of the GCF.

III.2.5 System's Dynamics

As described in the previous sections, there are two dynamic processes considered in this modeling framework: technological change dynamics and climate change dynamics. Productivity changes of sustainable energy technologies and fossil energy technologies influence the decision making process of economic agents. Climate change dynamics influence the need for policy intervention affecting the size of the policy response required for mitigation, and, in turn, also affecting the incentives and decisions of economic agents.

In order to model the cascading effects of climate and technological change, and in the same fashion as Acemoglu et al. (2012), I assume that at each time period all sectors in the economy are in equilibrium. Therefore, the dynamics of the system are described by how technological and climate change (equations *e1,e23* and *e24*) affect primary energy prices, technology prices, the demand for technologies, the allocation of labor across the two primary energy sectors, and the allocation of entrepreneurs across the two technological sectors. In the following paragraphs, I describe this inter-temporal equilibrium; note that the equilibrium equations used in this model resemble the same equilibrium expressions in the model of Acemoglu et al. (2012). Differences in these equilibrium conditions arise due to two assumptions: 1) this model assumes in equation *(e28)* that the accumulation of experience results in lower technology costs, and 2) this model assumes that the properties of the two technological sectors are different (i.e. γ_j and η_j). Thus, these factors are kept in all the required equilibrium expressions.

Production of primary energy

Partially solving the maximization problem of secondary energy producers described in equation *(e4)* (see Appendix A.1), I obtain:

$$\frac{Y_{se}^{k}(t)}{Y_{fe}^{k}(t)} = \left(\frac{p_{fe}^{k}(t)*(1+\tau)}{p_{se}^{k}(t)}\right)^{\varepsilon} \qquad (e35)$$

This indicates that as prices of sustainable energy decline, the demand for sustainable energy increases. Since both types of primary energy are substitutes (ε>1), then a marginal increase in the use of sustainable energy also entails the same marginal decrease in the use of fossil energy. If exogenous demand grows (equation *e7*) then the use of both energy sources could increase.

Technology prices

Partially solving the maximization problem of technology producers results in the describing technology prices as a function of production cost (see Appendix A.2), such that:

$$p_{ji}(t) = \frac{\psi_j(t)}{\alpha} \qquad (e36)$$

as more experience is accumulated in one technology sector, then the production costs of technologies decline and this induces a reduction in the market price of these technologies.

Demand for technologies

Using result *(e36)* and the first order conditions of primary energy producers' leads to the equilibrium demand for technologies (see Appendix A.2):

$$x_{ji}^k(t) = \left(\frac{\alpha^2 p_j^k(t)}{(1-t_{set})\psi_j(t)}\right)^{\frac{1}{1-\alpha}} L_j^k A_{ji}^k \qquad (e37)$$

this demand function shows that demand in technologies increases with positive changes in primary energy prices (for the sector being supported by these technologies), as well as with reductions in technology prices through technology subsidies and the accumulation of experience. Also, improvements in technologies' productivity incentivize the usage of sector specific technologies for primary energy production.

Expected profits of research and development

Combining equations *(e36)* and *(e37)* (see Appendix A.3) results in the equilibrium level of research in both sectors:

$$\frac{\Pi_{set}^k(t)}{\Pi_{fet}^k(t)} = (1 + q_{se}^k) * \frac{\eta_{se}}{\eta_{fe}} * \frac{1}{(1-t_{set}^k)^{\frac{1}{1-\alpha}}} * \left(\frac{\psi_{fe}}{\psi_{se}}\right)^{\frac{\alpha}{1-\alpha}} * \left(\frac{p_{se}^k(t)}{p_{fe}^k(t)}\right)^{\frac{1}{1-\alpha}} * \frac{L_{se}^k(t)}{L_{fe}^k(t)} * \frac{A_{se}^k(t)}{A_{fe}^k(t)} \qquad (e38)$$

If this ratio is greater than one, then the majority of research and development is directed towards sustainable energy technologies (equation *e15*). In the tradition of Acemoglu (2002) and Acemoglu et al. (2012) framework, equation *(e38)* shows that there are three key forces determining which sector captures the greater share of entrepreneurial activity: 1) the "direct productivity effect" $\frac{A_{se}^k(t)}{A_{fe}^k(t)}$ incentivizing research in the sector with the more advanced and productive technologies, 2) the "price effect" $\frac{p_{se}^k(t)}{p_{fe}^k(t)}$ incentivizing research in the energy sector with the higher energy prices and 3) the market size effect $\frac{L_{se}^k(t)}{L_{fe}^k(t)}$ pushing R&D towards the sector with the highest market size. In addition to these forces, in my modeling framework, two more factors are at play: 1) the "experience effect" $\left(\frac{\psi_{fe}}{\psi_{se}}\right)^{\frac{\alpha}{1-\alpha}}$ pushing innovative activity towards the sector that more rapidly reduces technological production costs, and 2) the "innovation propensity effect" $\frac{\eta_{se}}{\eta_{fe}}$ incentivizing R&D in the sector that more rapidly yields new technologies (i.e. I assume that $\eta_{se} \neq \eta_{fe}$). Note also that the research and technologies subsidies also incentivize R&D in sustainable energy technologies.

Prices of primary energy

Combining equation *(e37)* with the FOCs of primary energy producers results in relative prices as a function of relative technological productivity (see Appendix A.4):

$$\frac{p_{se}^k(t)}{p_{fe}^k(t)} = \left(\frac{A_{fe}^k(t)}{A_{se}^k(t)}\right)^{(1-\alpha)} \left(\frac{(1-t_{set}^k)\psi_{se}(t)}{\psi_{fe}(t)}\right)^{\alpha} \tag{e39}$$

since $\frac{d\frac{p_{se}^k}{p_{fe}^k}}{dA_{se}^k} < 0$ then improvements in SETs productivity lead to a decline in the relative price of sustainable energy. Similarly, since $\frac{d\frac{p_{se}^k}{p_{fe}^k}}{dt_s^k} < 0$ and $\frac{d\frac{p_{se}^k}{p_{fe}^k}}{d\psi_{se}} < 0$ then a decline in the relative production cost of SETs leads to lower sustainable energy prices.

Labor allocations

Combining equations *(e7), (e35), (e37)* and *(e39)* it is possible to expresses relative labor as a function of relative productivity and relative technologies cost (see Appendix A.5):

$$\frac{L_{se}^k(t)}{L_{fe}^k(t)} = \left(1+\tau_{fe}^k\right)^{\varepsilon} \left(\frac{(1-t_{set}^k)\psi_{se}(t)}{\psi_{fe}(t)}\right)^{\alpha(1-\varepsilon)} \left(\frac{A_{se}^k(t)}{A_{fe}^k(t)}\right)^{-(1-\alpha)(1-\varepsilon)} \tag{e40}$$

Note that equation *(e40)* indicates that increases in productivity in SETs create a greater market for sustainable energy (i.e. labor augmenting technological change (Acemoglu, 2002)). Similarly, a greater tax to fossil energy and a reduction in SETs costs leads to a greater market for sustainable energy.

Production of primary energy

Finally, combining equation *(e6)* and equation *(e37)* leads to the equilibrium levels of primary energy production as a function of labor, technological productivity and technology costs: (see Appendix A.7):

$$Y_j^k(t) = \left(\frac{\alpha^2 p_j^k(t)}{(1-t_{set}^k)\psi_j(t)}\right)^{\frac{\alpha}{1-\alpha}} L_j^k(t) A_j^k(t) \qquad (e41)$$

Market clearing conditions

As described in equation *(e18)*, consumption and investment in technologies are the only two uses of the final good considered in this framework. The dynamics of consumption in region "k" are expressed by:

$$C^k(t) = Y^k(t) - \psi_{se}\int_0^1 x_{se,i}^k(t)di - \psi_{fe}\int_0^1 x_{fe,i}^k(t)di \qquad (e42)$$

III.2.6 Optimal Policy Response

I define the optimal policy as the policy intervention that maximizes the intertemporal utility of the representative consumer in the advanced and the emerging region, subject to the equilibrium conditions and to the budget constraint in both regions.

The optimal policy considers ten different elements for intervention:

i. *Duration of policy intervention:* P_D
ii. *Carbon tax in advanced region:* τ_{fe}^A
iii. *Carbon tax in emerging region:* τ_{fe}^E
iv. *Technology subsidy in advanced region:* t_s^A
v. *Technology subsidy in emerging region:* t_s^E
vi. *R&D subsidy in advanced region:* q_s^A
vii. *R&D subsidy in emerging region:* q_s^E
viii. *GCF technology subsidy in emerging region: :* t_s^{GCF}
ix. *GCF R&D subsidy in emerging region: :* q_s^{GCF}

Formally, the optimal policy is the solution to the following maximization problem:

$$Max_{P_D,\tau_{fe}^A,\tau_{fe}^E,t_s^A,t_s^E q_s^A,q_s^E,t_s^{GCF},q_s^{GCF}} \int_0^T \frac{1}{(1+\rho)^t}\left(u^A\big(C(t),S(t)\big) + u^E\big(C(t),S(t)\big)\right)dt \qquad (e43)$$

s.t.

(e35), (e36), (e38), (e39), (e40), (e41), (e42)

$$\int_{t_0}^{P_D}\left(t_s^A p_{ji}(t)+q_s^A\left(p_{ji}(t)-\psi_{set}(t)\right)\right)\int_0^1 x_{ji}^A(t)di\,dt$$

$$+$$

$$\int_{t_0}^{P_D}\left(t_s^{GCF} p_{ji}(t)++q_s^{GCF}\left(p_{ji}(t)-\psi_{set}(t)\right)\right)\int_0^1 x_{ji}^E(t)di\,dt$$

$$\leq \int_{P_0}^{P_D}\tau_{fe}^A p_{fe}^A(t)Y_{fe}^A(t)\,dt \qquad (e44)$$

$$\int_{P_0}^{P_D}\left(t_s^E p_{ji}(t)+q_s^E\left(p_{ji}(t)-\psi_{set}(t)\right)\right)\int_0^1 x_{ji}^E(t)di\,dt \leq \int_{P_0}^{P_D}\tau_{fe}^E p_{fe}^E(t)Y_{fe}^E(t)\,dt \qquad (e45)$$

There are important considerations to take into account with respect to the optimal policy in the context of this maximization problem. First, the objective function (equation *e43*) weights equally the utility of the representative consumer in both regions. Second, the duration of the policy intervention is part of the options that can be considered for designing the optimal policy. Third, the optimal policy is subject to budget constraints; equations *(e44)* and *(e45)* indicate that each region's contribution to the optimal policy should not be greater than the funds collected through the carbon tax. This makes technology policy intervention costly, it also means that without taxation on fossil fuels, it is not possible to mobilize the resources necessary to fund complementary technology policy in this context, especially with respect to the contributions to the GCF. Finally, differently to other more traditional frameworks in which the taxation tends to zero once the steady state has been reached, I assume that the values of the policy elements remain constant during the duration of the intervention, such that the optimal policy corresponds to a "shock" policy that is in place during the period of time necessary to achieve the international decarbonization of the energy sector.

III.3 Model Validation

This section focuses on discussing the validity of the model described in the previous paragraphs. I focus on two aspects of model validation. First, I compare simulation output against historical data of energy use across advanced and emerging nations. Second, I compare model's behavior against empirical findings from previous modeling studies.

III.3.1 Validation of Model's Behavior Against Historic Trend

One of the main motivations of this study is that fact that energy consumption (in particular fossil energy consumption) in emerging nations has been growing more rapidly than fossil energy consumption in advanced nations. In fact, as of 2006 the consumption of fossil energy in Non-OECD countries is greater than the consumption of fossil energy in OECD countries. As a result, it is of particular importance for this modeling study to test whether or not the simplified and aggregated model described in the previous sections can replicate such a fundamental transitional pattern.

For this historic comparison, I assume that the model's advanced region represents closely OECD nations, and that the model's emerging region is described by nations outside the OECD group. This classification works well for this comparison because the energy consumption patterns and technological capabilities of these two groups of nations (i.e. OECD and Non-OECD) matches reasonably well with two important modeling assumptions: 1) the advanced region is more technologically advanced than the emerging region, and 2) energy demand is higher in the emerging region than in the advanced region.

Figure 3.1 shows fossil energy consumption (i.e. Petroleum, Natural Gas and Coal) from 1983 to 2012 for the advanced region (i.e. OECD countries) and for the emerging region (i.e. Non-OECD countries) using data from the U.S Energy Information Administration (EIA, 2015). The top panel shows model's simulated output using the parameter values described in Table 3.1. The blue line indicates fossil energy consumption in the advanced region, and the green line denotes fossil energy consumption in the emerging region. The bottom panel describes fossil energy consumption in OECD (i.e. light blue line) and Non-OECD countries (i.e. light green line). This comparison against the historic record is important for demonstrating the validity of the model and also for pointing at some of its limitations.

Before discussing the results presented in Figure 3.1, it is worth noting some important aspects of the parameters listed in Table 3.1. First, these parameters should not be seen as empirical estimations (econometric estimation of these parameters is outside the scope of this simulation study). Moreover, in this exploratory analysis, I consider these parameters to be deeply uncertain and thus in subsequent chapters I use multiple parameter combinations to construct an ensemble of future scenarios. Second, for this validation exercise, I have chosen conservative values for the elasticity of substitution "ε" and the capital intensity "α". These values are line with the conservative values used in the Acemoglu et al. (2012) study. This is a prudent approach, especially for the case of the elasticity of substitution, which has generated substantial debate in the empirical literature. Third, for this base run, the parameters r^A and r^E in equation *(e8)* are set differently for the advanced and emerging regions. This is to match the fact that population growth in both regions followed different paths in the period considered in this validation analysis. In the OECD region, population grew from 1,007 million in 1983 to 1,245.2 million in 2012; while in the Non-OECD region, population grew from 3,684 million in 1983 to 5,752 million in 2012 (OECD Stat, 2015). The exponential rates' values in Table 3.1 are estimated to match these different population growth rates in the two regions. This approach is in line with the augmented endogenous growth model of Aghion and Howitt (1998) pp. 407, and it effectively introduces an exogenous growth rate in the two regions. As argued by the authors, this inclusion takes into account the fact that more populous economies tend to grow faster. Fourth, I assume that the technological development of the renewable energy sector has been on average faster than the development of the fossil energy sector (i.e. $\eta_{se}>\eta_{fe}$ and $\gamma_{se}> \gamma_{fe}$) and that it is easier to imitate and adapt energy technologies than developing new ones (i.e. $\nu_{se}>\eta_{re}$ and $\nu_{se}>\eta_{fe}$). Finally, I do not consider learning-by-doing effects in this validation analysis (i.e. ω_{se}=0 and ω_{fe}=0).

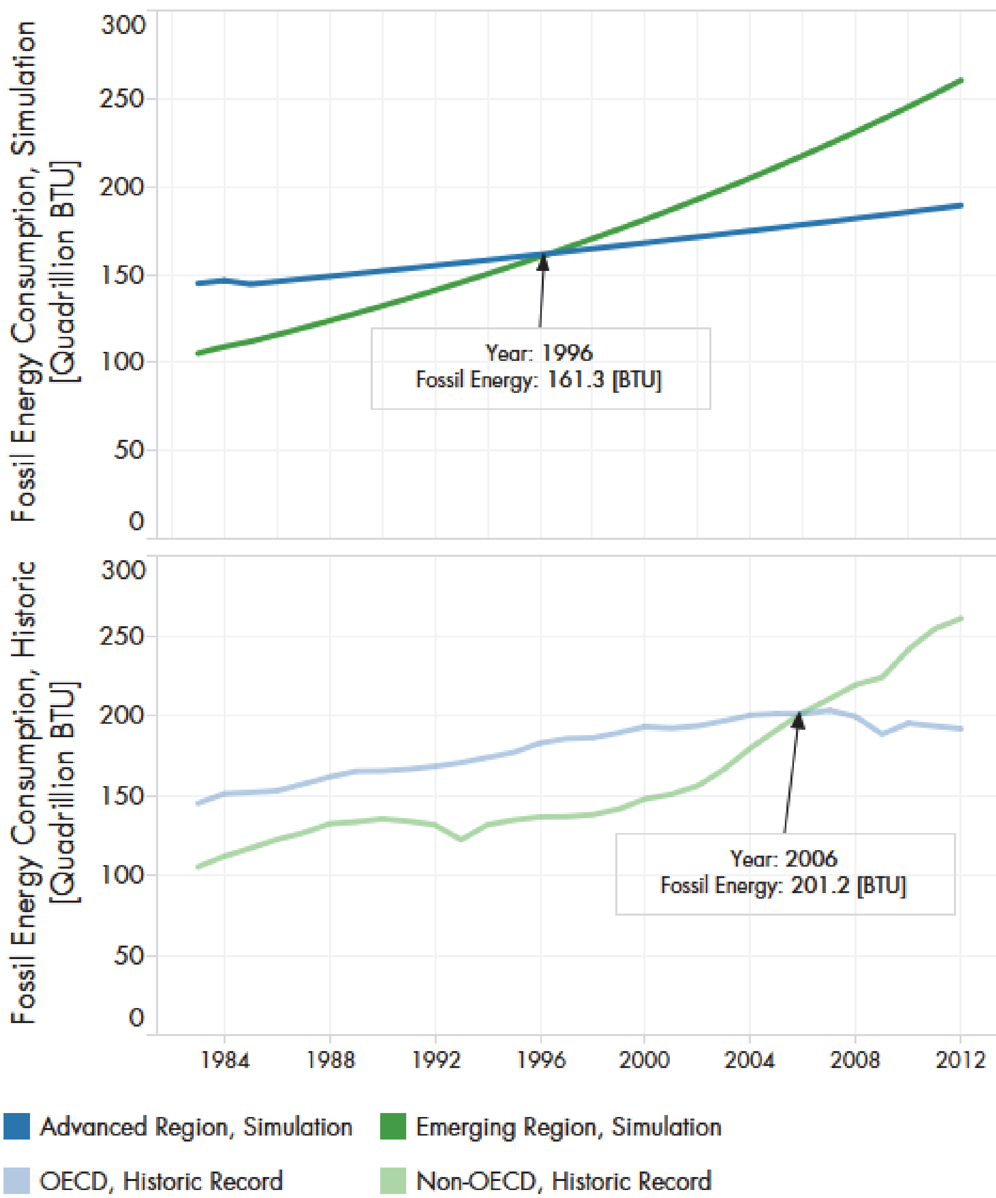
Overall, the parametrization of this validation run depicts a multi-regional context in which technologies being developed in the advanced region are imitated and adapted in the emerging region to meet its growing energy demand. In the emerging region, growth is supported by technological catching-up dynamics and by higher demographic growth, while in the advanced region, less use of fossil energy is possible because of more rapid developments in the renewable energy technologies sector.

The bottom panel in Figure 3.1 shows that in 1983 fossil energy consumption in non-OECD countries was lower than fossil energy consumption in OECD countries. By 2012, this energy consumption pattern was reversed. Figure 3.1 shows that the simulated output successfully captures this key crossover in fossil energy consumption. It also shows that the simulated levels of fossil energy consumption in both regions are within reasonable and realistic bounds. For instance for the last year of this base case simulation (i.e. 2012), emerging region's consumption of fossil energy amounts to 260.2 Quadrillion BTU; in comparison, the historic record shows that Non-OECD countries consumed in 2012, 260.7 Quadrillion BTU of fossil energy. Similarly, the model's estimated fossil energy consumption in the advanced region equals 189.2 Quadrillion BTU, while the historic record estimates that OECD countries consumed in 2012, 191.7 Quadrillion BTU.

This small experiment shows that the model is capable of replicating an important transition seen in the historic record (i.e. Non-OECD countries fossil energy consumption crossover) within realistic bounds of energy consumption for both regions, relying primarily on the assumption that growth in energy consumption is propelled by endogenous technological change and by exogenous population growth. However, at the same time, this validation exercise also points to some of the limitations of the model in terms of accuracy and realism. Figure 3.1

shows that the model depicts a simplified dynamic path in comparison with the more complex pattern registered the historical record.

Figure 3.1
Fossil Energy Consumption Across Regions Simulated Output vs Historic Record
SOURCE: U.S. Energy Information Administration (EIA, 2015)



NOTES: The color legend denotes the two regions considered in the analysis. The top panel shows results of the validation simulation run. The blue line indicates advanced region's consumption of fossil energy, the green line emerging region's consumption of fossil energy. The bottom panel shows the historic record for both OECD countries (light blue line), and Non-OECD nations (light green line). The crossover for fossil energy consumption is indicated for both cases.

Table 3.1
Validation Run Parameters

Parameter Name	Value	Parameter Name	Value
ε	3.5	ω_{set}	0
α	0.33	ω_{fet}	0
η_{set}	0.03 [per year]	r^A	0.008
η_{fet}	0.021[per year]	r^E	0.015
γ_{set}	0.3 [per year]	$Y^A_{set,1983}$	25.1 [Q BTU]
γ_{fet}	0.25 [per year]	$Y^A_{fet,1983}$	144.9 [Q BTU]
v_{set}	0.032[per year]	$Y^S_{set,1983}$	9.0 [Q BTU]
v_{fet}	0.032[per year]	$Y^S_{fet,1983}$	105.3 [Q BTU]

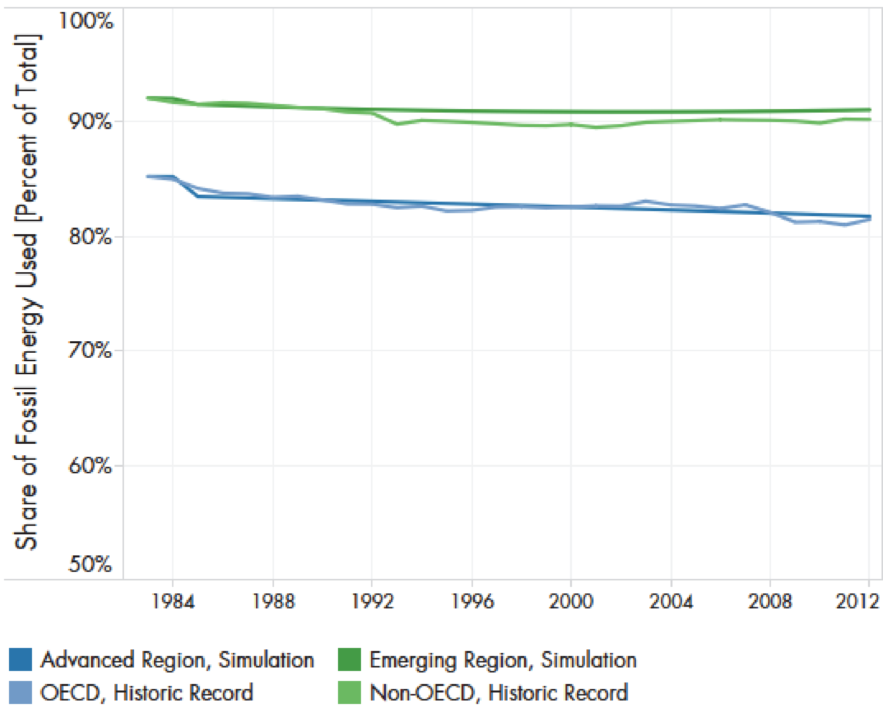
NOTES: Initial conditions for the simulation run are set to energy consumption levels of 1983 for OECD and Non-OECD countries. The value of technological parameters assume that technological development of the renewable energy sector has been on average faster than the development of the fossil energy sector (i.e. $\eta_{set}>\eta_{fet}$ and $\gamma_{set}>\gamma_{fet}$) and that it is easier to imitate and adapt energy technologies than developing new ones (i.e. $v_{ret}>\eta_{ret}$ and $v_{set}>\eta_{fet}$). Learning-by-doing effects are not considered in this validation analysis (i.e. $\omega_{ret}=0$ and $\omega_{fet}=0$).

Over the last 30 years the use of renewable energy has grown steadily in both regions. Therefore, another relevant comparison for this validation exercise is the historical decarbonziation rate of the energy sector in both regions. Figure 3.2 compares this trend in the historic record against the output of the simulation run. The vertical axis denotes the share of fossil energy used for secondary energy production. The blue line refers to the advanced region's simulated output, and the green line refers to the emerging region. Similarly, the light blue line describes this trend for OECD countries, and the light green line describes this trend for Non-OECD countries.

Figure 3.2 shows that in the last 30 years, the share of fossil energy used for secondary energy production declined in both OECD and Non-OECD countries. In 1983, the share of fossil energy used in OECD countries amounted to 85% and in Non-OECD countries to 92%. In 2012, this share of fossil energy used declined to 81% in OECD countries and to 90% in Non-OECD countries. It is possible to see that this mild decarbonization in both regions is replicated successfully by this validation run. Similarly to the comparison with fossil energy consumption, the dynamics produced by the simulation run are noticeably simpler than the historic record. Yet, the model's behavior follows the same pattern than the historical record and the estimated rate of decarbonization is within close proximity of the historic record.

The comparisons made in Figure 3.1 and Figure 3.2 demonstrate that the model produces plausible and valid results for this simulation study. Yet, it is important to remind the reader that the objective of this simulation study is not to forecast "when" and at "which" level of energy consumption, a transition towards renewable energy will be achieved in both regions, nor which will be the penetration of renewable energy in both regions in the coming years. More importantly, this model has been developed to understand under which technological, climate and policy conditions such transition is plausible. Therefore, within that realm of interest, this validation exercise proves the usefulness and appropriates of the model.

Figure 3.2
Dynamics of Decarbonization in Advanced and Emerging Regions



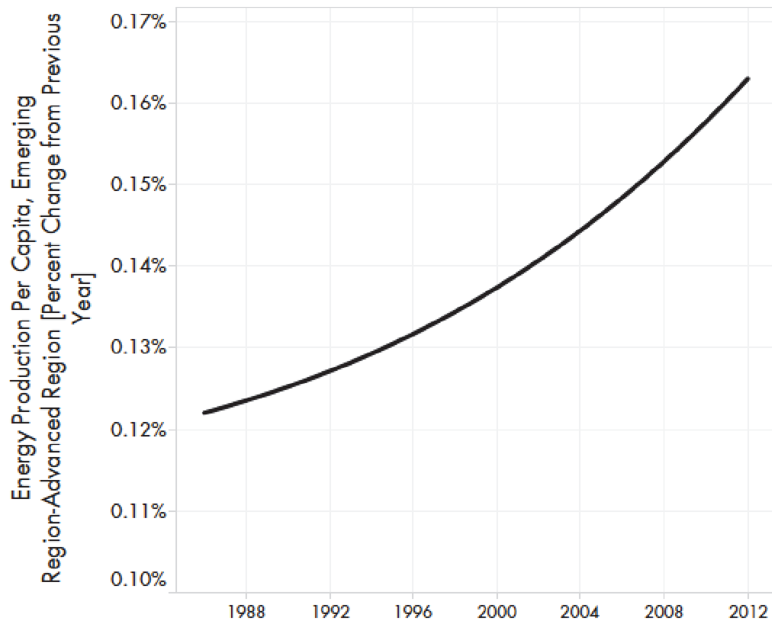
NOTES: The vertical axis denotes the share of fossil energy used for secondary energy production. The blue line refers to the advanced region's simulated output, and the green line refers to the emerging region. The light blue line describes this trend for OECD countries, and the light green line describes this trend for Non-OECD countries.

III.3.2 Validation of Model's Behavior Against Previous Empirical Findings

Comin, Hobijn and Rovito (2006) use a database containing data on diffusion of 155 technologies across 150 countries, covering the last 200 years. Their analysis shows that technological convergence across countries is common, and that this speed of convergence is accelerating. They estimate the speed of convergence in energy production per capita to be on average 1% per year across countries.

Following a similar approach to the one used by Comin, Hobijn and Rovito (2006), Figure 3.3 compares the rate of convergence in energy production per capita between the emerging region and the advanced region, as estimated by the validation simulation run. The vertical axis denotes the rate at which the energy production per capita gap closes between the two regions. Positive values indicate that the gap between the two regions reduces, thus converging to using similar technologies for energy production.

Figure 3.3
Energy Production Per Capita Convergence Across Regions for Validation Run



NOTES: The vertical axis denotes the percent change in the difference in energy production per capita between the advanced and emerging region. Positive values indicate that the gap in productivity closes compared to the previous year. The graph shows that the validation simulation reproduces the accelerating technological convergence reported in the empirical literature.

The trend depicted in Figure 3.3 indicates that the model's behavior is in line with the empirical findings of Comin, Hobijn and Rovito (2006). It shows that the two regions are converging to similar levels of technological productivity at an average rate of 0.14% per year. In addition, this upward trend indicates that the speed of convergence between the two regions is accelerating, which is also in line with the empirical findings of the authors.

As noted frequently throughout this chapter, the model developed by Acemoglu et al. (2012) is a key foundation for the dynamic model described in this chapter. Therefore, an important validation exercise is to compare the results of this multi-regional continuous expansion against the empirical findings reported by Acemoglu et al. (2012). Demonstrating that the model displays a dynamic behavior in line with Acemoglu et al. (2012) previous study is an important element of confidence in the results derived from the model described in this chapter.

I run a similar empirical experiment as the one described by Acemoglu et al. (2012). The parameters used for this empirical validation are listed in Table 3.2. In order to make behavioral comparisons as close as possible, all parameter values are set to the same values used by Acemoglu et al. (2012). Differences arise with respect to climate change equations described in section III.2.1 because these parameters were calibrated using data from IPCC's general circulation model: *bcc-csm1-1*, and because this model is continuous rather than discrete. Also it is important to note that the initial conditions of this empirical validation runs are set to the conditions of 2012 and that no exogenous labor growth is considered for this empirical validation.

Table 3.2
Empirical Validation Parameters

Parameter Name	Value	Parameter Name	Value
ε	[3.0,10]	ξ	0.01
α	0.33	δ	0.0018
η_{set}	0.02 [per year]	$CO_{2\|6.0^{\circ}C}$	1,298.2 [ppm]
η_{fet}	0.02 [per year]	$CO_{2,0}$	289.4 [ppm]
γ_{set}	0.25 [per year]	ω_{set}	0
γ_{fet}	0.25 [per year]	ω_{fet}	0
ν_{set}	0.02 [per year]	r^A	0
ν_{fet}	0.02 [per year]	r^E	0
ρ	[.001,.015] [per year]	$Y^A_{set,2012}$	43.5 [Q BTU]
λ	0.1443	$Y^A_{fet,2012}$	191.7 [Q BTU]
σ	2.0	$Y^S_{set,2012}$	28.2 [Q BTU]
β	4.99	$Y^S_{fet,2012}$	260.7 [Q BTU]

NOTES: The parameter values for the empirical validation runs are listed. Different values for the elasticity of substitution ε and the discount rate ρ are taken into account. Initial conditions are set to the year 2012. Differences between technological sectors are not considered.

Figure 3.4 presents the results of this experiment. The two top panels describe the optimal response for the parameters listed in Table 3.2. The top panel shows the carbon tax rate in the emerging region and the middle panel the carbon tax rate in the advanced region. The bottom panel describes temperature rise in degrees Celsius relative to the pre-industrial era. The simulation runs in black color correspond to low elasticity of substitution cases (ε=*3*), and the runs in grey color denote high elasticity of substitution cases (ε=*10*). The simulation runs denoted in thicker lines correspond to high discount rate cases (ρ=0.015 per annum), while the results denoted by thinner lines correspond to low discount rate cases (ρ=0.001 per annum). For the simplicity of this empirical comparison, Figure 3.4 does not report the R&D subsidies and technological subsidies that are part of the optimal policy response, but for each of the simulations runs, the optimal policy response includes R&D subsidies and technological subsides in both regions.

The results presented in Figure 3.4 provide similar insights as the empirical experiment reported in Acemoglu et al. (2012). It is possible to see that for the high elasticity of substitution cases (ε=*10*), policy intervention is more effective at incentivizing a transition away from fossil energy and that policy intervention only needs to remain in place for a limited period of time (i.e. 50 years) before achieving its goal. Figure 3.4 also shows that this behavior is robust for different values of the discount rate (i.e. thin grey line is contained inside the think grey line). These two results are consistent with the findings of Acemoglu et al. (2012). In addition, these results show that in low elasticity of substitution cases (*ε=3*), the optimal policy response is more costly and less effective than in the high elasticity of substitution cases (*ε=10*). In comparison with the high elasticity of substitution, in these cases the dark lines show that temperature continues rising regardless of policy intervention, that the policy response remains in place during a greater period of time and that it requires higher carbon taxes in the advanced region . These results are also consistent with the findings of Acemoglu et al. (2012).

The results of the two empirical validation exercises described in this section show that the model's behavior is consistent with the previous studies of Comin, Hobijn and Rovito (2006) and Acemoglu et al. (2012), which are two important empirical foundations for this dissertation.

III.4 Summary

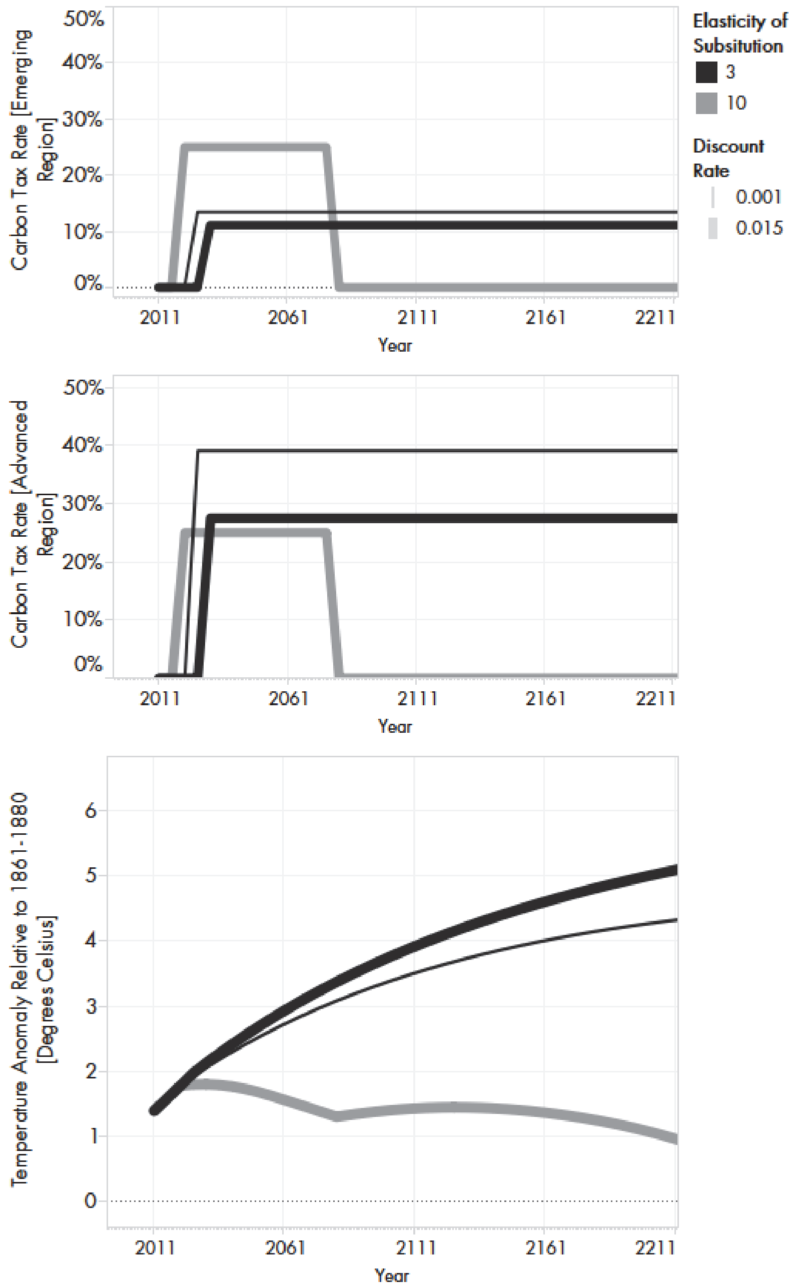
This chapter describes an exploratory dynamic integrated assessment model (EDIAM) for analyzing international technological change and climate policy that is used in subsequent chapters as the future generator in the context of an RDM study. This model combines elements of different modeling and empirical studies. In particular, it attempts to provide a more detailed and disaggregated description of international technological change and technological competition in the context of climate change mitigation policy.

Two generic abstract regions are modeled: a technologically advanced region and a more populous emerging region, with less technological capabilities. It focuses on the individual decision making processes of various economic agents, including: technology entrepreneurs and primary energy producers, and how technological change dynamics and climate change dynamics affect economic agents' decisions.

Technological change is described as a competition process between sustainable energy technologies and fossil energy technologies. It is assumed that new energy technologies are developed in the advanced region and then these technologies are imitated and adapted in the emerging region.

The results of two validation exercises show that the model's behavior replicates the historical pattern of fossil energy consumption and decarbonization, as well as important empirical findings from previous studies. These validation exercises also show that model displays highly simplified dynamics in comparison to the historical record. I emphasize that this model has been developed to study long term transition paths and the effectiveness of multi-regional policy intervention in mitigating climate change; therefore, for this this study, the model is more important for its capacity to generate plausible scenarios, than for its capacity to match perfectly the historical record.

Figure 3.4
Optimal Policy Performance For Various Elasticity of Substitution and Discount Rate Combinations



Notes: The two top panels describe the optimal policy response. The top panel shows the carbon tax rate in the emerging region and middle panel the carbon tax rate in the advanced region. The bottom panel describes temperature rise in degrees Celsius relative to the pre-industrial era. The simulation runs in black color correspond to low elasticity of substitution cases (ε=3), and the runs in grey color denote high elasticity of substitution cases (ε=10). The simulation runs denoted in thicker lines correspond to high discount rate cases (ρ=0.015 per annum), while the results denoted by thinner lines correspond to low discount rate cases (ρ=0.001 per annum).

CHAPTER IV

Optimal Policy Response and Climate Deep Uncertainty: A Robust Decision Making Analysis

IV.1 Introduction

This chapter presents a full RDM study which focuses on understanding role that climate change deep uncertainty has on the structure and effectiveness of optimal environmental regulation across advanced and emerging nations.

In section IV.2 I describe the main elements of this RDM study. The uncertainties (X) considered include 12 CMIP5 climate change scenarios, 10 elasticity of substitution and 5 discount rate scenarios, yielding a total of 600 different futures. Eight policy regimes (L) and two climate change policy targets are taken into consideration (M). The EDIAM model (R) is used as the scenario generator in this study. The quantitative examples presented in this section show that individually each source of uncertainty has the potential of influencing both the structure and effectiveness of the optimal policy response.

The analysis presented in section IV.3 focuses on describing the changes in the structure of optimal environmental regulation across the uncertainty space and on highlighting differences between the GCF based policy regimes and the non-cooperative policy regimes. In addition, scenario discovery methods (Bryant and Lempert, 2010) are used for describing the vulnerability conditions of different policy regimes. The results show that the structure of GCF and non-GCF policy regimes varies greatly in terms of the level of effort required across regions and across different uncertainty conditions. The scenario discovery analysis yields quantitative descriptions of the vulnerable regions of different policy regimes. These results show that end-of-century temperature rise target is met in greater number of futures than the CO_2 stabilization target.

Finally, in section IV.4 I use robustness criteria to map the least-regret policy response across the uncertainty space to understand under which conditions each policy regime is best suited to meet the two climate change objectives of interest. This mapping process demonstrates that cooperation through the GCF is the least-regret policy alternative to achieve the CO2 stabilization and/or the two degrees Celsius temperature rise targets. Yet, it also illustrates that the scale and structure of cooperation changes across the uncertainty space.

IV.2 Scoping of RDM Analysis

IV.2.1 Uncertainties (X)

I focus the analysis of this chapter on three uncertainties: the elasticity of substitution between fossil energy and sustainable energy, the policy discount rate and climate deep uncertainty.

Elasticity of substitution

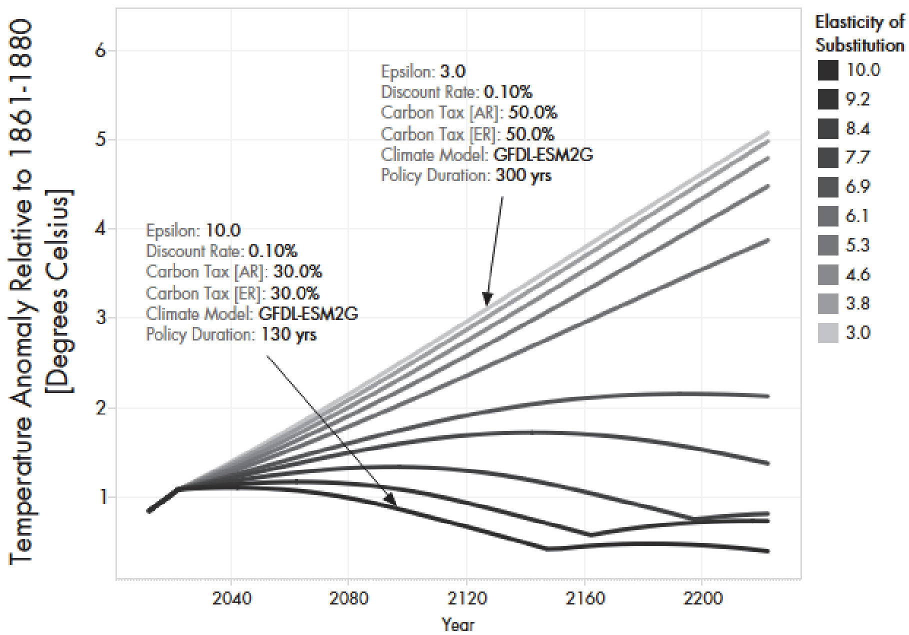
Acemoglu et al. (2012) study spurred an important debate with regards to the value of the elasticity of substitution between the fossil energy sector and the sustainable energy sector. In their study, they argue that the most relevant empirical case is that in which the two sectors are gross substitutes ($\varepsilon>1$). This implies that successful sustainable energy technologies will be used to substitute the functions of fossil energy technologies in secondary energy production. In economic terms, this entails that a decline in the price of sustainable energy (i.e. driven by improvements in the productivity of SETs) decreases the demand of fossil energy. In their study, they do not estimate empirically this parameter, but rather consider two extreme situations (low substitution $\varepsilon=3$, and high substitution $\varepsilon=10$) to highlight the importance of this effect.

The results of Acemoglu et al. (2012) have spurred interest amongst empirical researchers on estimating more accurately the potential level of substitution between the two sectors. At present, initial empirical results show that the short and long term values of the elasticity of substitution are likely to be closer to the low substitution case considered in Acemoglu et al. (2012), but more importantly, these initial results show that the strength of the substitution effect in the long-term is highly uncertain. For instance, Papageorgiou, Saam and Schulte (2013) use cross-country sectoral energy data and nested CES production functions to estimate this parameter. They find evidence that the elasticity of substitution is the short-term is more likely to be in the low substitution range ($\varepsilon=3$) of Acemoglu et al. (2012) study, but in the long-term is plausible that this parameter falls in the low and high range values used in (Acemoglu et al., 2012). Another study by Pottier, Hourcade and Espagne (2014) argues that the elasticity of substitution between sustainable energy and fossil energy is also likely to be in the low substitution range ($\varepsilon=3$), perhaps even below one ($\varepsilon<1$). They argue that this is the case mainly because capital stocks for most of the energy system last for many decades, and this delays substitution away from fossil energy. However, the authors consider that in the long-term, as innovation broadens the range of technological possibilities, it is plausible that all energy sources will be fairly substitutable.

These results and the debate among researchers on this topic support the notion that the elasticity of substitution between sustainable and fossil energy is a deeply uncertain parameters. These empirical findings show that current state of science does not provide sufficient and adequate evidence to estimate accurately this parameter. They also suggest that in the long-term a wide range of values are plausible.

In this RDM analysis, I consider the elasticity of substitution "ε" as a deeply uncertain parameter. I explore the implications of varying levels of substitutability between the two sectors by considering ten different scenarios for this parameter. Figure 4.1 lists the different elasticity of substitution scenarios considered in this analysis and exemplifies their effect on temperature rise stabilization. The vertical axis denotes temperature rise with respect to pre-industrial levels for different simulated time series. The color legend indicates the level of substitutability between the two sectors; the darker colors denote scenarios of high elasticity of substitution and the clearer colors scenarios of low elasticity of substitution. The structure of the optimal policy response, as well the climate scenario and discount rate parameters used for the simulations are highlighted for the highest and lowest elasticity of substitution scenarios.

Figure 4.1
Effect of Different Discount Elasticity of Substitution Scenarios on Optimal Policy Response's Structure and Effectiveness



NOTES: The vertical axis denotes temperature rise with respect to pre-industrial levels for different simulated time series. The color legend indicates the level of substitutability between the two sectors; the darker colors denote scenarios of high elasticity of substitution and the clearer colors scenarios of low elasticity of substitution. The structure of the optimal policy response, as well the climate scenario and discount rate parameters used for the simulations are highlighted for the highest and lowest elasticity of substitution scenarios.

Figure 4.1 shows that the ten scenarios considered for the elasticity of substitution can result in substantially different outcomes. For instance, it shows that for three high levels of substitutability scenarios: ε=10.0, ε=9.2 and ε=8.4, it is possible to induce a full self-reinforcing transition away from fossil energy before the end of the simulation runs (i.e. policy duration<300 yrs). In contrast, for the low elasticity of substitution scenarios: ε=3.0, ε=3.8, ε=4.6 and ε=5.3, it is necessary to sustain policy intervention (i.e. harmonized carbon tax in both regions) during the entire simulation at a high level (i.e. 50%) to delay temperature rise. This shows that the cost and effectiveness of policy intervention is closely linked to the degree of substitutability between the fossil and sustainable energy sectors. The less substitutable these sectors are, the more effort is required to induce a successful transition towards sustainable energy and the decarbonization of secondary energy production in both regions.

Discount Rate

Under the dynamic framework described in chapter three, the discount rate is an important factor in determining the structure of the optimal policy response. In scenarios in which the discount rate is too high, then short-term outcomes are more significant than long-term outcomes. In these scenarios, high temperature rise levels far in the future are less significant, and as a result, the magnitude of the policy response is less decisive in the short-term (i.e. smaller carbon tax, smaller technology and research subsidies). The discount rate is a mathematical formalism that helps us express future costs and gains at today's equivalent value. In the context of climate change, this parameter attempts to describe how societies of today value the environmental and economic outcomes of the future.

Controversy over the proper value of the discount rate lies at the heart of many of the debates associated with climate change policy. It should not be a surprise that studies that use different discounting values reach different conclusions regarding the structure of the optimal environmental policy required to stabilize global temperature rise.

This debate is best exemplified by Nordhaus and Stern's research on the level of carbon taxation needed to keep temperature rise at sustainable levels. In short, Nordhaus, using a discount rate of 1.50% per year, finds that an initial small carbon tax that increases over time would guarantee that temperature rise will be kept below three degrees Celsius in the long-term, while Stern, using a discount rate of 0.10% per year, argues that a higher initial carbon tax is needed to achieve temperature rise stabilization sooner and avoid future significant damage from climate change. Focusing on this debate, Acemoglu et al. (2012) shows that when considering endogenous technological change, other economic factors are found to be more significant than the discount rate in determining the structure of the optimal response. Yet, the disagreement over the discount rate in the climate change policy community persists. From an RDM perspective, this disagreement among climate experts is evidence of the deep uncertainty associated with the discount rate. From this point of view, it is ill advice to favor one vision over the other. Thus is more fruitful to consider both perspectives simultaneously in the analysis in order to understand under which future conditions these differences associated with the discount rate play a significant role in defining the structure and effectiveness of optimal environmental regulation.

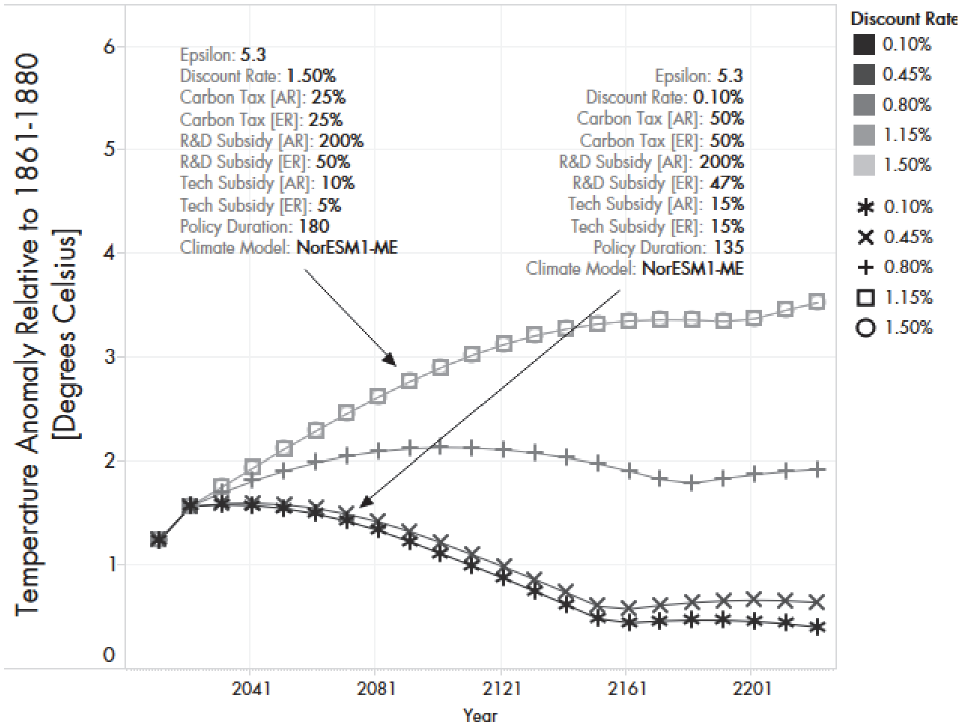
In addition to this disagreement among experts, the discount rate is associated with deep uncertainty on its own merit. At its heart, in the climate change context, the discount rate represents human attitudes towards future environmental outcomes. It is clear that as climate change consequences become more relevant to our daily lives, societies will likely change their attitudes towards the value of the environment, perhaps by putting more interest in long-term environmental outcomes. However, it is not possible to estimate or anticipate the extent of this change in attitudes, nor when it can occur. There is also the fact that different governments and societies may value differently future environmental outcomes (i.e. use different discount rates). All these aspects make it appropriate to consider the discount rate as a deeply uncertain parameter in the context of an RDM study.

In this analysis I explore this uncertainty by considering a diverse set of discount rate scenarios. To develop these scenarios, I assume that the maximum value that this parameter can take is the one proposed by Stern (i.e. 1.15% per year), and that the minimum value is the one proposed by Stern (i.e. 0.10% per year). However, I also consider three more possibilities in between to explore in more detail the role of varying levels of discounting on the structure of the optimal policy response.

Figure 4.2 lists the five discount rate scenarios considered in this analysis. Each line represents a simulated temperature rise time series for a specific discount rate scenario. For these example simulation, all input parameters, other than the discount rate, are held constant (i.e. ε=5.3 and Climate Model=NorESM1-ME). The resulting optimal environmental policy is highlighted for the two bounding cases. For each case the different elements of the policy response are listed, including: Carbon Tax, R&D Subsidies, Technology Subsidies and Policy Duration for both regions.

Figure 4.2 provides an illustrative example of the discount rate's role in determining the structure of the policy response. By comparing the optimal policy response across the Stern (i.e. 0.10% per year) and Nordhaus (i.e. 0.10% per year) limits, it is possible to see that in the first case policy intervention is more decisive across both regions than policy intervention in the second case. For instance, the policy response with the 0.10% per year discount rate uses higher levels of carbon taxation and technology subsides in both regions. As a result, the environmental outcomes are also significantly different, for the 0.10% discount rate, temperature rise is kept below two degrees Celsius throughout the entire simulation, while for the 1.15% discount rate, temperature rise continues for over a century until it is stabilized at approximately three degrees Celsius. In this case the cost of policy intervention is higher for the 0.10% discount rate, but it is important to note that in comparison to the 1.15% discount rate policy, this policy requires to be implemented during a shorter period of time (i.e. 135 vs 180 years), thus under alternative climate conditions, it is also feasible that both policies display similar intervention costs, or that in fact, that the 0.10% discount rate policy becomes cheaper. These simulation runs exemplify the impact that considering alternative discount rates can have on the structure and efficacy of the optimal policy response.

Figure 4.2
Effect of Different Discount Rate Scenarios on Optimal Policy Response's Structure and Effectiveness



NOTES: Each line describes a single simulation run for a specific discount rate scenario. All other input parameters are held constant (ε=5.3 and Climate Model=NorESM1-ME). The resulting optimal environmental policy is highlighted for two cases: for each, the different elements of the policy response are listed, including: Carbon Tax, R&D Subsidies, Technology Subsidies and Policy Duration for both regions.

Climate Uncertainty

In chapter one, using the original CMIP5 ensemble of climate projections, I showed that for any given level of GHG emissions, there is a wide range of plausible temperature rise scenarios. This uncertainty associated with the speed of temperature rise is associated with the limitations of our understanding of the global climate system. Each general circulation model used by the IPCC and included in the CMIP5 ensemble uses different assumptions and parameter values to describe the atmospheric changes resulting of growing anthropogenic GHG emissions, and, as a result, the magnitude of the estimated changes varies greatly among different modeling groups.

Considering this source of uncertainty in climate assessment models is extremely important because the speed of temperature rise does not only affect the level of damage that can be expected from rising GHG emissions, but also the degree of effort required to stabilize GHG emissions at temperature levels that are environmentally sustainable.

In the modeling framework described in chapter three, there are two channels through which climate uncertainty influences the structure of optimal policy response. For a fixed level of CO_2 emissions, for climate scenarios in which climate sensitivity to GHG is high (i.e.

parameter "β", *equation e3*), the societal cost of temperature rise is higher than for climate scenarios in which climate sensitivity is low. As a result, in order to maximize the objective function described in equation *(e43)*, in the former case, the optimal policy response requires stronger early intervention than in the latter climate change scenario. Another form in which climate uncertainty may affect the structure of the optimal policy response is associated with differences in the size of carbon sinks. In equation (*e1*), the carbon sink is represented by the initial level of the quality of the environment and the rate of rate of natural environmental regeneration (i.e. parameters S_0 and δ in equation *e1*). Evidently, this is a highly aggregated representation of how carbon sinks work, and more comprehensive climate models offer much higher details of this aspect of the global climate system; yet, this modeling structure does capture the fact that for different climate change models, the period time that CO_2 can remain in the atmosphere atmospheric is not fixed across models. Therefore, for climate scenarios in which carbon sinks are higher, it is possible to reduce atmospheric CO_2 concentrations at a faster rate than for climate scenarios in which these carbon sinks are smaller. In this case, climate scenarios with small carbon sinks require that policy intervention remains in place for a longer period of time in order to avoid adverse environmental outcomes.

One of the innovations of this study is the use of the CMIP5 climate data ensemble to calibrate the parameters ξ, δ, β and S_0 in equations *(e1)* and *(e3)*. This is relevant because it allows me to incorporate into the analysis empirically plausible climate change scenarios developed by an international community of experts and used widely in assessment and adaptation studies among the climate change policy community. In this way, it is possible to study the implication of climate uncertainty, represented by the various CMIP5 climate scenarios.

Table 4.1 lists the estimated parameters for the 12 CMIP5 climate models included in this study, the parameters of equations *(e1)* and *(e3)* are listed for each climate model. I estimate these parameters by using an autoregressive model and the CO_2 emission levels' variation across representative concentration pathways (RCPs) in the CMIP5 climate models ensemble. Appendix C describes in more detail the methodology used for the statistical estimation of these parameters.

Table 4.1 shows that this calibration exercise yields a heterogeneous set of climate scenarios that vary in terms of the climate sensitivity of GHG (β) and the size of the carbon sink (δ, S_0). Interestingly, some of these scenarios such as GFDL-ESM2M and GFDL-ESM2G portrait "good news" scenarios in which climate sensitivity is low and the capacity of the carbon sink is high. In contrast, scenarios such as MIROC-ESM-CHEM and GFDL-CM3 portrait "bad news" scenarios in which climate sensitivity is high and the carbon sink's capacity is low.

Table 4.1
Estimated Simulation Parameters Using CMIP5 Climate Models

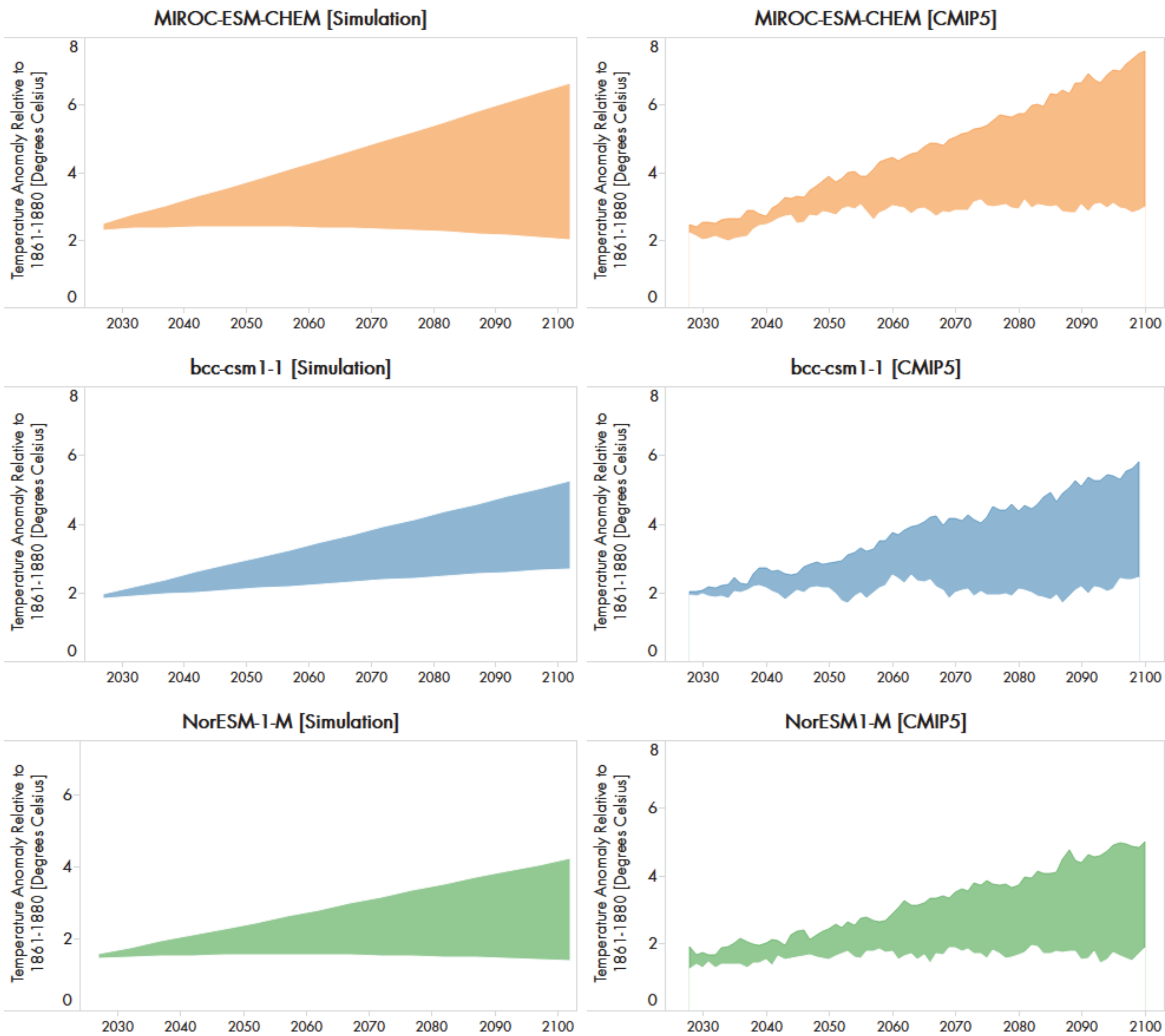
Climate Scenario	β	ξ	δ	S_0
MIROC-ESM-CHEM	6.13	0.010	0.00278	590
GFDL-CM3	6.11	0.010	0.00259	635
MIROC-ESM	5.93	0.010	0.00260	633
bcc-csm1-1	5.00	0.010	0.00182	916
MPI-ESM-LR	4.67	0.010	0.00161	1042
MPI-ESM-MR	4.67	0.010	0.00161	1045
NorESM1-ME	4.34	0.010	0.00136	1236
MRI-ESM1	4.26	0.010	0.00130	1294
NorESM1-M	4.13	0.010	0.00119	1415
MIROC5	4.12	0.010	0.00119	1417
GFDL-ESM2M	3.29	0.010	0.00071	2403
GFDL-ESM2G	3.19	0.010	0.00063	2695

NOTES: The table lists the estimated parameters for the 12 CMIP5 climate models included in this study, the parameters of equations (e1) and (e3) are listed for each climate model. These parameters are estimated using CO_2 emission levels' variation across representative concentration pathways (RCPs) for each of the climate models in an autoregressive model. Appendix C describes in more detail the methodology used for this estimation.

Figure 4.3 compares the behavior of a subset of these models across the CMIP5 dataset and the simulated output using the parameters listed in Table 4.1. The right panel shows CMIP5 temperature rise time series for three models: MIROC-ESM-CHEM, bcc-csm1-1 and NorESM1-M. For each time step, the upper limit of each envelope denotes the maximum temperature rise level across all RCPs in CMIP5 (i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5), while the lower limit denotes the minimum temperature rise level. Thus, each envelope indicates the range for plausible temperature rise levels for each time step. Similarly, the left panel shows temperature rise levels for a subsample of simulation runs that describe similar emission pathways as the RCPs. The remaining comparisons for the climate models not included in Figure 4.3 are presented in Appendix D. In this appendix, I also present a graphical description of the emission pathways considered for these comparisons.

Figure 4.3 shows that there is a hierarchy among climate models in terms of how rapidly temperature rise could occur for a fixed emissions' pathway, and that this hierarchy is retained in the simulated output. For example, climate model *MIROC-ESM-CHEM* portraits a more drastic temperature rise scenario than climate models *bcc-csm1-1* and *NorESM1-M,* in both the CMIP5 database and in the simulated output. Figure 4.3 also shows that plausible temperature rise levels across the CMIP5 data ensemble and the simulated output are within the same ranges. These comparisons show that the climate scenario calibration used in this study results in model behavior that is in accordance with the outcomes of the CMIP5 climate projections. This makes it possible to study how the different CMIP5 climate models influence the structure of the optimal policy response.

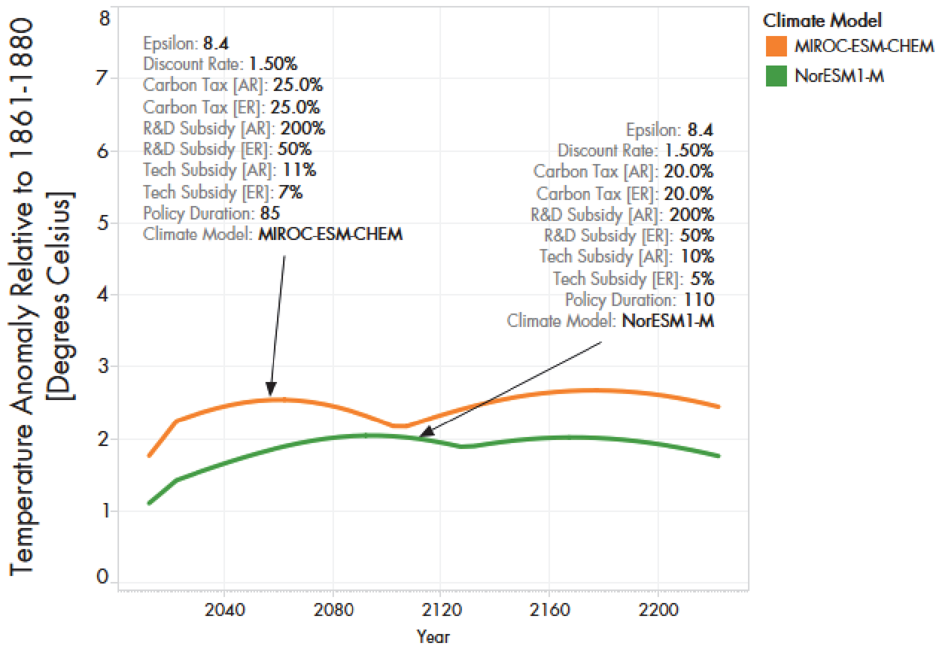
Figure 4.3
Comparison between Simulated (Left Panel) versus Original (Right Panel) CMIP5 Models' Temperature Rise Trajectories



NOTES: The right panel shows CMIP5 temperature rise time series for three models: MIROC-ESM-CHEM, bcc-csm1-1 and NorESM1-M. For each time step, the upper limit of each envelope denotes the maximum temperature rise level across all RCPs in CMIP5 (i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5), while the lower limit denotes the minimum temperature rise level. Thus, each envelope indicates the range for plausible temperature rise for each time step. Similarly, the left panel shows temperature rise ranges for a subsample of simulation runs that describe similar emission pathways as the RCPs.

Figure 4.4 provides an illustrative example of how is that different climate scenarios may lead to a different structure of the optimal environmental policy. This figure shows temperature rise time series for two simulation experiments. Both simulations used the same parameter values for the elasticity of substitution (i.e. 8.4) and the discount rate (i.e. 1.50% per year), but are run for different climate scenarios: *MIROC-ESM-CHEM* (i.e. orange line) and *NorESM1-M* (i.e. green). For each simulation, the pointing arrows indicate the resulting optimal policy as a combination of carbon taxes, research subsidies and technology subsidies across both regions.

Figure 4.4
Effect of Different Climate Scenarios on Optimal Policy Response's Structure and Effectiveness



NOTES: This figure shows temperature rise time series for two simulation experiments. Both simulations used the same parameter values for the elasticity of substitution (i.e. 8.4) and the discount rate (i.e. 1.50% per year), but are run for different climate scenarios: MIROC-ESM-CHEM (i.e. orange line) and NorESM1-M (i.e. green). For each simulation, the pointing arrows indicate the resulting optimal policy as a combination of carbon taxes, research subsidies and technology subsidies across both regions.

Figure 4.4 illustrates a plausible form in which alternative climate scenarios influence the structure of the optimal policy response. It shows that for a more abrupt climate scenario, such as *MIROC-ESM-CHEM*, it is possible than under certain circumstances, the optimal policy uses a higher mix of carbon taxes, research subsidies and technology subsidies than in the case of a less abrupt climate scenario like *NorESM1-M*. It also shows that the environmental outcomes between both scenarios are different: in this case, for both simulation runs temperature rise is successfully mitigated, but this occurs at a higher level for climate scenario *MIROC-ESM-CHEM* than for scenario *NorESM1-M*. It also shows that the cost of policy intervention is unambiguously higher for climate scenario *MIROC-ESM-CHEM* because although the rate of carbon taxation is smaller in climate scenario *NorESM1-M*, policy intervention lasts longer in the latter case. Evidently, this results can change when combined with other uncertainties, yet if offers an illustrative example of the interplay between the optimal policy response and the different climate scenarios.

IV.2.2 Policy Levers (L)

From the perspective of optimal policy response, I model alternative policy levers as combinations of constraints in the optimization problem described in equation *(e43)*. This allows me to study a diverse set of proposed architectures for cooperation under the GCF. For example, in its current form, the funding from the GCF is planned to be primarily targeted towards financing sustainable energy projects in emerging nations, this would effectively work as a technology subsidy in emerging countries because it would reduce the costs of implementation of these technologies in these countries. However, under the framework described in chapter three, it would also be possible to use the GCF to co-fund the development of endogenous innovative capacities in emerging nations (i.e. R&D subsidies). Since it would be possible to use the GCF funds in both sectors, it also becomes interesting to study under which circumstances it would be more cost-effective to use the GCF funding in both sectors, or in just one of them.

In addition to considering various forms of coordination through the GCF, for completeness, I also consider a diverse set of benchmark cases that are relevant for assessing the impact of cooperation in climate change mitigation. First, I consider in the analysis the future without action (FWA), this is the policy scenario in which no significant climate policy is implemented. Second, I consider two policy cases in which cooperation through the GCF does not take place, but still each region independently implements climate policy. In one case, climate mitigation is carried out through independent carbon taxes across both regions; in the other case, both regions invest independently in comprehensive policies that use combinations of carbon taxes, R&D subsidies and technology subsidies. These additional policy cases offer a benchmark to analyze under which conditions is effective to expand climate policy beyond carbon taxes and also to understand under which conditions non-cooperative comprehensive climate policy might be more suitable than the cooperative GCF approach.

Table 4.2 lists the complete set of policies considered in this study. For each policy, I indicate in which sectors (i.e. carbon tax, technology subsidies and R&D subsidies) cooperative actions are implemented, and in which sectors individual independent actions are carried out. Thus, each policy can be represented as a mix of individual and cooperative actions across sectors. In addition, I list the set of restrictions used to represent each policy regime in the optimization framework.

In total Table 4.2 describes eight different policy regimes. The future without action (FWA) represents the benchmark policy case in which climate policy is not implemented (i.e. laissez-faire economy). In this scenario, economic growth is not slowed down by policy intervention, but temperature continues rising at an accelerating pace. The policy regime "*P1. I. Carbon Tax [Both]*" represents a non-cooperative case in which both regions implement independently climate policy. This intervention considers only the implementation of carbon taxes and no-complementary technology policy. In addition, the optimal taxation rate does not need to be the same across regions. Policy case "*P2. I. Carbon Tax + I.Tech-R&D[Both]*" depicts a different non-cooperative policy regime. In this case, the optimal policy response includes independent levels of taxation, technology subsidies and R&D subsidies for both regions. Thus, this represents a case in which significant climate actions are taken in both regions, but there are no co-funded efforts under the GCF.

Table 4.2
Description of Alternative Policy Regimes Considered

Policy Regime	Independent Sectors	Cooperation Sectors	Formalism In Optimization Problem
P0 FWA: Future Without Action	• None	• None	$\tau_{fe}^A, \tau_{fe}^E, t_s^A, t_s^E, q_s^A, q_s^E, t_s^{GCF}, q_s^{GCF} = 0$
P1 I. Carbon Tax [Both]	• Carbon tax	• None	$\tau_{fe}^A, \tau_{fe}^E > 0$ $t_s^A, t_s^E, q_s^A, q_s^E, t_s^{GCF}, q_s^{GCF} = 0$
P2 I. Carbon Tax + I.Tech-R&D[Both]	• Carbon tax • Technology subsidies • R&D subsidies	• None	$\tau_{fe}^A, \tau_{fe}^E, t_s^A, t_s^E, q_s^A, q_s^E > 0$ $t_s^{GCF}, q_s^{GCF} = 0$
P3 H. Carbon Tax + Co-Tech[GCF]+R&D[AR]	• No R&D subsidies in emerging region	• Harmonized carbon tax • Co-funded technology subsidies	$\tau_{fe}^A = \tau_{fe}^E > 0$ $t_s^A, q_s^A > 0$ $t_s^E = t_s^{GCF} > 0$ $q_s^E, q_s^{GCF} = 0$
P4 H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both]	• Independent R&D subsidies	• Harmonized carbon tax • Co-funded technology subsidies	$\tau_{fe}^A = \tau_{fe}^E > 0$ $t_s^A, q_s^A, q_s^E > 0$ $t_s^E = t_s^{GCF} > 0$ $q_s^{GCF} = 0$
P5 H. Carbon Tax + Co-R&D[GCF]+Tech[AR]	• No technology subsidies in emerging region	• Harmonized carbon tax • Co-funded R&D subsidies	$\tau_{fe}^A = \tau_{fe}^E > 0$ $t_s^A, q_s^A > 0$ $q_s^E = q_s^{GCF} > 0$ $t_s^E, t_s^{GCF} = 0$
P6 H. Carbon Tax + Co-R&D[GCF]+I. Tech[Both]	• Independent technology subsidies in emerging region	• Harmonized carbon tax • Co-funded R&D subsidies	$\tau_{fe}^A = \tau_{fe}^E > 0$ $t_s^A, t_s^E, q_s^A > 0$ $q_s^E = q_s^{GCF} > 0$ $t_s^{GCF} = 0$
P7 H. Carbon Tax + Co-Tech-R&D[GCF]	• None	• Harmonized carbon tax • Co-funded R&D subsidies • Co-funded Technology subsidies	$\tau_{fe}^A = \tau_{fe}^E > 0$ $t_s^A, q_s^A > 0$ $t_s^E = t_s^{GCF} > 0$ $q_s^E = q_s^{GCF} > 0$

NOTES: For each policy regime it is indicated in which sectors (i.e. carbon tax, technology subsidies and/or R&D subsidies) cooperative actions are implemented, and in which sectors individual independent actions are carried out. Thus, each policy regime can be represented as a mix of individual and cooperative actions across sectors. The set of mathematical restrictions used to represent each policy regime in the optimization framework are noted.

Multiple cooperation scenarios under the GCF are described in Table 4.2. For all these policy cases, I assume that regions agree initially on the implementation of a harmonized carbon tax as proposed by Nordhaus (2011); therefore, the carbon tax rate is the same across both regions. I also assume that cooperation under the GCF does not have to follow a unique architecture and that it is possible to cooperate in certain sectors, while allowing independent action in others. Policy case "*P3: H. Carbon Tax + Co-Tech[GCF]+R&D[AR]*" considers the case of a harmonized carbon tax across regions and cooperation in co-funded technology subsidies under GCF. However, in this case, independent R&D subsidies are only implemented in the advanced region. Policy "*P4: H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both]*" expands on the latter case by considering that independent R&D subsidies are implemented in both regions.

Policy "*P5. H. Carbon Tax + Co-R&D[GCF]+Tech[AR]*" includes the implementation of a harmonized carbon tax in both regions, co-funded R&D subsidies under the GCF and independent technology subsidies in the advanced region. Policy regime "*P6. H. Carbon Tax + Co-R&D[GCF]+I.Tech[Both]*" expands policy case P5 by allowing for the implementation of independent technology subsides in both regions. Finally, policy regime*"P7: H. Carbon Tax + Co-Tech-R&D[GCF]"* considers the case in which in addition to a harmonized carbon tax, cooperation under the GCF includes co-funded R&D subsidies and technology subsidies.

IV.2.3 Relationships (R)

In the XLRM framework, relationships (R) describe the causal chains by which different factors relate to one another. These relationships are described by the mathematical formalisms embedded in computer models, which are used as scenario generators in RDM studies. These computer models describe how different future outcomes may evolve under different policy conditions and under different combinations of uncertain factors. Scenario generators are used to develop a vast set of plausible scenarios, which are then compared and analyzed in light of the policy metrics defined in collaboration with decision makers and relevant stakeholders (Lempert, Popper and Bankes, 2003).

I use the modeling framework described in chapter three as the scenario generator in this RDM analysis. It is important to emphasize that under this framework, the policy response is endogenously determined, as it is the solution to the optimization problem described in equations *(e43), (e44)* and *(e45)*. This implies that for any given combination of parameters, or for any given future scenario in the RDM framework, the optimal policy response is the option that best balances the economic cost and environmental benefits of climate policy intervention. Moreover, this optimal policy response weights equally the costs and benefits across regions, thus it should be viewed as the policy that seeks to maximize the benefit of climate policy in the entire system, without favoring a particular region. In the economic literature, this optimal policy is often described as the solution to the social planner's problem.

From an RDM perspective, this optimal policy response can be viewed as the no-regret policy for both regions. This implies that for a specific future, the no-regret policy guarantees that there is no other policy vector that provides the same environmental outcome at a lower cost. Thus, implementing a policy other than the no-regret option implies that one or both regions incur in higher costs, or that worse environmental outcomes are achieved.

In addition, from a game theoretic perspective, the no-regret policy option also represents the Nash-equilibrium policy for both regions. In Appendix B, I show that for both regions the no-regret policy is the dominant strategy because any other policy that considers higher or lower efforts is dominated by the no-regret policy. This is because the objective function weights equally both regions and because the no-regret policy guarantees that there is no other policy that displays pareto improvements.

In this study, the optimal policy is merely a mathematical abstraction that is used to analyze the tradeoffs of climate policy and the changes in the structure of climate policy across the uncertainty space. This mathematical abstraction relies on basic rationality and perfect information assumptions. Evidently, these assumptions are made to simplify this complex system and make it feasible and scientifically useful to focus only on parts of this complexity (i.e. climate change uncertainty and technological uncertainty). Thus, the optimal policy response should not be viewed as a normative fixed reference for climate policy design; rather, in this modeling framework, the optimal policy response should be discussed in the context of decision relevant futures that are under discussion and as useful starting point for illuminating the challenges and opportunities of climate change policy across different climate and technological scenarios.

IV.2.4 Metrics (M)

I use various metrics to evaluate the performance of policies and compare the desirability of different scenarios. In order to make this analysis more relevant for policy circles, I focus primarily on the outcome that policy intervention has on the economic and environmental conditions by the end of the century. This aligns the scope of this work to the discussions among the climate change policy community regarding the various end-of-the century temperature rise and stabilization targets.

From an economic perspective, for each future scenario (i.e. combination of uncertainties) I estimate the cost of policy intervention by comparing consumption levels across the policy intervention case and the future without action case (i.e. laissez-faire economy). Then, the higher the reduction in consumption compared to the FWA, the higher the costs of policy intervention.

From an environmental perspective I consider two metrics: the end-of-the century temperature rise level and end-of-century CO_2 concentrations. The first metric is useful for comparing policies in terms of the temperature levels that are plausible with its implementation. The second metric is useful to analyze whether or not a policy stabilizes CO_2 emissions such that temperature permanently stops rising.

These measures allow for a more comprehensive comparison of policies' performance. For instance, a particular policy could be effective in mitigating temperature rise below a certain end-of-the century target (e.g. two degrees Celsius), but at the same time it could fail to achieve CO_2 stabilization before the end of the century, which would imply that temperature rise will continue growing after the end of the century. In contrast, an alternative policy could be effective in both mitigating temperature rise below a specific target and also be effective in stabilizing CO_2 emissions. Since the costs of policy intervention are estimated and comparable for both policies, then it is possible to shed light over the cost-effectiveness tradeoff that exist between the two policies and to study how these results changes across different future scenarios.

IV.2.5 Experimental Design and Case Generation

I use the elements outlined in the previous section to conduct several simulation experiments. The experimental design includes a full factorial sampling design across the uncertain exogenous factors, this includes:

- 12 Climate scenarios
- 10 elastic of substitution scenarios
- 5 discount rate scenarios

I considered all possible combinations of these uncertain exogenous factors for developing individual future scenarios, this yields a total of 600 futures.

The eighth policy regimes described in the previous section are analyzed against this common set of futures, yielding a total of 4,800 cases considered. Each simulation case was run using the modeling framework described in chapter three for a period of 300 years. For each inputs combination and policy regime an optimal policy response is estimated. Figure 4.5 summarizes the scope of the experimental design of this study using the XLRM framework.

Figure 4.5
XLRM Summary of Climate Uncertainty Analysis

Uncertainties (X)	Policy Levers (L)
Climate Uncertainty: • 12 Climate Scenarios Economic Uncertainty: • 10 Elasticity of Substitution Scenarios • 5 Discount Rate Scenarios	• P0. FWA (Future Without Action) • P1. I. Carbon Tax [Both] • P2. I. Carbon Tax + I.Tech-R&D[Both] • P3. H. Carbon Tax + Co-Tech[GCF]+R&D[AR] • P4. H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both] • P5. H. Carbon Tax + Co-R&D[GCF]+Tech[AR] • P6. H. Carbon Tax + Co-R&D[GCF]+I. Tech[Both] • P7. H. Carbon Tax + Co-Tech-R&D[GCF]
System Relationships (R)	**Metrics (M)**
• Exploratory Dynamic Integrated Assessment Model (EDIAM)	• End-of-century temperature rise • Stabilization of GHG emissions • Economic costs of policy intervention

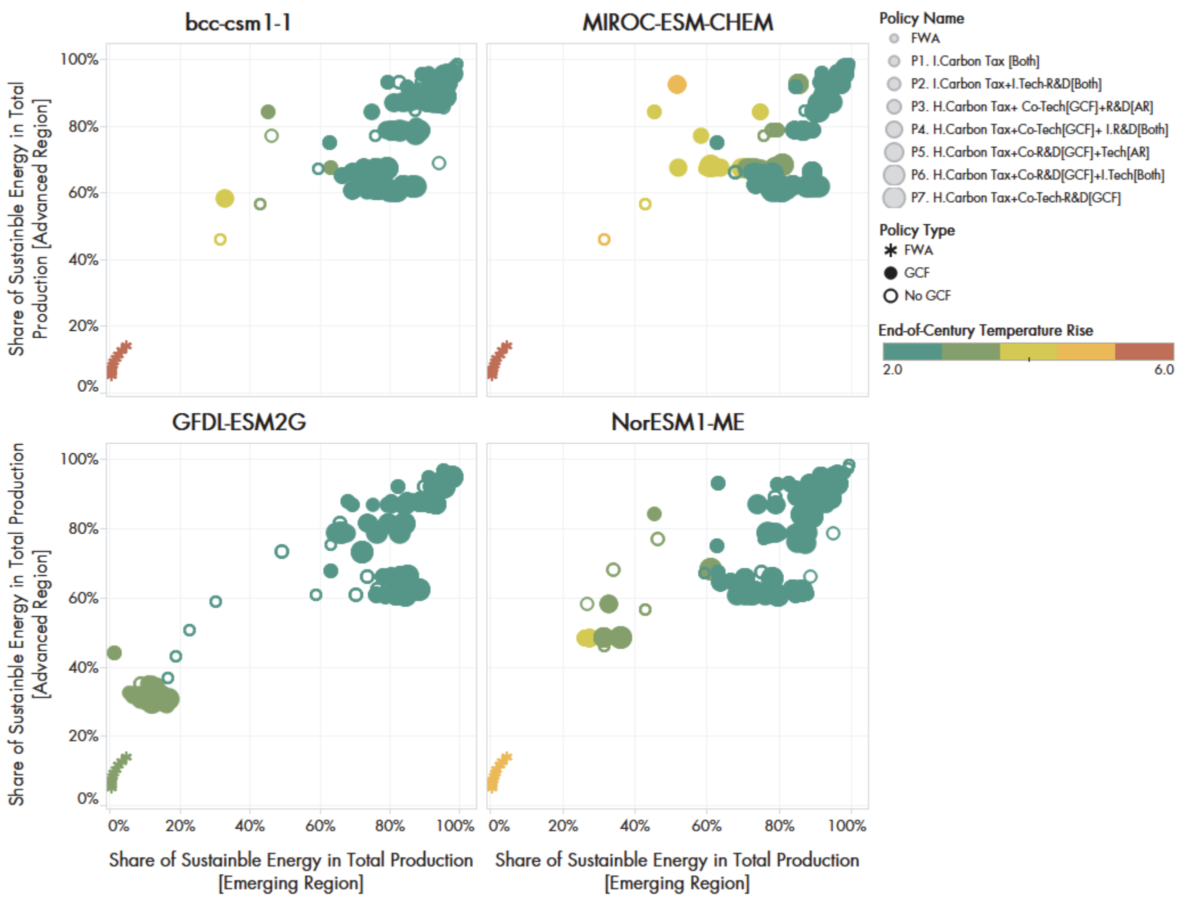
NOTES: The main components of the exploratory analysis are grouped according to four different categories: 1) the deep uncertainty scenario taken into account (i.e. 12 climate scenarios, 10 Elasticity of Substitution Scenarios and 5 Discount Rate Scenarios), 2) the policy regimes analyzed (i.e. 8 different policy regimes, 3) the system relationship that links actions to consequences (i.e. EDIAM model), and 4) the metrics considered to analyze the performance of different policies.

IV.3 Exploratory Analysis

IV.3.1 Optimal Policy Performance Across Many Futures

Results from the simulations runs generated by the experimental design are shown in Figure 4.6. Each point represents a single future; it describes the penetration of sustainable primary energy as percent of total secondary energy production for the emerging region (x-axis) and for the advanced region (y-axis). The size of the points reflects the type of policy response, the smaller points denote policy response schemes which include the FWA and the two non-GCF policies (i.e. P1 and P2), bigger points indicate GCF based policies (i.e. P3,P4,P5,P6 and P7). The color legend indicates end-of-the century temperature rise, the green points describe temperature rise conditions closer to the two degrees Celsius, while red points describe temperature rise conditions closer to the environmental disaster condition of six degrees Celsius. The figure includes four panes; each pane displays results for a different climate scenario. Only four out of twelve climate change scenarios are displayed in this figure.

Figure 4.6
Example of Experiment Results Across Different Climate Scenarios

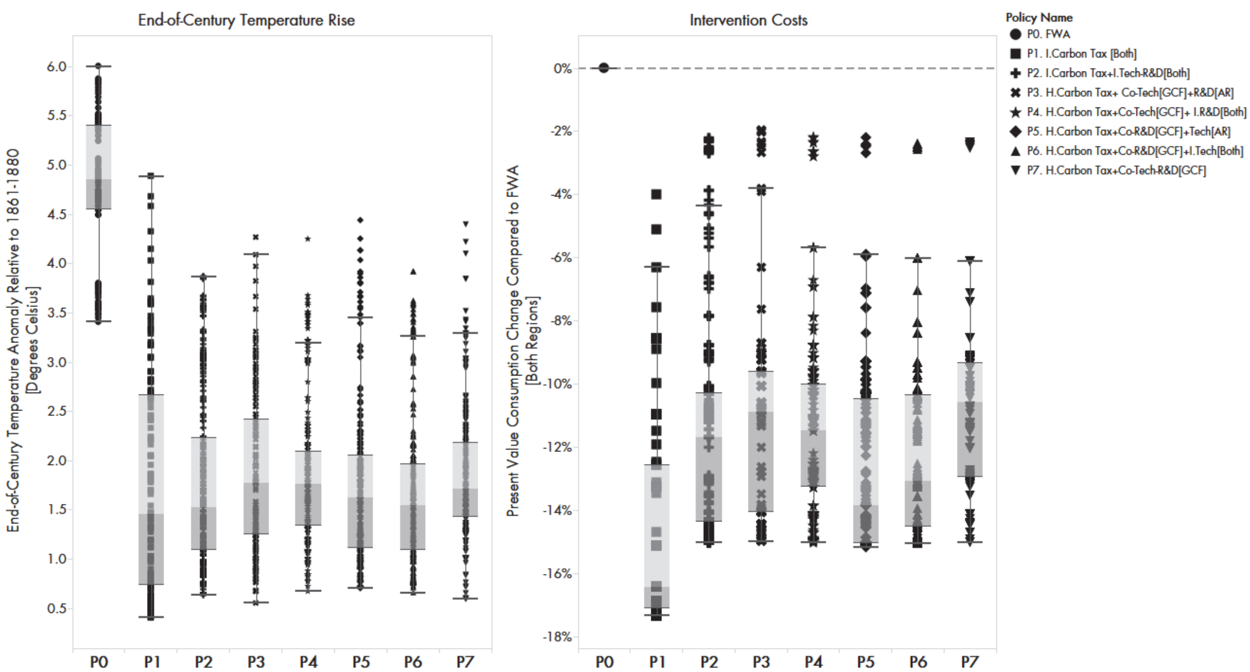


NOTES: Each point describes an individual future through the penetration of sustainable primary energy as percent of total secondary energy production for the emerging region (x-axis) and for the advanced region (y-axis). The size of the points reflects the type of policy regime, the smaller points denote policy regimes which include the FWA and the two non-GCF policies (i.e. P1 and P2), and bigger points indicate GCF based policies (i.e. P3, P4, P5, P6 and P7). The color legend denotes end-of-the century temperature rise, the green points describe temperature rise conditions closer to the 2 °C target, while red points describe temperature rise conditions closer to the environmental disaster condition of 6 °C. The figure includes four panes; each pane displays results for a different climate scenario.

These results are useful for highlighting some of the features of the system and of the policy response. The figure shows that there is ample variation with respect to the penetration levels of sustainable energy that can be achieved through the various policy regimes. It is possible to see that the FWA results in limited penetration of sustainable energy across both regions, and as a result, end-of-century temperature rise levels are close to the environmental limit (i.e. 6 °C). Figure 4.6 also reveals that the best environmental outcomes are concentrated in the upper right corner of these panes. These futures represent scenarios in which the policy response induces a successful transition towards sustainable energy across both regions. It is possible to see that the no-GCF policies (i.e. P1 and P2) can achieved similar high levels of penetration of sustainable energy in both regions than GCF based policies (i.e. P3-P7). These results also show that policy performance varies across climate scenarios in terms of the penetration of sustainable energy and the resulting temperature rise.

Comparing these results across multiple different dimensions is also important. One way of doing this is by visualizing results via using boxplot summaries of all futures considered. Figure 4.7 shows the distribution of results across all futures considered (i.e. 600) for all policy regimes. These box plots summarize the distributional pattern alone without making any assumption about the likelihood of any of the futures. The right pane shows the distribution of costs and the left pane depicts end-of-century temperature levels.

Figure 4.7
Box Plot Summaries Describing End-of-Century Temperature and Intervention Costs for Different Policy Regimes



NOTES: Distribution of results across all futures considered (i.e. 600) for all policy regimes. This box plots summarize the distributional pattern alone without making any assumption about the likelihood of any of the futures. The right pane shows the distribution of costs and the left pane depicts the end-of-century temperature levels.

The boxplot summaries in the left pane show that the FWA always leads to temperature rise levels above the 2°C target and, under many circumstances, to disastrous temperature levels before the end of the century. In contrast, the distribution of results across the different policies shows that in many future scenarios the optimal policy response is capable of maintaining end-of-century temperature rise levels below the 2°C target. The spread of results varies noticeably across policies; in particular, the independent carbon tax policy (i.e. *P1. I. Carbon Tax [Both]*) shows the greatest spread of outcomes when compared to the other policy options.

The right pane in Figure 4.7 shows that policy intervention costs vary more widely across policies. The policy costs are estimated as the percent change in net present value of consumption with respect to the future without action (FWA). This implies that the higher the reduction in consumption, with respect to the future without action, the higher the cost of policy intervention. In economic terms, this cost estimation describes the share of consumption that consumers in both regions forgo in exchange of better environmental outcomes. The results show that the independent carbon tax policy is the highest cost policy in a large number of futures. It also shows that under some circumstance the GCF based policies can be more costly intervention than the no-GCF policies. For instance, it is possible to see that for a number of futures, the cost of the comprehensive independent policy (i.e. *P2.I.Carbon Tax +I.Tech-R&D[Both]*) is lower than the cost of the comprehensive GCF policy (i.e. *P7.H.Carbon Tax + Co-Tech-R&D[GCF]*).

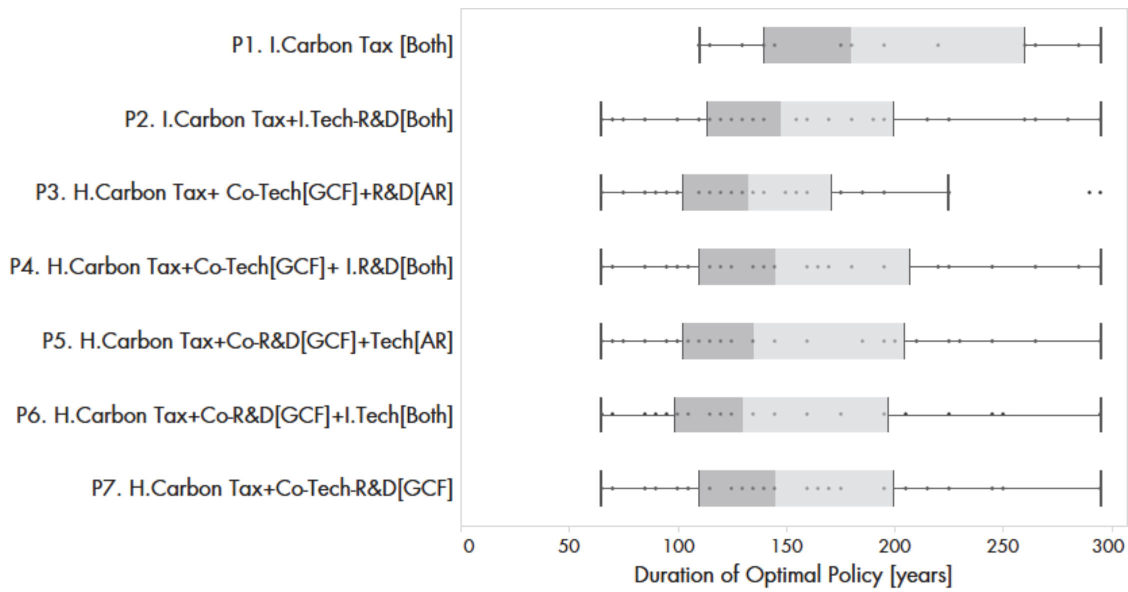
From a policy perspective, it is important to compare the performance of different policies in terms of the end-of-century temperature rise level because in multi-lateral climate change negotiations, the architecture of the policy response is designed towards meeting an end-of-century temperature target. The most commonly used temperature target is 2 °C; however, for some climate change experts and decision makers this target is perceived as weighting too high the quality of the environment over the health of the economy. Thus, they argue that the climate policy response should be designed for an end-of-century temperature rise of 3°C. Although these types of environmental objectives are controversial, these have been found to be very useful in climate change negotiations because these are perceived as tangible objectives towards which the climate change policy community can work towards to.

In addition to these temperature caps, end-of-century CO_2 emissions stabilization is also a policy objective that is critical to consider. For example, it is feasible that although temperature rise is kept below a target, at the same time, anthropogenic CO_2 emissions continue growing. In such cases, policy intervention would still be required after the end of the century to continue controlling temperature rise until successful decarbonization is achieved.

In the context of the modeling framework used in this study, the stabilization of CO_2 emissions is also an important signal of the successful decarbonization of both regions. Stabilization is achieved once the rate of CO_2 emissions from fossil energy use is below the capacity of the carbon sync (i.e. $\delta S > \xi\left({Y_{fe}}^{A} + {Y_{fe}}^{E}\right)$, *equation e1*), which can only occur at high penetration levels of sustainable energy across both regions, which in turn can only occur when SETs are more productive technologies than FETs (*equation e38*). From this perspective, the optimal policy is the response option that successfully induces the decarbonization of both regions at the lowest possible economic and environmental cost. Then, the optimal policy only needs to remain in place during a finite period of time: once the technological and market conditions are such that decarbonization is successfully induced, then policy is no longer needed.

Figure 4.8 presents boxplots summaries of the duration of policy intervention for all futures scenarios across all policies. The results show that under this modeling framework stabilization of CO_2 emissions is only possible after several decades of implementation (i.e. at least 50 years). This figure also highlights that there are noticeable differences among policies in terms of the period of time required to achieve stabilization. The use of independent carbon taxes requires at least one hundred years for achieving international decarbonization. Policies that include complementary R&D and technology subsides show that it is possible to successfully induce the decarbonization in a shorter period of time. However, these results also show that for a considerable number of futures, policy intervention needs to remain in place for as long as 300 years.

Figure 4.8
Box Plot Summary of Optimal Policy's Duration Across Different Regimes



NOTES: Boxplot summaries describing the duration of policy intervention for all futures across all policies. The results show that under this modeling framework stabilization of CO2 emissions is only possible after several decades of implementation (i.e. at least 50 years). It also highlights that there are noticeable differences among policies in terms of the period of time required to achieve stabilization.

For this analysis, I focus primarily on the end-of-century conditions because these are more relevant for current climate change policy discussions. Therefore, I consider a future is acceptable (not vulnerable) when the temperature target (i.e. 2 °C, 3 °C) and/or the stabilization targets are met. This suggests that there are four possible cases of success:

1. Futures in which the 2 °C end-of-century temperature rise target is met
2. Futures in which the 3 °C end-of-century temperature rise target is met
3. Futures in which the 2 °C end-of-century temperature rise target and CO_2 stabilization are met
4. Futures in which the 3 °C end-of-century temperature rise target and CO_2 stabilization are met

Table 4.3 summarizes the performance of each policy across the 600 futures considered for the four vulnerability cases described. As expected, the FWA does not meet any of the climate change objectives. It also shows that for the independent carbon taxes policy (i.e. P1) in the majority of futures it is possible keep temperature rise below the 2 °C and 3 °C targets, but in none of the cases, this policy is able to stabilize CO_2 emissions. This shows that this policy is effective in delaying temperature rise, but is less effective at inducing successful decarbonization across regions. In contrast, policies that complement carbon taxes with R&D and technology subsidies are able to meet the CO_2 stabilization targets in a higher number of futures. It is possible to see that the stabilization targets are met in less than one third of the futures considered. In this respect, some of the GCF based policies (i.e. *P4 and P7*) are slightly more effective than the non GCF policy (i.e. *P2*) in meeting the stabilization target.

Table 4.3
Performance of Optimal Policy Response Across Different Policy Regimes

Policy Name	**Number (Percentage) of Futures Meeting the End-of-Century Climate Policy Target**			
	CO_2 Stabilization Achieved		**CO_2 Stabilization Not Achieved**	
	Temperature Rise Below 2 °C	**Temperature Rise Below 3 °C**	**Temperature Rise Below 2 °C**	**Temperature Rise Below 3 °C**
P0. FWA	0 (0)	0 (0)	0 (0.0)	0 (0.0)
P1. I. Carbon Tax [Both]	0 (0)	0 (0)	375 (62.5)	505 (84.2)
P2. I. Carbon Tax + I. Tech-R&D[Both]	153 (25.5)	160 (26.7)	398 (66.3)	528 (88.0)
P3. H. Carbon Tax + Co-Tech[GCF]+R&D[AR]	130 (21.7)	155 (25.8)	344 (57.3)	544 (90.7)
P4. H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both]	153 (25.5)	175 (29.2)	391 (65.2)	537 (89.5)
P5. H. Carbon Tax + Co-R&D[GCF]+Tech[AR]	130 (21.7)	176 (29.3)	395 (65.8)	535 (89.2)
P6. H. Carbon Tax + Co-R&D[GCF]+I. Tech[Both]	145 (24.2)	175 (29.2)	415 (69.2)	533 (88.8)
P7. H. Carbon Tax + Co-Tech-R&D[GCF]	165 (27.5)	190 (31.7)	402 (67.0)	532 (88.7)

NOTES: The table summarizes the performance of each policy across the 600 futures considered for the four vulnerability cases described. The number (percentage) of futures meeting the different end-of-century climate policy targets are listed under each column.

IV.3.2 Structure of Optimal Policy Response Across Futures

The structure of the optimal environmental policy varies across the uncertainty space in order to meet the climate policy targets described. This variation in the structure of the optimal response has important implications for policy design because it provides another dimension through which it is possible to compare the performance of different alternatives. It also provides a better understanding of how different policy regimes would need to be adapted to respond to uncertain climate change and economic dynamics.

I focus on analyzing the variation of the optimal policy response across two contrasting policy regimes: the independent comprehensive policy case (i.e. *P2. I. Carbon Tax + I. Tech-R&D[Both])* and the GCF comprehensive policy case (i.e. *P7. H. Carbon Tax + Co-Tech-R&D[GCF]*). This a relevant empirical comparison for this study because in this way it is possible compare in a direct way the effect that GCF cooperation can have on the structure of the optimal response across all intervention sectors.

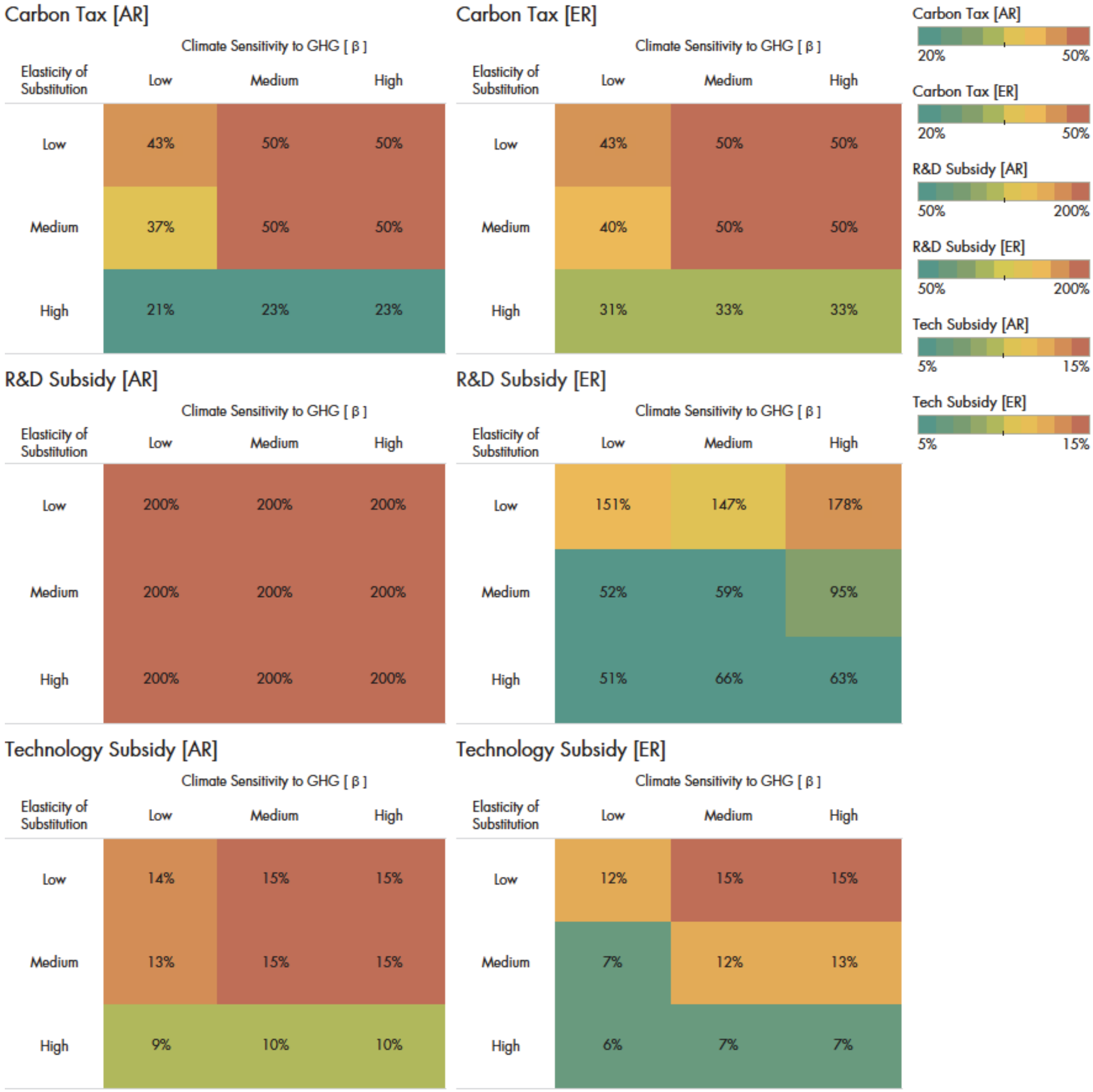
Structural Changes in the Independent Comprehensive Policy: "P2. I. Carbon Tax + I. Tech-R&D[Both]"

Under this policy regime both regions implement comprehensive climate policy that includes carbon taxes, R&D subsidies and technology subsidies. This is done independently such that each region sets its own carbon tax level to fund the R&D and technology subsidies required to mitigate temperature rise and induce the successful decarbonization of their energy sectors.

Figure 4.9 shows how the optimal response changes across two uncertainties: the elasticity of substitution (i.e. "ε" in equation *(e5)*) and climate sensitivity to GHG (i.e. "β" in equation *(e3)*). The left panes describe changes in the structure of the optimal policy in the advanced region (AR) and the right panes describe changes in the emerging region (ER). The top panes show results for the individual carbon taxes, the middle panes for R&D subsidies and the bottom pane for technology subsidies. Uncertainty values are described using three bins; for the elasticity of substitution these bins are defined as low: [3:5), medium: [5:8) and high: [8:10); similarly, the climate sensitivity bins are defined as low:[3:5) , medium:[5:6) and high: [6,7). The legend of each cell represents the mean value of the policy element for the subset of futures describe by the intersecting bins. The color legend denotes the effort level of the policy response: colors towards red denote higher effort policies; colors toward green denote lower effort policies.

As expected, Figure 4.9 shows that the structure of the optimal policy is very sensitive to the combined effect of the elasticity of substitution and climate sensitivity: the higher the climate sensitivity and the lower the elasticity of substitution, then the higher the effort of the optimal policy response.

Figure 4.9
Changes In Optimal Response's Structure Across Different Elasticity of Substitution and Climate Sensitivity Scenarios-P2: I. Carbon Tax + I. Tech-R&D [Both]-



NOTES: The left panes describe changes in the structure of the optimal policy in the advanced region (AR) and the right panes describe changes in the emerging region (ER) for the independent comprehensive policy regime (P2). The top panes show results for the individual carbon taxes, the middle panes for R&D subsidies and the bottom pane for technology subsidies. Uncertainty values are described using three bins; for the elasticity of substitution these bins are defined as low, medium: [5:8) and high: [8:10); for climate sensitivity these bins are defined as low:[3:5) , medium:[5:6) and high: [6,7). The legend of each cell represents the mean value of the policy element for the subset of futures describe by the intersecting bins (elasticity of substitution and climate sensitivity). The color legend denotes the effort level of the policy response: colors towards red denote higher effort policies; colors toward green denote lower effort policies.

The discount rate is another important factor that influences the structure of the optimal policy response. Figure 4.10 describes changes in the structure of the optimal policy across different scenarios of the elasticity of substitution and the discount rate. As expected, it shows that the strength of the policy response increases as the discount rate diminishes. However, in this case it is possible to see that as the elasticity of substitution increases, the influence of the discount rate in the structure of the optimal policy diminishes. For high elasticity of substitution scenarios it is possible to see that the structure of the optimal policy is insensitive to changes in the discount rate.

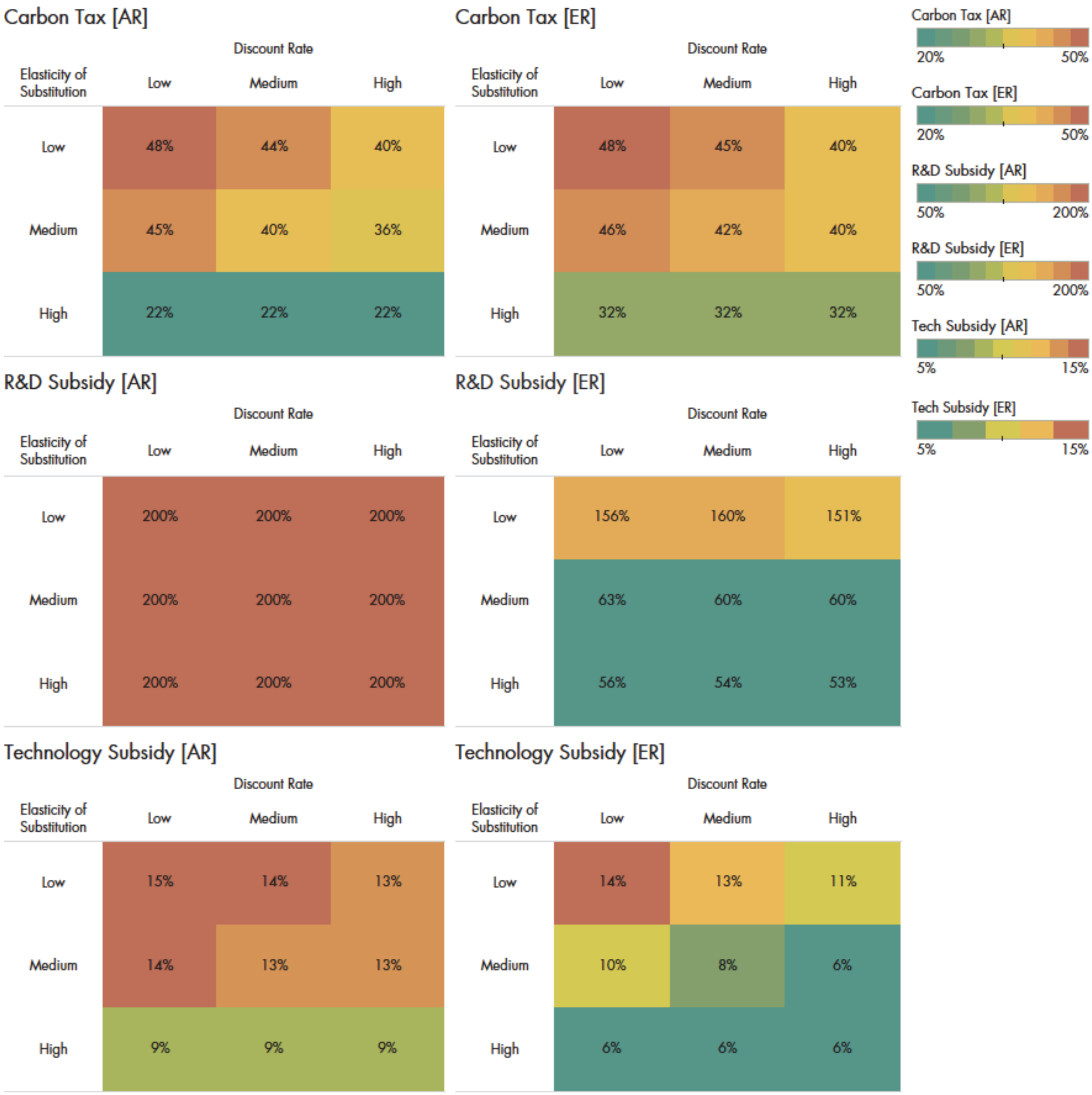
The results presented in Figure 4.9 and Figure 4.10 also highlight the importance of regional differences in defining the structure of optimal environmental regulation. These results show that in the emerging region carbon taxation is always equal or higher than carbon taxation in the advanced region. In contrast, the technology policy elements of optimal environmental regulation are higher in the advanced region than in the emerging region. Since technologies are developed in the advanced region, then the optimal policy prioritizes accelerating technology development over taxation in this region, while in the emerging region, higher taxation creates a strong market niche for sustainable energy, which is used more effectively by R&D and technology subsides that accelerate the technological catching up process.

Structural Changes in the GCF Comprehensive Policy: "P7. H. Carbon Tax + Co-Tech-R&D[GCF]"

In this section I focus on analyzing structural changes in the optimal policy for the case in which the GCF includes the co-funding R&D subsidies and technology subsidies across both regions. Under this policy regime, both regions set their carbon taxes at the same level, and investments in R&D and technology subsidies in the emerging region are financed by both regions (i.e. $t_s^E = t_s^{GCF}$, $q_s^E = q_s^{GCF}$). This policy describes a highly cooperative policy intervention in which both regions share resources through the GCF to coordinate across all sectors. It also describes a more rigid policy regime in which individual regional adjustments are not possible.

In the same fashion as in previous cases, Figure 4.11and Figure 4.12 track structural changes in the optimal policy across three uncertainties: Figure 4.11 displays changes across different scenarios of the elasticity of substitution and the speed of temperature rise, and Figure 4.12 displays changes across different elasticity of substitution and discount rate scenarios. Note that in both figures, the right panes display the combined level of effort in the emerging region through the GCF.

Figure 4.10
Changes In Optimal Response's Structure Across Different Elasticity of Substitution and Discount Rate Scenarios- P2: I. Carbon Tax + I. Tech-R&D [Both]-



NOTES: The left panes describe changes in the structure of the optimal policy in the advanced region (AR) and the right panes describe changes in the emerging region (ER) for the independent comprehensive policy regime (P2). The top panes show results for the individual carbon taxes, the middle panes for R&D subsidies and the bottom pane for technology subsidies. Uncertainty values are described using three bins; for the elasticity of substitution these bins are defined as low, medium: [5:8) and high: [8:10); for climate sensitivity these bins are defined as low:[3:5) , medium:[5:6) and high: [6,7). The legend of each cell represents the mean value of the policy element for the subset of futures describe by the intersecting bins (elasticity of substitution and discount rate). The color legend denotes the effort level of the policy response: colors towards red denote higher effort policies; colors toward green denote lower effort policies.

Figure 4.11
Changes In Optimal Response's Structure Across Different Elasticity of Substitution and Climate Sensitivity Scenarios- P7. H. Carbon Tax + Co-Tech-R&D [GCF]-

Carbon Tax [AR]

Elasticity of Substitution	Climate Sensitivity to GHG [β] Low	Medium	High
Low	39%	42%	44%
Medium	29%	29%	29%
High	22%	22%	22%

Carbon Tax [ER]

Elasticity of Substitution	Climate Sensitivity to GHG [β] Low	Medium	High
Low	39%	42%	44%
Medium	29%	29%	29%
High	22%	22%	22%

R&D Subsidy [AR]

Elasticity of Substitution	Climate Sensitivity to GHG [β] Low	Medium	High
Low	200%	200%	200%
Medium	200%	200%	200%
High	200%	200%	200%

GCF Co-R&D Subsidy [ER]

Elasticity of Substitution	Climate Sensitivity to GHG [β] Low	Medium	High
Low	138%	331%	334%
Medium	105%	102%	102%
High	106%	104%	105%

Technology Subsidy [AR]

Elasticity of Substitution	Climate Sensitivity to GHG [β] Low	Medium	High
Low	13%	14%	14%
Medium	11%	11%	11%
High	10%	10%	10%

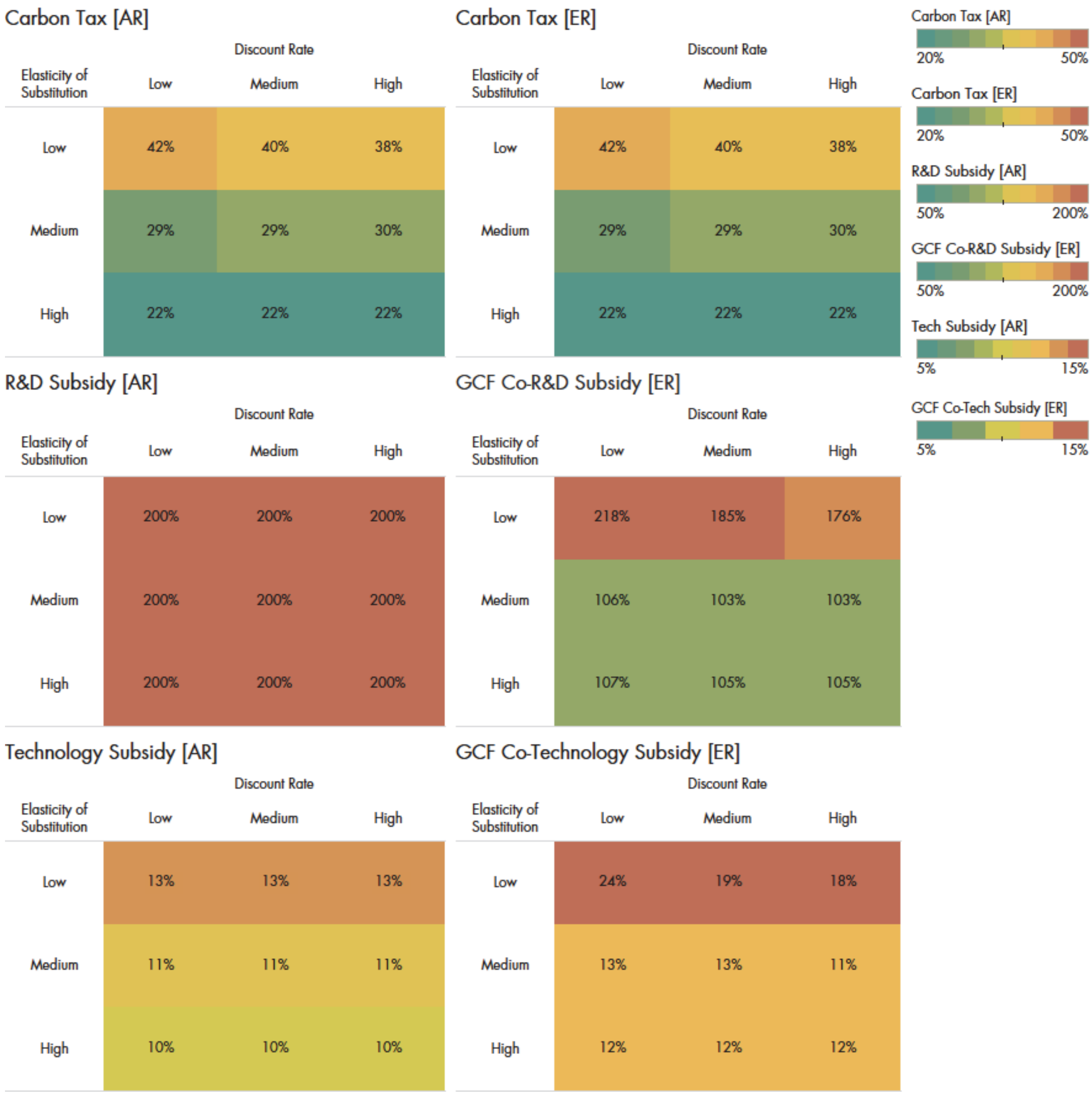
GCF Co-Technology Subsidy [ER]

Elasticity of Substitution	Climate Sensitivity to GHG [β] Low	Medium	High
Low	19%	24%	25%
Medium	12%	13%	13%
High	12%	12%	12%

Carbon Tax [AR] 20% 50%
Carbon Tax [ER] 20% 50%
R&D Subsidy [AR] 50% 200%
GCF Co-R&D Subsidy [ER] 50% 200%
Tech Subsidy [AR] 5% 15%
GCF Co-Tech Subsidy [ER] 5% 15%

NOTES: The left panes describe changes in the structure of the optimal policy in the advanced region (AR) and the right panes describe changes in the emerging region (ER) for the comprehensive GCF based policy regime (P7). The top panes show results for the individual carbon taxes, the middle panes for R&D subsidies and the bottom pane for technology subsidies. Uncertainty values are described using three bins; for the elasticity of substitution these bins are defined as low, medium: [5:8) and high: [8:10); for climate sensitivity these bins are defined as low:[3:5) , medium:[5:6) and high: [6,7). The legend of each cell represents the mean value of the policy element for the subset of futures describe by the intersecting bins (elasticity of substitution and climate sensitivity). The color legend denotes the effort level of the policy response: colors towards red denote higher effort policies; colors toward green denote lower effort policies.

Figure 4.12
Changes In Optimal Response's Structure Across Different Elasticity of Substitution and Climate Sensitivity Scenarios - P7. H. Carbon Tax + Co-Tech-R&D [GCF]-



NOTES: The left panes describe changes in the structure of the optimal policy in the advanced region (AR) and the right panes describe changes in the emerging region (ER) for the comprehensive GCF based policy regime (P7). The top panes show results for the individual carbon taxes, the middle panes for R&D subsidies and the bottom pane for technology subsidies. Uncertainty values are described using three bins; for the elasticity of substitution these bins are defined as low, medium: [5:8) and high: [8:10); for climate sensitivity these bins are defined as low:[3:5) , medium:[5:6) and high: [6,7). The legend of each cell represents the mean value of the policy element for the subset of futures describe by the intersecting bins (elasticity of substitution and discount rate). The color legend denotes the effort level of the policy response: colors towards red denote higher effort policies; colors toward green denote lower effort policies.

There results show that for this policy regime, the elasticity of substitution is more influential in determining the structure of GCF environmental policy than the other two uncertainties considered (i.e. climate sensitivity and discount rate). These patterns show that the influence of the speed of temperature rise and the discount rate is more noticeable for the low elasticity of substitution scenarios than it is for the medium and high elasticity of substitution scenarios.

Contrasting the results described in Figure 4.11 and Figure 4.12 against the results displayed in Figure 4.9 and Figure 4.10 points at important differences in the structure of the optimal policy between the two policy regimes. These results show that under the GCF (i.e. P7) the level of carbon taxation reduces for both regions compared to the level of taxation in the non-cooperative policy regime (i.e. P2.). It is also possible to see that under the GCF, the optimal level of effort in R&D and technology subsidies in the emerging region is one average higher than the optimal level of effort in the non-cooperative policy regime. This indicates that under the GCF, it is feasible for the emerging region to make higher investments in R&D and technology subsidies and reduce the rate of taxation. Similarly, for the advanced region it shows that it is possible to reduce the level of carbon taxation by co-funding R&D and technology subsidies in the emerging region. Finally, the results show that in the most adverse scenarios under the GCF (i.e. low elasticity of substitution and high climate sensitivity) optimal environmental regulation requires higher R&D and technology subsidies in the emerging region than in the advanced region.

IV.3.3 Identifying Decision-Relevant Scenarios

In this section I use scenario discovery methods (Bryant and Lempert, 2010) to understand in more detail the conditions under which the different policy regimes considered in the analysis fail to meet the CO_2 stabilization targets and/or the temperature rise targets.

For each policy regime, I classify simulation outcomes into two groups: 1) future scenarios in which the policy target is met and 2) future scenarios in which the policy target is not met. Then I use scenario discovery cluster-finding algorithms that parse the simulation database to provide a concise description of the uncertainty conditions under which the optimal policy response meets the climate change targets.

This process is done iteratively using various combinations of statistical characterizations of the uncertainties with the objective of describing the sets of vulnerable futures in a concise and decision-relevant cluster.

In scenario discovery, three statistical measures are used to describe the suitability of a decision relevant cluster. Coverage is the percent of total vulnerable futures that are represented by the cluster. Density is the percent of futures within the cluster that are vulnerable.

Interpretability is the ease by which the uncertainty conditions that defined the cluster can be communicated to policy audiences (e.g. decision makers, relevant stakeholders). Generally, the fewer dimensions used by the cluster, the easier its interpretation. In this monograph I use a classification algorithm called PRIM (Patient Rule Induction Method)(Friedman and Fisher, 1999) to support this scenario discovery exercise.

End-of-Century CO_2 Stabilization at 2 °C

I focus first on using scenario discovery to understand the futures in which end-of-century CO_2 stabilization at 2 °C is no met. These are futures in which CO_2 stabilization is not achieved and in which end-of-century temperature rise is above 2 °C. From a policy perspective, these vulnerable futures are relevant because these can illuminate the vulnerabilities of the optimal policy response in meeting the most ambitious climate change policy target.

Figure 4.13 shows the results of this clustering analysis. The figure shows a series of scatter plots of all futures for different policy regimes. Filled circles show non vulnerable cases, where the CO_2 stabilization and temperature rise targets are met, and open circles indicate futures in which one of these two targets is not met. These futures are plotted across the two uncertainty dimensions that are found to be most relevant using PRIM: 1) the elasticity of substitution and 2) the climate sensitivity to GHG[8]. High values of the elasticity of substitution describe scenarios in which the technologies across sectors are highly substitutable, which are more favorable for climate policy. Low values of the elasticity of substitution denote scenarios in which sectors are less substitutable, which makes it harder to move away from fossil energy. For the case of climate sensitivity, high values describe climate scenarios in which global temperature rises rapidly with growing CO_2, thus making it harder to keep temperature levels below the 2 °C target. Low values are associated with climate scenarios for which global temperature rises less abruptly with growing CO_2 emissions. Finally, the shaded regions highlighted in red and orange were selected using scenario discovery to describe these sets of vulnerable futures.

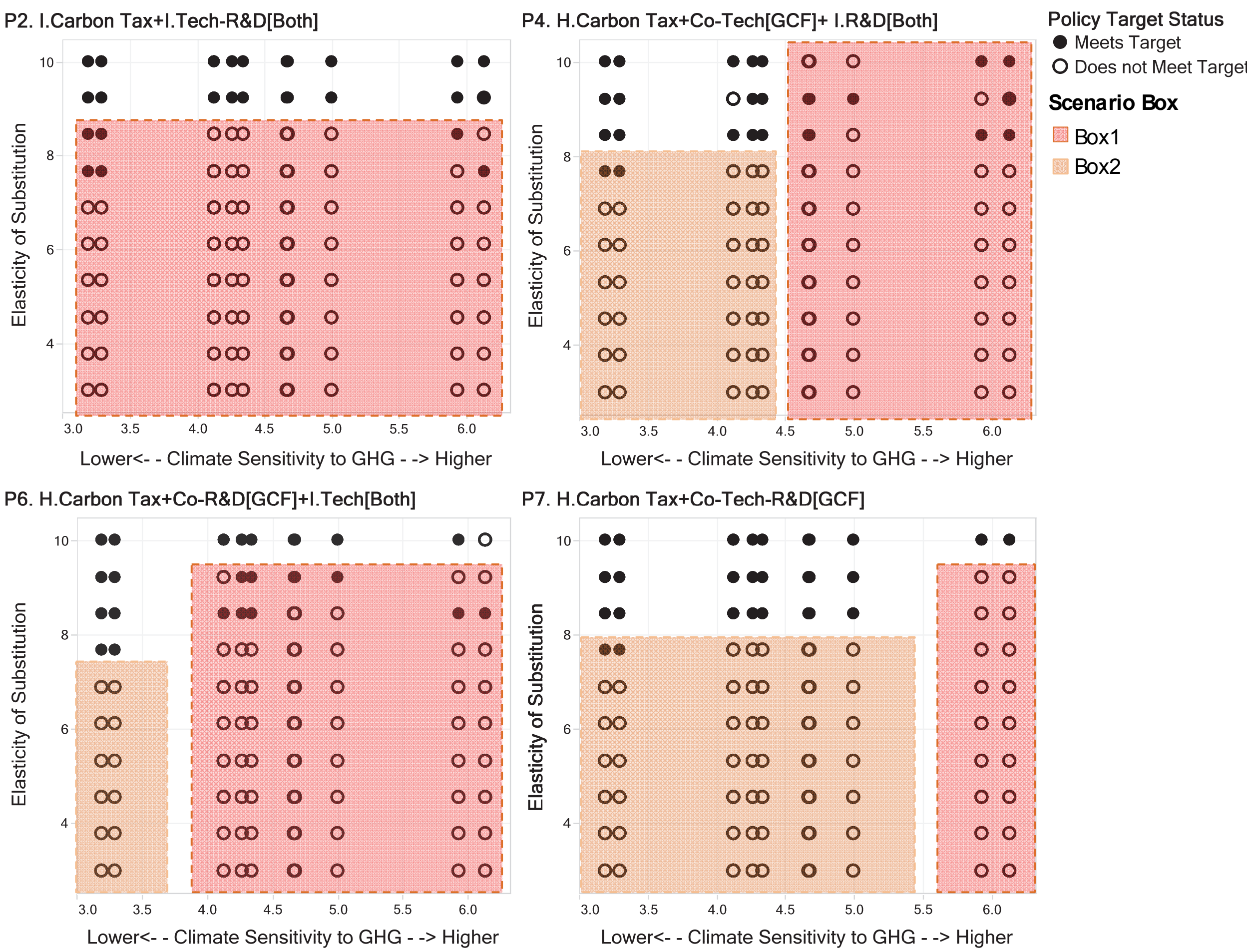
These shaded regions define decision-relevant scenarios that best describe the vulnerability conditions of each policy. Table 4.4 provides a detailed description of the boundary conditions of each scenario box, as well as the corresponding coverage and density statistics that describe to which extend these scenario boxes adequately capture the vulnerable conditions of each policy.

The results presented in Figure 4.13 and Table 4.4 show that the vulnerability region varies slightly across the different environmental policy regimes. For the independent

[8] Climate sensitivity to GHG is represented by the value of parameter "β" in equation *(e3)*. Thus this parameter describes how much temperature rises for a fixed level of CO_2 emissions. More adverse climate scenarios are associated with higher values of "β", less adverse climate scenarios are represented by lower values of "β".

comprehensive policy *("P2 I. Carbon Tax+I. Tech-R&D[Both]")*, the vulnerability region is defined solely by the elasticity of substitution. The optimal policy under this regime fails to meet the stabilization target in all scenarios that do not display a high elasticity of substitution. For the other three policy regimes, the vulnerability region is described both by the elasticity of substitution and climate sensitivity. Scenario box 1 describes "high climate sensitivity futures", while Scenario box 2 describes "medium-to-low elasticity of substitution scenarios". Differences in the vulnerable region exists among these three policy architectures, namely that the comprehensive GCF policy (*"P7. H. Carbon Tax +Co-Tech-R&D[GCF]")* shows a greater area of success than the other three policy architectures.

Figure 4.13
PRIM Boxes Describing Decision Relevant Scenarios



NOTES: Filled circles show non vulnerable cases, where the CO2 stabilization and temperature rise targets are met, and open circles indicate futures in which one of these two targets is not met. These futures are plotted across the two uncertainty dimensions that are found to be most relevant using PRIM: 1) the elasticity of substitution and 2) the climate sensitivity to GHG.

Table 4.4
Scenario Discovery Analysis Summary Results For Stabilization Target

Policy Name	Scenario Box	Scenario Description	Coverage	Density
P2. I. Carbon Tax + I. Tech-R&D[Both]	Box1	• Elasticity of Substitution < 9.0	99% (445/447)	93% (413/447)
P4. H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both]	Box1	• Climate Sensitivity to GHG >4.5	53% (237/447)	80% (190/237)
	Box2	• Elasticity of Substitution <8.0 • Climate Sensitivity to GHG <4.5	45% (202/447)	95% (182/202)
P6. H. Carbon Tax + Co-R&D[GCF]+ I.Tech[Both]	Box1	• Elasticity of Substitution <9.5 • Climate Sensitivity to GHG >4.0	86% (392/455)	87% (341/392)
	Box2	• Elasticity of Substitution <7.6 • Climate Sensitivity to GHG <4.0	13% (60/455)	100% (60/60)
P7. H. Carbon Tax + Co-Tech-R&D[GCF]	Box1	• Elasticity of Substitution <9.5 • Climate Sensitivity to GHG >5.5	30% (130/435)	97% (126/435)
	Box2	• Elasticity of Substitution <8.0 • Climate Sensitivity to GHG >5.5	70% (305/435)	97% (296/305)

NOTES: The table summarizes the statistical properties (i.e. coverage and density) of the scenario boxes describing the vulnerability conditions of each policy regime. The quantitative thresholds defining each scenario box are listed.

These results also show that out of the three uncertainties considered in this analysis: 1) elasticity of substitution, 2) climate change uncertainty and 3) the discount rate, only the first two determine whether or not the optimal policy achieves the objective of stabilizing CO_2 emissions at sustainable levels before the end of the century. Arguably, out of these two factors, the elasticity of substitution plays a more fundamental role in determining the vulnerability of the policy response, as all scenarios that display medium to low elasticity of substitution are vulnerable across all policy regimes, while high speed temperature rise scenarios induce vulnerability at high elasticity of substitution scenarios for three out of the four policy regimes considered.

End-of-Century 2 °C Temperature Rise Target

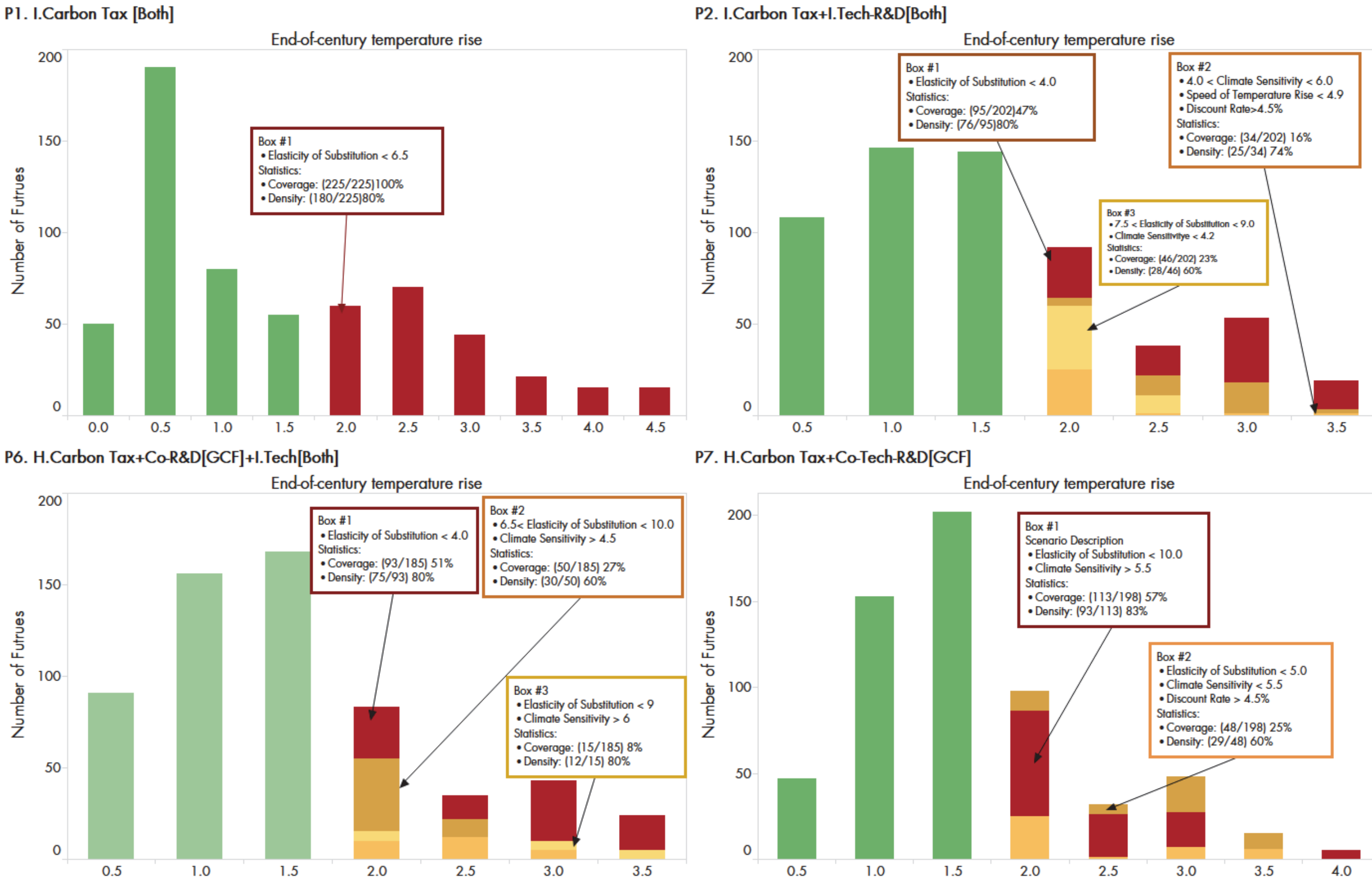
The end-of-century 2 °C temperature rise target is met in a greater number of futures than the stabilization target. This implies that the former is a more achievable target than the later. Certainly, meeting the stabilization target would be highly beneficial as this would imply that climate change would not be a prevailing public policy problem after the end of the century; however, the results show that this target is met only under very favorable economic and environmental circumstances.

From a policy perspective, the 2 °C temperature rise target is also very relevant because although climate regulation would still be necessary after the end of the century, meeting this objective would guarantee that temperature rise levels would remain within sustainable limits during this century.

Scenario discovery results for this type of vulnerability are presented in Figure 4.14. Each pane displays a histogram describing the temperature rise target results across the 600 futures considered for each policy regime. The histograms are colored to signify the futures that are described by the different scenario boxes identified (red, orange and light yellow) and those futures that are not vulnerable (green). Boundary conditions and the corresponding statistics are highlighted for each scenario box.

These results show that the elasticity of substitution is also highly influential in determining vulnerability conditions. For instance, the vulnerability of the independent carbon tax regime ("*P1: I. Carbon Tax [Both*]") with respect to the 2 °C temperature rise target can be described entirely by those scenarios that display medium-to-low elasticity of substitution. For the other more comprehensive policy regimes, vulnerability conditions of the optimal policy are described by three different scenario cluster: 1) low elasticity of substitution, 2) medium elasticity of substitution and high speed of temperature rise, and 3) high discount rate scenarios.

Figure 4.14
Scenario Discovery Analysis Summary Results For Temperature Rise Target



NOTES: Each pane displays a histogram describing the temperature rise target results across the 600 futures considered for each policy regime. The histograms are colored to signify the futures that are described by the different scenario boxes identified (red, orange and light yellow) and those futures that are not vulnerable (green). Boundary conditions and the corresponding statistics are highlighted for scenario box.

IV.4 Robust Mapping of Optimal Policy Response

The exploratory analysis describes vulnerability conditions individually for each policy regime for the two relevant objectives considered. These results also show that for some futures it is possible to meet the climate policy objectives using different policy regimes. Thus, it is also important to analyze under which uncertainty conditions one policy regime is preferred over the other.

In line with the RDM framework, I employ the robustness criteria developed by Lempert et al. (2006) to map the alternative policy regimes across the uncertainty space under consideration. For this mapping process, I calculate the performance regret of alternative strategies. This regret metric is the difference between the performance of a future strategy, given a value a function, and the best performing strategy for that same future. Formally:

$$Regret(j,f) = Max_{j'}[V(j',f)] - V(j,f) \qquad \textit{(e46)}$$

where "j" refers to one of the policy regimes under consideration (i.e. Table 4.2), "f" refers to a particular future (i.e. combination of uncertainties) and "V()" denotes the value function use to evaluate the performance of alternatives strategies. In my modeling framework, this value function is given by:

$$V(j,f) = \int_0^{100} \frac{1}{(1+\rho)^t}\left(u_{j,f}^A + u_{j,f}^E\right)dt \qquad \textit{(e47)}$$

where $u_{j,f}^A$ and $u_{j,f}^E$ denote the utility of consumers in the advanced and emerging regions for policy regime "j" and future "f". Note that as defined in equation (*e19)*, consumers' utility is a function of the level of consumption and the quality of environment. This means that under this value function, the performance of each policy regime is evaluated in terms of both its environmental and economic costs.

Finally, for each future "f", I compare performance regret of all policy regimes and choose the policy alternative "j" that minimizes regret, formally:

$$Policy\ Regime(f) = Min_{j'}[Regret(j,f)] \qquad \textit{(e48)}$$

Figure 4.15 depicts the results of this mapping process. Each cell in this map describes the intersection of different uncertainty conditions. In this map, I transform the continuous uncertainty dimensions into categorical levels. For each uncertainty dimension, these levels are defined as follows:

$$lasticity\ of\ Substitution: \begin{cases} low: & \varepsilon < 5.3 \\ medium: & 5.3 \leq \varepsilon < 8.0 \\ high: & \varepsilon \geq 8.0 \end{cases}$$

$$Climate\ Sensitvity\ to\ GHG: \begin{cases} low: & \beta < 4.0 \\ medium: & 4.0 \leq \beta < 5.0 \\ high: & \beta \geq 8.0 \end{cases}$$

$$Discount\ Rate: \begin{cases} low: & \rho < 0.5\% \\ medium: & 0.5\% \leq \rho < 1\% \\ high: & \rho \geq 1.0\% \end{cases}$$

The label and the color legend in each cell denote the corresponding least regret policy. Rows describe the different elasticity of substitution bins. Columns denote combinations of climate sensitivity and discount rate scenarios.

The results presented in Figure 4.15 show that under this mapping framework, GCF cooperation represented by policy regimes P3 through P7 is always preferred over non GCF cooperation, which is represented by policy regimes P1 and P2. The results also show that only under few scenarios the discount rate influences the least regret policy selected. For instance, for futures that combine high climate sensitivity and medium substitution, the least regret policy for the high discount rate scenarios is *"P4: H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both]",* while for the low and medium discount rate scenarios, the least regret policy is *"P6: H. Carbon Tax + Co-R&D[GCF]+I. Tech[Both]"*. Then for this combination of elasticity of substitution and climate sensitivity conditions, it is possible to see that the discount rate determines the focus of GCF cooperation. For discount rate scenarios in which short-term outcomes are more important (i.e. high discount rate), then the least regret policy regime selected (i.e. "P4") uses the GCF for co-funding of technology subsidies, while each region independently funds their R&D policy programs. In contrast, for discount rate scenarios in which long-term outcomes are more important (i.e. low and medium discount rates), then the focus of cooperation changes from co-funding of technology subsides to co-funding of R&D programs.

This map also highlights the role of the elasticity of substitution and of climate sensitivity in determining the least regret policy. In the first case, it is possible to see that the degree of cooperation is inversely proportional to the elasticity of substitution, this is: the lower the elasticity of substitution, the higher the level of cooperation. In the second case, the level of cooperation is proportional to the level of climate sensitivity: the higher the climate sensitivity, the higher the level of cooperation, the exceptions are those cases in which the discount rate also influences the least regret policy selected.

These mapping of alternatives shows that cooperation through the GCF is the least-regret policy alternative to achieve the CO_2 stabilization and/or the two degrees Celsius temperature rise targets. However, the cost and effectiveness of cooperation changes across the uncertainty space, such that full cooperation is the more robust alternative under the "low elasticity of substitution and low climate sensitivity" scenarios and under the "medium elasticity of substitution and medium climate sensitivity" scenarios. The simplest policy regime *"P3: H. Carbon Tax + Co-Tech[GCF]+R&D[AR]"* is the least-regret alternative only under the most favorable scenario: "high elasticity of substitution and low climate sensitivity", while for the remaining scenarios, the policy regime *"P4: H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both]"* is the policy most frequently selected.

Figure 4.15
Robust Mapping of Policy Alternatives

	Low Climate Sensitivty			Medium Climate Sensitivity			High Climate Sensitivity		
	Low Discount Rate	Medium Discount Rate	High Discount Rate	Low Discount Rate	Medium Discount Rate	High Discount Rate	Low Discount Rate	Medium Discount Rate	High Discount Rate
High Substitution	*P3*	*P3*	*P3*	*P4*	*P4*	*P4*	*P4*	*P4*	*P4*
Medium Substitution	*P4*	*P4*	*P4*	*P7*	*P7*	*P7*	*P6*	*P6*	*P4*
Low Substitution	*P7*	*P7*	*P7*	*P7*	*P4*	*P3*			

NOTES: Each cell in this map describes the intersection of different uncertainty conditions. The label and the color legend denote the corresponding least regret policy. Rows describe the different elasticity of substitution bins. Columns denote combinations of climate sensitivity and discount rate scenarios.

IV.5 Summary

This chapter describes an RDM study that focuses on understanding the role that climate change deep uncertainty has on the structure and effectiveness of optimal environmental regulation across advanced and emerging regions.

The EDIAM model is used as the scenario generator in this RDM study. The scope of the computational experiment in the study considers eight different policy regimes and six hundred different futures. These scenarios combine three sources of uncertainty: climate change, elasticity of substitution and discount rate uncertainty. The performance of the different policy regimes is evaluated in terms of the end-of-century conditions. Particularly, the performance of each policy regime is evaluated in terms of its capacity to meet two climate change objectives: 1) the stabilization of CO_2 emissions and 2) the two degrees Celsius temperature rise target.

The analysis shows that the structure of optimal environmental regulation changes markedly across the uncertainty space. The results show that the optimal policy response is most affected by climate uncertainty and the elasticity of substitution uncertainty. In particular, the strength of the optimal policy response is directly proportional to the level of climate sensitivity to GHG, and inversely proportional to the gross elasticity of substitution between the sustainable energy and fossil energy sectors. I also show that the discount rate does affect the structure of the optimal policy response, but its influence is less significant when compared to the influence of climate sensitivity and gross substitution.

The comparison of GCF based policy regimes and non-GCF policy regimes shows that the GCF does affect the structure of environmental regulation. These results show that under the GCF the level of carbon taxation reduces for both regions compared to the level of taxation in the non-cooperative policy regimes. Also under the GCF, the optimal level of effort in R&D and technology subsidies in the emerging region is one average higher than the optimal level of effort in the non-cooperative policy regime. This indicates that under the GCF, it is feasible for the emerging region to make higher investments in R&D and technology subsidies and reduce the rate of taxation. Similarly, for the advanced region it is shown that it is possible to reduce the level of carbon taxation by co-funding R&D and technology subsidies in the emerging region.

Scenario discovery methods (Bryant and Lempert, 2010) are used to describe the vulnerability conditions of the different policy regimes. These results show that the objective stabilizing CO_2 emissions below two degrees Celsius before the end of the century is rarely met. Two decision relevant scenarios describe this type of vulnerability: 1) high climate sensitivity to GHG and 2) medium-low elasticity of substitution. In contrast, the two degrees Celsius temperature rise target without CO_2 stabilization is met in a greater number of cases. For both types of vulnerability the role of discount rate in defining the vulnerability conditions is found to be minimal.

Finally, I implement robustness criteria to map the least-regret policy across the entire uncertainty space. This mapping process shows that cooperation through the GCF is the least-regret policy alternative to achieve the CO_2 stabilization and/or the two degrees Celsius temperature rise targets. Yet, it is shown that the architecture of cooperation changes across the uncertainty space, such that full cooperation is the more robust alternative under the “low elasticity of substitution and low climate sensitivity” scenarios and under the “medium elasticity of substitution and medium climate sensitivity” scenarios, while for the majority of scenarios, the policy regime “P4” which combines GCF-technology subsidies and independent R&D efforts across regions is found to be most robust policy regime.

CHAPTER V

Mapping Optimal Climate Policy Across Multiple Climate and Technological Scenarios

V.1 Introduction

This chapter presents an expansion of the RDM study described in chapter four. This expansion focuses on analyzing the interplay of climate and technological uncertainty in the context of optimal environmental regulation across advanced and emerging nations. In addition, in this chapter I used recent expansions of RDM methods and concepts for developing a dynamic architecture of cooperation under the GCF.

In section V.2 I describe how RDM methods can be combined with integrated assessment models (IAMs) to analyze jointly climate change and technological uncertainties. I also describe the expanded elements of this RDM study. The uncertainties (X) considered include 12 CMIP5 climate change scenarios and 300 scenarios which combine different elasticity of substitution and technological properties, yielding a total of 3,600 different futures. Eight policy regimes (L) and two climate change policy targets are taken into consideration (M) in the analysis and the EDIAM model (R) is used as the scenario generator in this study. A set of illustrative simulation runs show that technological uncertainty on its own merit can have significant impacts on the structure and effectiveness of optimal environmental regulation.

The analysis presented in section V.3 describes how the structure of the optimal policy response changes across the uncertainty space and how the GCF based policy regimes influence the structure and effectiveness of policy intervention. I find that the structure of optimal environmental regulation is strongly influenced by the GCF, such that in the most adverse climate and technological futures, the GCF enables a stronger policy response in the emerging region which would not be possible otherwise. Yet, I also find that under the most favorable scenarios, comprehensive GCF cooperation may lead unnecessarily to high cost policy interventions.

In section V.4 I combine traditional scenario discovery methods (Bryant and Lempert, 2010) with high-dimensional stacking methods (Suzuki, Stern and Manzocchi, 2015; Taylor et al., 2006; LeBlanc, Ward and Wittels, 1990) for describing the vulnerability conditions of different policy regimes. This yields quantitative descriptions of the vulnerability conditions of different policy regimes. The results show that the objective of stabilizing CO_2 emissions before the end of the century is met under a limited number of futures that describe favorable climate and technological conditions. In contrast the two degrees Celsius target (without CO_2 stabilization) can be met in a greater number of futures.

I also find that different policy regimes are more effective under different uncertainty conditions and that for various scenarios it is possible to meet the climate change targets through more than one policy regime. I use robustness criteria to map the least cost regret policy response across the uncertainty space. This mapping process shows that that there is not one single policy regime that dominates over the entire uncertainty space. On the contrary, my analysis shows that by combining different types of policy architectures (i.e. GCF based and non-GCF based) it is possible meet one or the two climate change policy targets in a greater number of futures.

Finally, in section V.6, I describe a method by which it is possible to combine the results of scenario discovery and of the robust mapping analysis to construct a dynamic architecture of low cost technological cooperation. This dynamic architecture consists of adaptive pathways that describe near-term actions and different effort levels of technological cooperation that are triggered with unfolding climate and technological conditions.

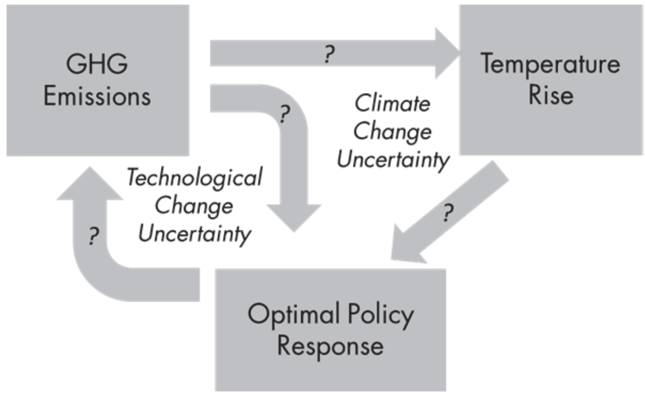
V.2 Addressing the Uncertainty Loop in IAMs Using RDM Methods

In this chapter I expand the RDM analysis presented thus far by considering the interaction of both climate and technological uncertainty. As in the case of other IAMs considering technological and climate deep uncertainty is relevant for the modeling framework described in chapter three. The interaction of these two sources of uncertainty in IAMs is commonly referred as the IAMs' uncertainty loop (Roberts, 2015).

Figure 5.1 describes the workings of this uncertainty loop in the context of the EDIAM modeling framework. The arrows indicate the links among the different elements in the system. The technological and climate change feedbacks are indicated such that these two sources of uncertainty affect both the structure and the effectiveness of the optimal policy response.

Figure 5.1 indicates that different technological scenarios lead to different feasible greenhouse emission levels. Similarly, for a fix level of GHG emissions, different climate scenarios describe different plausible temperature rise levels. Figure 5.1 also shows that both sources uncertainty endogenously determine the structure of the optimal policy response in the modeling framework used in this RDM study. For instance, as shown in chapter four, the intensity of the optimal policy response is proportional to the climate sensitivity of different climate change scenarios: the more sensitive the climate system is to GHG emissions, the more intense is the policy response.

Figure 5.1
Climate Uncertainty Loop In The Context Of The Optimal Policy Response



NOTES: Each box represents a different element of the modeling framework used in this study. The arrows link these different elements to describe the circular causality links (i.e. loops) that influence the structure and effectiveness of the policy response. The question marks indicate that deep uncertainty is associated with these causal links.

Technological change uncertainty also influences the structure of the policy response in a similar way. However, in this case, the technological characteristics of both the SETs sector and the FETs sector simultaneously determine the intensity of the policy response. For instance, if the technological characteristics of the SETs sector are more favorable for innovation than the characteristics of the FETs sector, then the intensity of the policy response is lower than in the case in which the FETs sector displays more favorable technological characteristics.

In the context of climate change policy it is fundamental to study how different policy proposals are affected by the dynamics of this uncertainty loop. In this chapter, I use RDM methods to study the implications of these two uncertainty sources in the context of different proposals for international optimal environmental regulation and cooperation. For this, I expand the RDM analysis described in chapter four by considering also different technological scenarios for the SETs and FETs technological sectors.

V.2.2 Technological Change Uncertainty (X)

I describe the technological characteristics of innovation in the SETs and FETs sectors through three different properties. R&D returns (i.e. parameter "γ" in equation *e23* and *e24*) describe the average positive change in technological productivity yield by R&D investments in a particular sector. Innovation propensity (i.e. parameter "η" in equation *e23*) describes the probability of developing and successfully commercializing new energy technologies in a particular sector. Finally, transferability (i.e. parameter "ν" in equation *e24*) describes emerging regions' capacity to successfully imitate and adapt foreign energy technologies in its energy market.

I use these technological properties to develop a large set of technological scenarios and study the implications of these scenarios in the structure and effectiveness of the optimal policy response. The resulting ensemble is diverse and complex as it considers interactions of these characteristics across both technological sectors. For instance, by combining these technological properties it is possible to develop scenarios in which the transferability of SETs is higher than the transferability of FETs, but that at the same time, R&D returns and innovation propensity are higher in the FETs sector.

In order to illustrate the potential effects that these alternative technological scenarios may have in the context of the optimal policy response across regions, in the following paragraphs I describe the sensitivity of the system across each one of these technological properties.

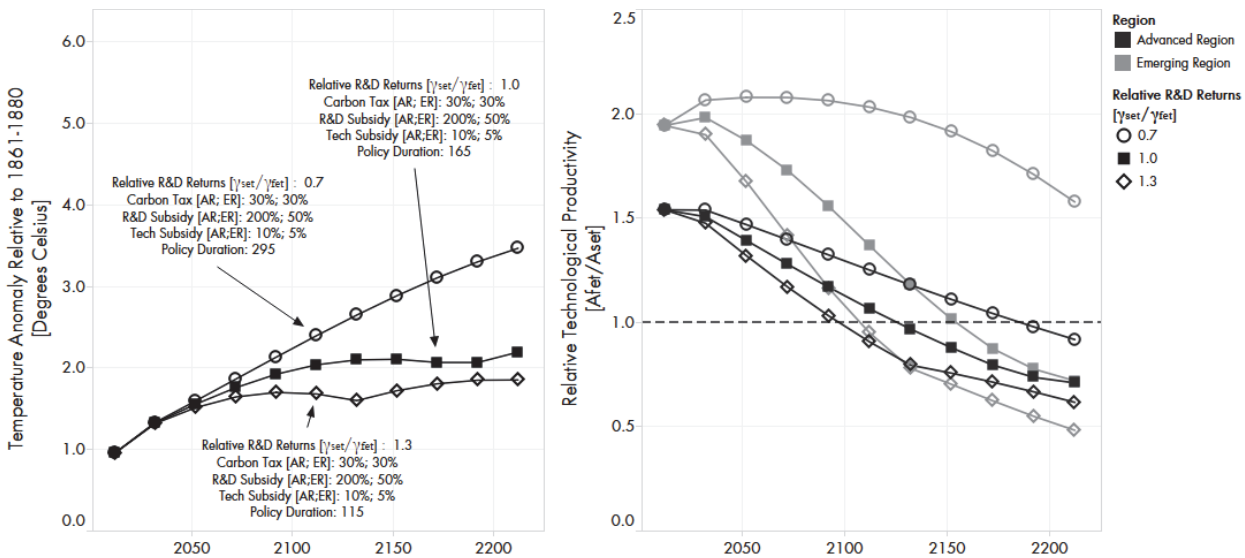
Returns to R&D

I explore the potential implications of varying levels of R&D returns across both technological sectors by considering three contrasting scenarios. The first scenario depicts a condition in which the R&D returns in SETs are lower than in FETs (i.e. $\gamma_{set}/\gamma_{fet}$=0.7). The second scenario considers a condition in which the R&D returns across both sectors are equal (i.e. $\gamma_{set}/\gamma_{fet}$=1.0). The third scenario describes the case in which R&D returns in are higher in SETs than in FETs.

Figure 5.2 presents simulation results for these three technological change scenarios. For these simulations runs all other parameters are held constant, including the other two technological parameters (i.e. $\eta_{set}= \eta_{fet}$=0.02 and $\nu_{set}= \nu_{fet}$=0.02). Thus these results focus on exemplifying the effect that alternative R&D returns scenarios can have on the structure of the optimal policy response and on the dynamics of technological change across both regions. The left pane describes temperature rise dynamics for the three technological scenarios (shape legend); the structure of the optimal policy response is indicated for the three scenarios. The right pane presents for each scenario the dynamics of technological change in the emerging region (grey lines) and in the advanced region (black lines). In the latter, technological change dynamics are represented by comparing the technological productivity of both sectors (i.e. A_{fet}/A_{set}). The dash line indicates the threshold at which both technological sectors are equally productive.

Figure 5.2 shows that alternative R&D returns scenarios can yield quite different outcomes. For instance, the simulation results between the scenarios of low relative R&D returns (i.e. $\gamma_{set}/\gamma_{fet}$=0.7) and the high relative R&D returns (i.e. $\gamma_{set}/\gamma_{fet}$=1.3) display differences in the structure of the optimal policy response and also in the dynamics of temperature rise and technological change. In the first case (i.e. $\gamma_{set}/\gamma_{fet}$=0.7) temperature rise continues rising, while in the second case (i.e. $\gamma_{set}/\gamma_{fet}$=1.3) temperature rise is kept below the 2 °C target. The structure of the optimal policy response displays a notable difference in terms of the duration of policy intervention, differing by over one hundred years across both scenarios.

Figure 5.2
Effect of Different Relative R&D Returns ($\gamma_{set}/\gamma_{fet}$) Scenarios on Optimal Policy Response's Structure and Effectiveness



NOTES: The figure describes the effect that different R&D returns scenarios can have on the structure of the optimal policy response and on the dynamics of technological change across both regions. The left pane describes temperature rise dynamics for the three technological scenarios (shape legend); the structure of the optimal policy response is indicated for the three scenarios. The right pane presents for each scenario the dynamics of technological change in the emerging region (grey lines) and in the advanced region (black lines). Technological change dynamics are described by comparing the technological productivity of both sectors (i.e. Afet/Aset). The dash line indicates the threshold at which both technological sectors are equally productive.

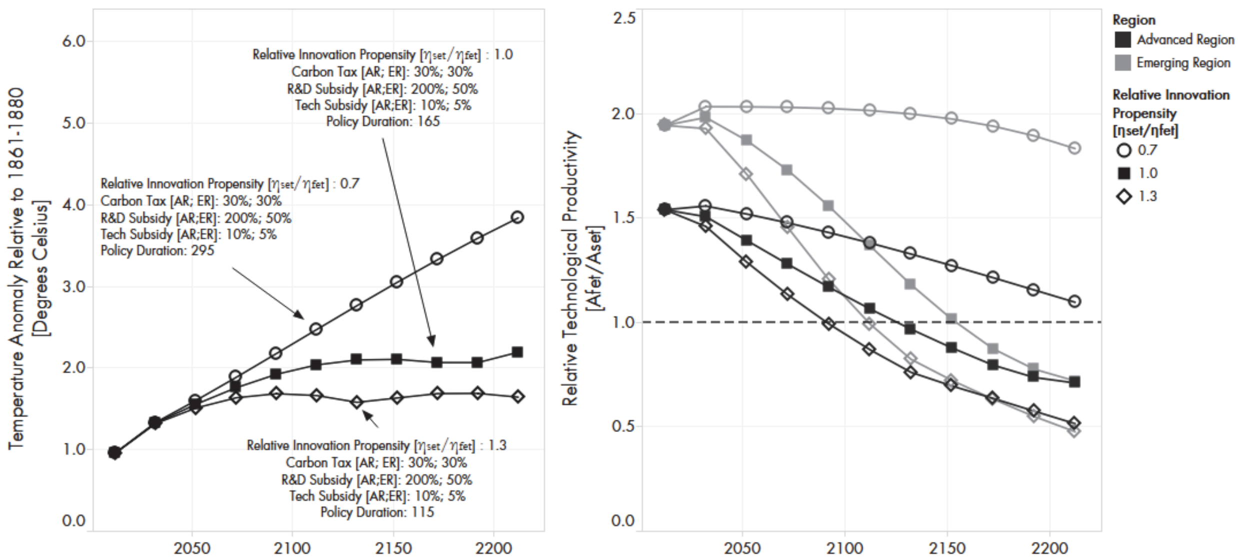
The dynamics of technological change are substantially different across scenarios. In particular it is possible to see that variations in R&D returns have a higher impact in the technological dynamics in the emerging region than in the advanced region. For instance, for the two technological scenarios in which R&D returns in SETs are equal or higher than R&D returns in FETs, it is possible to see that policy intervention accelerates the development of SETs in such a way that its productivity catches-up with the productivity of the FETs sector in relatively the same period of time in both regions. In contrast, for the scenario in which R&D returns are higher in the FETs sector, the time required for matching the productivity of FETs differs significantly across both regions: in the advanced region it takes approximately 150 years to do this, while in the emerging region it takes over 200 years to reach this threshold.

Innovation Propensity

I also explore the implications of considering different innovation propensity scenarios for both sectors. For this, I consider three different scenarios: one scenario in which SETs' innovation propensity is lower than FETs' innovation propensity (i.e. η_{set}/η_{fet}=0.7), another scenario in which the innovation propensity is the same in both sectors (i.e. η_{set}/η_{fet}=1.0) and a final scenario in which SETs' innovation propensity is higher than FETs' innovation propensity (i.e. $\gamma_{set}/\gamma_{fet}$=1.3).

Figure 5.3 presents the simulations results for these three scenarios using the same layout as in the experiment described above. Similarly, for these simulations runs all other parameters are held constant, including the other two technological parameters (i.e. $\gamma_{set}= \gamma_{fet}=0.25$ and $\nu_{set}= \nu_{fet}=0.02$). These simulations highlight the potential impact that different levels of innovation propensity can have in the policy response and the resulting technological transition dynamics.

Figure 5.3
Effect of Different Relative Innovation Propensity (η_{set}/η_{fet}) Scenarios on Optimal Policy Response's Structure and Effectiveness



NOTES: The figure describes the effect that different innovation propensity scenarios can have on the structure of the optimal policy response and on the dynamics of technological change across both regions. The left pane describes temperature rise dynamics for the three technological scenarios (shape legend); the structure of the optimal policy response is indicated for the three scenarios. The right pane presents for each scenario the dynamics of technological change in the emerging region (grey lines) and in the advanced region (black lines). Technological change dynamics is described by comparing the technological productivity of both sectors (i.e. Afet/Aset). The dash line indicates the threshold at which both technological sectors are equally productive.

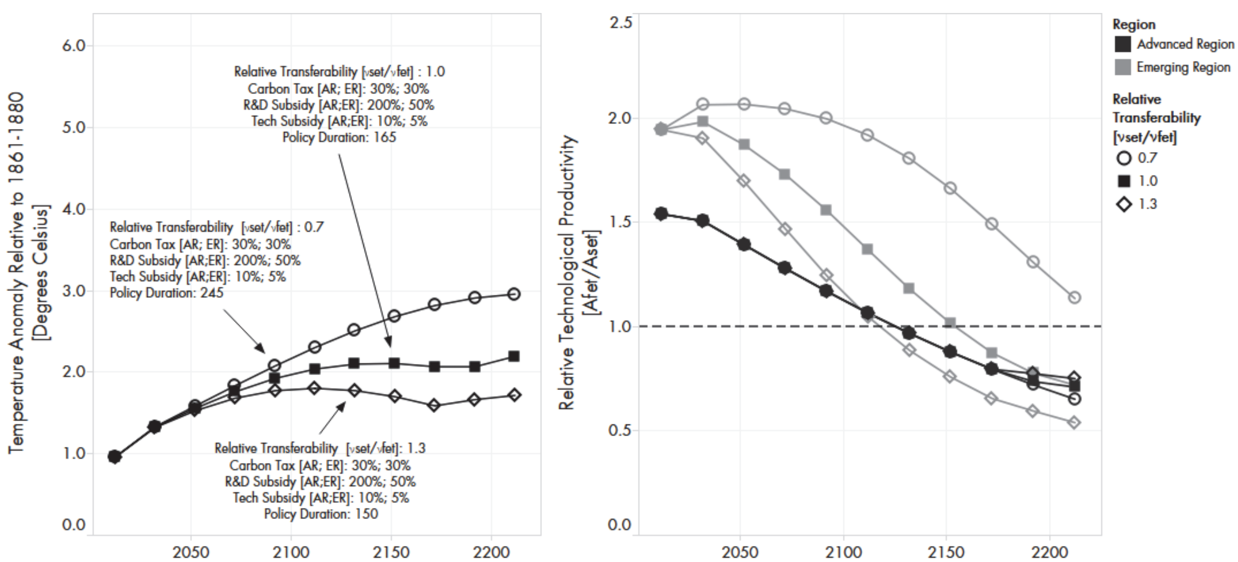
As expected, the results displayed in Figure 5.3 show that different innovation propensity scenarios can also lead to very different outcomes. In fact, the effect of alternative innovation propensity scenarios on the structure and on the effectives of the optimal policy response is very similar to the effect of different R&D returns scenarios. For instance, the left pane also shows that temperature rise trajectories are diverging across scenarios, while the right pane shows that technological change dynamics in the emerging region are more influenced by alternative innovation propensity scenarios than the technological dynamics in the advanced region.

Technological transferability

Finally I explore the potential impact of alternative transferability scenarios. In a similar fashion to the previous two cases, I compare simulations results across three different transferability scenarios. The first scenario describes a condition in which the transferability of FETs is higher than the transferability of SETs (i.e. ν_{set}/ν_{fet}=0.7). The second scenario considers the case in which transferability is the same across both sectors (i.e. ν_{set}/ν_{fet}=1.0). Finally, the third scenario describes a condition in which the transferability of SETs in higher than the transferability of FETs (i.e. ν_{set}/ν_{fet}=1.3).

Figure 5.4 displays the simulations results for these three illustrative technological scenarios. In the same fashion as in the previous two cases, for these simulation runs the other technological parameters are held constant (i.e. γ_{set}= γ_{fet}=0.25 and η_{set}= η_{fet}=0.02). Therefore, these results illustrate the potential effect that alternative transferability levels can have on the structure and on the effectiveness of optimal environmental regulation.

Figure 5. 4
Effect of Different Relative Transferability (ν_{set}/ν_{fet}) Scenarios on Optimal Policy Response's Structure and Effectiveness



NOTES: The figure describes the effect that different transferability scenarios can have on the structure of the optimal policy response and on the dynamics of technological change across both regions. The left pane describes temperature rise dynamics for the three technological scenarios (shape legend); the structure of the optimal policy response is indicated for the three scenarios. The right pane presents for each scenario the dynamics of technological change in the emerging region (grey lines) and in the advanced region (black lines). Technological change dynamics is described by comparing the technological productivity of both sectors (i.e. Aset/Afet). The dash line indicates the threshold at which both technological sectors are equally productive.

The results presented in Figure 5.4 show that the transferability of technologies from the advanced region to the emerging region can also lead to contrasting outcomes. For instance it is possible to see that for the case in which FETs transferability is higher than SETs transferability, temperature rise continues rising throughout the simulation runs; however, it is worth noting that in comparison to the R&D returns and the innovation propensity scenarios, temperature rise occurs at a slower rate. This less impactful effect occurs because alternative transferability scenarios only affect technological change dynamics in the emerging region.

The right pane in Figure 5.4 shows that when the transferability of FETs is greater than the transferability of SETs, this delays substantially the transition towards SETs in the emerging region. Interestingly, in the opposite case, when the transferability of SETs is higher than the transferability of FETs, it is possible to see that in the emerging region the productivity of SETs crosses over slightly sooner than in the advanced region. This technological transition pattern shows that under this type of transferability scenario optimal environmental regulation induces a more rapid transition towards SETs in the emerging region than in the advanced region. It is important to note that this scenario does not entail that the SETs sector in the emerging region becomes more developed that the SETs sector in the advanced region. In fact, this is not possible because in this modeling framework the technological frontier is only pushed forward by entrepreneurs in the advanced region. Yet, this result shows that even though the SETs and FETs sectors in the emerging region are less developed than those in the advanced region, under these conditions, the SETs sector in the emerging region catches-up faster with the FETs sector.

The preceding discussion is useful to illustrate the potential and interesting effects that alternative technological change scenarios can have on both the structure of optimal environmental regulation across regions and also on the effectiveness of policy intervention. However, it is possible to conduct a much richer exploration of technological uncertainty by combining different values of these technological properties across both sectors. For this purpose, I developed a sample of 300 different combinations of these parameters across the limits describe in Table 5.1 using a Latin Hypercube design. The sample size was defined based on the computational resources available for this research (i.e. 60 CPUs) and based on the resolution level required for conducting the subsequent scenario discovery analysis. For the latter requirement, I compared the resolution of various alterative sample designs and only considered those that provided a sufficient number of scenarios (i.e. more than 100) across different combinations of the uncertainty dimensions. Note that the elasticity of substitution is included in this LHC sample design.

Table 5.1
Parameters' Value Ranges Explored Using LHC Sampling

Parameter Name	Min	Max	Units
ε	3.0	10.0	[1]
η_{set}	0.013	0.027	[per year]
η_{fet}	0.013	0.027	[per year]
γ_{set}	0.17	0.33	[per year]
γ_{fet}	0.17	0.33	[per year]
ν_{set}	0.013	0.027	[per year]
ν_{fet}	0.013	0.027	[per year]

NOTES: The table lists the range of parameters' values explored using LHC sampling to develop the 300 technological scenarios considered in this study.

V.2.3 Expanded Experimental Design

I use the elements described in the previous section to expand the experimental design used in chapter four. This allowed me to conduct a large computational experiment that explores the interplay of different climate change scenarios, different technological scenarios and also different policy architectures. Therefore, I used a mixed experimental design in this study, comprising of both factorial and Latin Hypercube Sampling across the uncertain exogenous factors. This experimental design includes:

- 12 Climate scenarios (full factorial sampling)
- 300 Technological scenarios (LHC sampling)

I considered all possible combinations of these uncertain exogenous factors for developing individual future scenarios, which results in 3,600 different futures.

The eighth policy regimes described in chapter four are analyzed against this common set of futures, yielding a total of 28,800 cases considered. Each simulation case was run using the modeling framework described in chapter three for a period of 300 years. For each inputs combination and policy regime an optimal policy response is estimated. The parameters listed in Table 5.2 are held constant in the experimental design.

Table 5.2
Constant Parameters' Values in Experimental Design

Parameter Name	Value	Parameter Name	Value
α	0.33	ω_{fet}	0
ρ	0.8% [per year]	r^A	0
λ	0.1443	r^E	0
σ	2.0	$Y^A_{set,2012}$	43.5 [Q BTU]
ξ	0.01	$Y^A_{fet,2012}$	191.7 [Q BTU]
δ	0.0018	$Y^S_{set,2012}$	28.2 [Q BTU]
ω_{set}	0	$Y^S_{fet,2012}$	260.7 [Q BTU]

NOTES: Constant parameters' values used in the simulation experiment are listed.

Finally, Table 5.3 summarizes the scope of the experimental design of this study using the XLRM framework.

Table 5.3
XLRM Summary of Climate and Technological Uncertainty Analysis

Uncertainties (X)	Policy Levers (L)
Climate Uncertainty: • 12 Climate Scenarios Technological Uncertainty: • 300 scenarios, combining: o Elasticity of Substitution o R&D Returns SETs o R&D Returns FETs o Innovation Propensity SETs o Innovation Propensity FETs o Transferability SETs o Transferability FETs	• P0. FWA (Future Without Action) • P1. I. Carbon Tax [Both] • P2. I. Carbon Tax + I.Tech-R&D[Both] • P3. H. Carbon Tax + Co-Tech[GCF]+R&D[AR] • P4. H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both] • P5. H. Carbon Tax + Co-R&D[GCF]+Tech[AR] • P6. H. Carbon Tax + Co-R&D[GCF]+I. Tech[Both] • P7. H. Carbon Tax + Co-Tech-R&D[GCF]
System Relationships (R)	**Metrics (M)**
• Exploratory Dynamic Integrated Assessment Model (EDIAM)	• End-of-century temperature rise • Stabilization of GHG emissions • Economic costs of policy intervention

NOTES: The main components of the exploratory analysis are grouped according to four different categories: 1) the deep uncertainty scenarios taken into account (i.e. 12 climate scenarios and 300 technological scenarios), 2) the policy regimes analyzed (i.e. 8 different policy regimes, 3) the system relationship that links actions to consequences (i.e. EDIAM model), and 4) the metrics considered to analyze the performance of different policies.

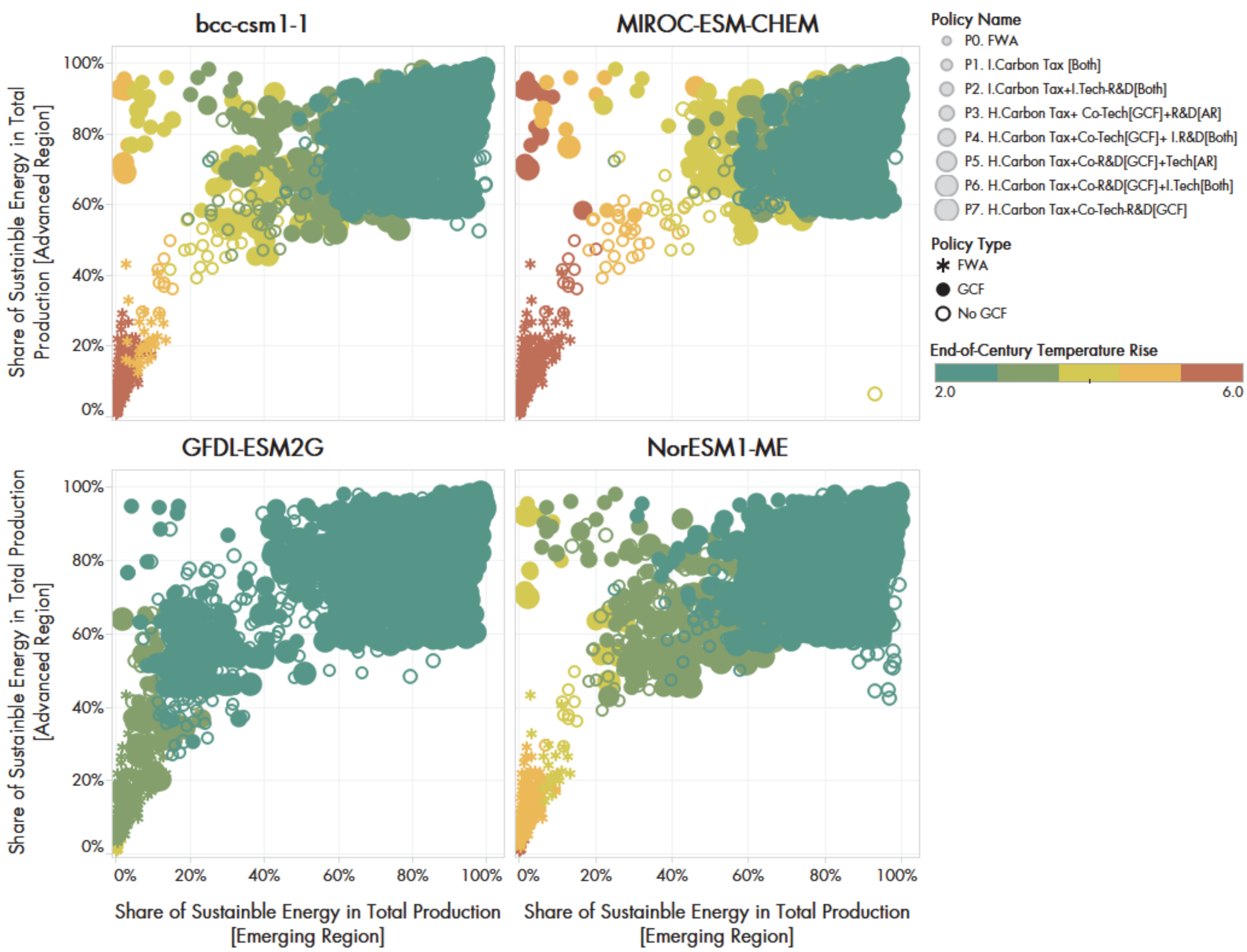
V.3 Dynamics of the Optimal Response Across Multiple Futures

V.3.1 Performance of Optimal Environmental Regulation Across Many Climate Change and Technological Futures

Results from the simulations runs generated by this expanded experimental design are shown in the scatter plots of Figure 5.5. Each point in these plots shows the end-of-century simulation outcome for a single future. The horizontal axis denotes the share of sustainable energy used in secondary energy production in the emerging region. The vertical axis shows the share of sustainable energy used in secondary energy production in the advanced region. The size of the points reflects the type of policy response, the smaller points denote policies that include the FWA and the two non-GCF policies (i.e. P1 and P2), bigger points indicate GCF based policies (i.e. P3, P4, P5, P6 and P7). The color indicates end-of-the century temperature rise, the green points describe temperature rise conditions closer to the 2 °C target, while red points describe temperature rise conditions closer to the environmental disaster condition of 6 °C. Figure 5.5

includes four panes; each pane displays results for a different climate scenario. For illustrative purposes only the effect of four climates are displayed in this figure.

Figure 5.5
Example of Experiment Results Across Different Climate and Technological Scenarios

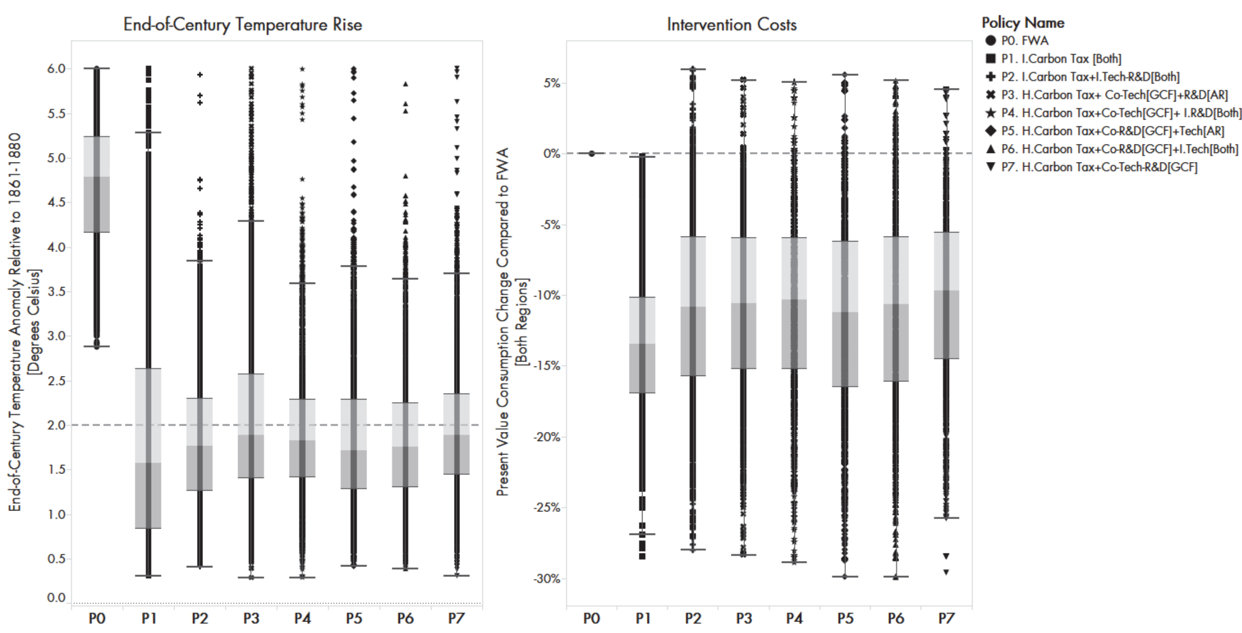


NOTES: Each point describes an individual future through the penetration of sustainable primary energy as percent of total secondary energy production for the emerging region (x-axis) and for the advanced region (y-axis). The size of the points reflects the type of policy regime, the smaller points denote policy regimes which include the FWA and the two non-GCF policies (i.e. P1 and P2), and bigger points indicate GCF based policies (i.e. P3, P4, P5, P6 and P7). The color legend denotes end-of-the century temperature rise, the green points describe temperature rise conditions closer to the 2 °C target, while red points describe temperature rise conditions closer to the environmental disaster condition of 6 °C. The figure includes four panes; each pane displays results for a different climate scenario.

Figure 5.5 shows that simulation results for this expanded experimental design are more diverse and complex than the results presented in chapter four. For instance, it is possible to see that for a minority of futures, the no action policy case (P0. FWA) avoids environmental collapse by the end of the century because renewable energy reaches high penetration levels in the advanced region, although for the majority of these cases end-of-century temperature rise remains above the 2 °C target. These results also show that the combination of technological and climate change uncertainty leads to highly heterogeneous results for both non-GCF based policy architectures and GCF based policy designs. For these two policy regimes, simulation results show that these comprehensive policies generally achieve higher penetration level of sustainable energy; however the degree of success varies widely across different technological and climate scenarios. For example, in a number of futures, the penetration of sustainable energy is lower in the emerging region than in the advanced region and, as a result, temperature rise levels remain above the 2 °C target.

Figure 5.6 describes the distribution of results across all futures considered (i.e. 3,600) for all policy regimes. These box plots summarize the distributional pattern alone without making any assumption about the likelihood of any of the futures. The right pane shows the distribution of costs and the lefts pane shows the end-of-century temperature levels. The cost of policy intervention is estimated by calculating the end-of-century present value (PV) of consumption changes induced by policy intervention. For each future, I estimate the difference in present value consumption (i.e. equation *e42*) between the FWA action case and the policy intervention case. Thus, policy intervention costs represent end-of-century economic activity changes with respect to the future in which energy production and consumption are not affected by optimal environmental regulation (i.e. laissez-faire economic outcome).

Figure 5.6
Box Plot Summaries Describing End-of-Century Temperature and Intervention Costs for Different Policy Regimes



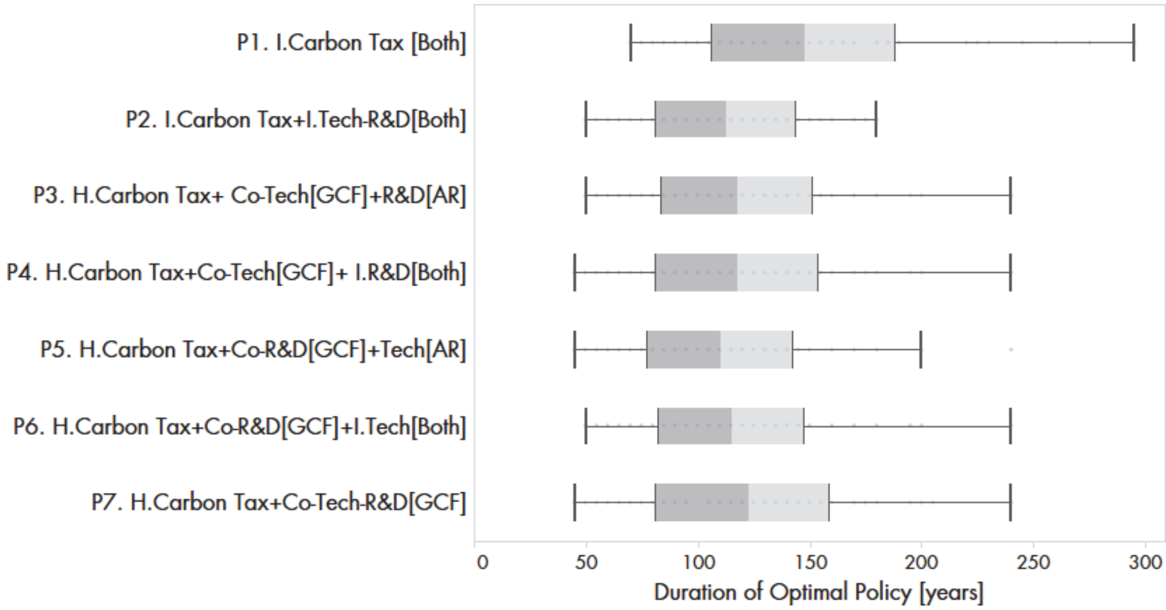
NOTES: Distribution of results across all futures considered (i.e. 3,600) for all policy regimes. This box plots summarize the distributional pattern alone without making any assumption about the likelihood of any of the futures. The right pane shows the distribution of costs and the lefts pane shows the end-of-century temperature levels.

Figure 5.6 highlights interesting features of the optimal policy response across this experimental design. The left pane shows that in some cases the comprehensive environmental policy is unable to keep end-of-century temperature rise below environmental disastrous levels. This exemplifies clearly the potential complications that can arise in the face of adverse climate and technological scenarios (i.e. climate scenarios highly sensitive to GHG emissions and technological scenarios favorable for FETs). The right pane shows that economic outcomes of policy intervention are equally diverse. It shows that policy intervention can be quite costly: in some futures consumption levels can be reduced by as much as thirty percent. Yet it also shows that in some futures, policy intervention is not costly, resulting in positive consumption gains (i.e. net positive economic green-growth). Although both scenario types represent rare simulation outcomes, they exemplify the potential and contrasting outcomes that the interplay of climate and technological uncertainty yield in this simulation experiment.

As described in chapter four, the duration of policy intervention is another important aspect to ponder when comparing the performance of optimal environmental regulation across different policy regimes. From this perspective, the optimal policy response is the intervention that successfully induces the decarbonization of both regions at the lowest possible economic and environmental cost.

In order to exemplify the differences that arise when considering different technological scenarios, I compare the duration of the optimal policy across two contrasting sets of technological scenarios. Figure 5.7 presents boxplots summaries of the duration of policy intervention for the sets of futures in which the three technological properties (i.e. R&D returns, innovation propensity and transferability) of the SETs sector are more favorable for innovation than the FETs sector's properties. The results show that for the majority of futures in this set, successful stabilization of CO_2 emissions is achieved after several decades of policy intervention (i.e. over 100 years), and that in some rare cases, the conditions for stabilization are reached in less than 50 years. These results also show that policy architectures which combine carbon taxes with complementary R&D and technology subsidies achieve stabilization conditions in a shorter period of time than the individual carbon tax policy (i.e. *P1: I. Carbon Tax [Both]*). These results also show under this set of futures, the independent comprehensive policy (i.e. *P2: I. Carbon Tax + I.Tech-R&D [Both]*) achieves stabilization conditions in a shorter period of time than the alternative GCF based policy architectures.

Figure 5.7
Box Plot Summary of Optimal Policy's Duration Across Different Regimes
Favorable Technological Scenarios



NOTES: Boxplot summaries describing the duration of policy intervention for all futures across all policy regimes. The results show that under the favorable technological scenarios CO_2 emissions stabilization is feasible after several decades of implementation (i.e. at least 50 years). It also highlights that there are noticeable differences among policies in terms of the period of time required to achieve stabilization.

Figure 5.8 presents similar boxplots summaries for the set of futures in which the three technological properties (i.e. R&D returns, innovation propensity and transferability) of the FETs sector are more favorable for innovation than the properties of the SETs sector. These summaries show that under these adverse technological scenarios differences among policies become less noticeable as all policies require a longer period of time to successfully stabilize CO_2 emissions. These results highlight once more the strong influence that different technological scenarios can have on the structure and effectiveness of the optimal policy response.

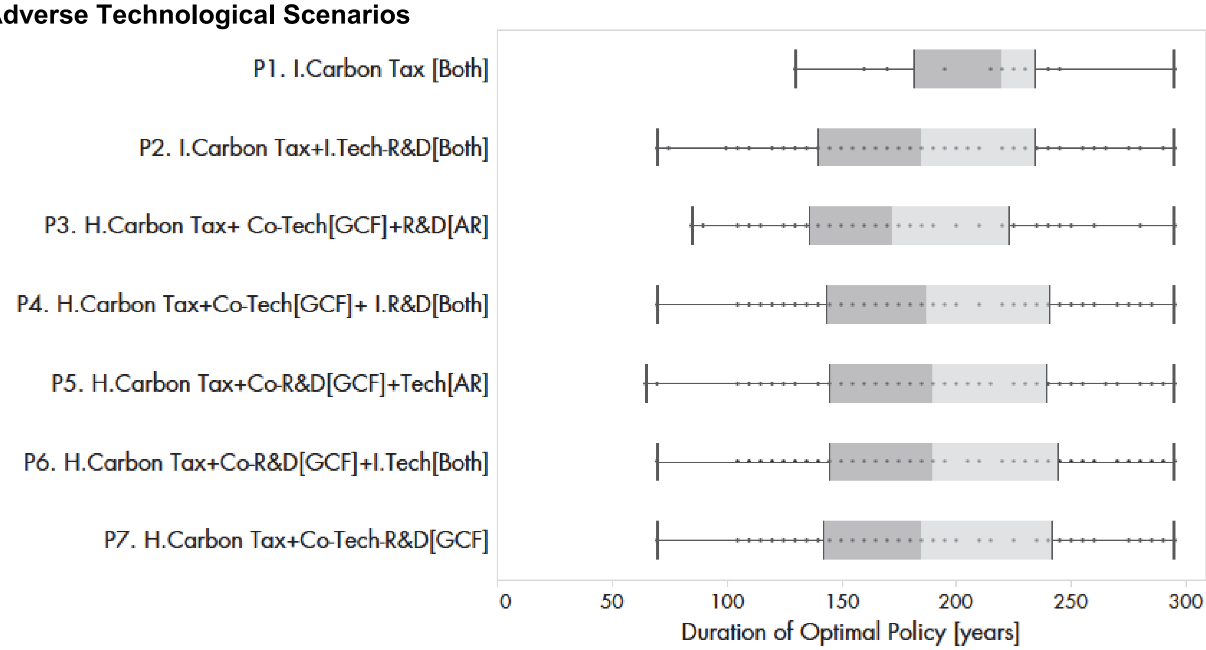
The previous sets of result provide a general description of the behavior of different policy architectures; however, it is equally important to compare the performance of these different policy proposals in the context of meeting different climate change policy targets. Following the same approach of chapter four, for this expanded analysis, I focus on the end-of-century conditions because these are more relevant for current climate change policy negotiations. Therefore, I consider a future is acceptable (not vulnerable) when the temperature target (i.e. 2 °C, 3 °C) and/or the stabilization targets are met. This suggests that there are four possible cases of success:

1. Futures in which the 2 °C end-of-century temperature rise target is met
2. Futures in which the 3 °C end-of-century temperature rise target is met

3. Futures in which the 2 °C end-of-century temperature rise target and CO_2 stabilization are met
4. Futures in which the 3 °C end-of-century temperature rise target and CO_2 stabilization are met

Table 5.4 summarizes the performance of each policy regime across the 3,600 futures considered under the four relevant policy objectives. It is worth highlighting the significance of some of the results displayed in this contingency table. For instance, it shows that the future without action (i.e. laissez-faire policy) does not meet the stabilization target or the 2 °C temperature rise targets in any of the futures considered. This is relevant because it shows that even for the technological futures in which the innovation properties of the SETs sector are superior to the innovation properties of the FETs sector, economic agents fail to exploit SETs technological potential because of the lack of a policy regime that creates incentives for mobilizing innovative activity towards SETs. This highlights the importance of optimal environmental regulation in this context.

Figure 5.8
Box Plot Summary of Optimal Policy's Duration Across Different Regimes
Adverse Technological Scenarios



NOTES: Boxplot summaries describing the duration of policy intervention for all futures across all policy regimes. The results show that under the adverse technological scenarios CO_2 emissions stabilization requires a longer period of time of policy intervention. It also highlights that for this subset of futures there are less evident different among policy regimes.

These results also show that the policies that combine carbon taxes and technology policies achieve more frequently the end-of-century climate change policy objectives than the policy regime that relies solely on carbon taxes (P1: I. Carbon Tax [Both]). Interestingly, the rate of success among these more comprehensive policies is very similar. This indicates that for some futures optimal environmental regulation achieves the climate policy objectives in more than one of the policy regimes considered, but it also indicates that different policy regimes achieve these objectives under different sets of futures. In the next step of this analysis, I use RDM methods to understand these differences among the different policy regimes.

Table 5.4
Performance of Optimal Policy Response Across Different Policy Regimes

Policy Name	Number (Percentage) of Futures Meeting the End-of-Century Climate Policy Target			
	CO_2 Stabilization Achieved		CO_2 Stabilization Not Achieved	
	Temperature Rise Below 2 °C	Temperature Rise Below 3 °C	Temperature Rise Below 2 °C	Temperature Rise Below 3 °C
P0. FWA	0 (0)	0 (0)	0 (0.0)	6 (0.2)
P1. I. Carbon Tax [Both]	299 (8.3)	327 (9.1)	2,127 (59.1)	2,999 (83.3)
P2. I. Carbon Tax + I. Tech-R&D[Both]	654 (18.2)	891 (24.8)	2,206 (61.3)	3,249 (90.3)
P3. H. Carbon Tax + Co-Tech[GCF]+R&D[AR]	506 (14.1)	651 (18.1)	1,994 (55.4)	3,072 (85.3)
P4. H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both]	706 (19.6)	891 (24.8)	2,180 (60.6)	3,282 (91.2)
P5. H. Carbon Tax + Co-R&D[GCF]+Tech[AR]	696 (19.3)	943 (26.2)	2,270 (63.1)	3,239 (90.2)
P6. H. Carbon Tax + Co-R&D[GCF]+I. Tech[Both]	650 (18.1)	907 (25.2)	2,267 (63.0)	3,290 (91.4)
P7. H. Carbon Tax + Co-Tech-R&D[GCF]	718 (19.9)	925 (25.7)	2,048 (56.9)	3,230 (89.7)

NOTES: The table summarizes the performance of each policy across the 3,600 futures considered for the four vulnerability cases described. The number (percentage) of futures meeting the different end-of-century climate policy targets are listed under each column.

V.3.2 Structure of Optimal Environmental Regulation Across Many Climate Change and Technological Futures

In this section I focus on describing how the structure of the optimal policy response changes across different climate and technological scenarios. The optimal policy framework used in this analysis (i.e. section III.2.6) assumes that the objective of optimal environmental regulation is to induce the decarbonization of the energy sectors in both regions at a rate that balances the economic costs and the environmental benefits of policy intervention. Thus the structure of the optimal response regulation adapts to the specific conditions pose by different combinations of climate and technological scenarios. For climate scenarios that are highly sensitive to GHG emissions, the optimal policy response needs to be stronger in comparison with climate scenarios that are less sensitive to greenhouse gas emissions. Similarly, for technological scenarios in which the innovation capacities of the FETs sector are greater than those of the SETs sector, the optimal policy response also needs to be stronger to successfully induce international decarbonization. Since there are multiple policy architectures that can be used to accomplish this objective, it is empirically relevant to describe differences in the adaptation of the optimal policy between different policy regimes and across different climate and technological scenarios.

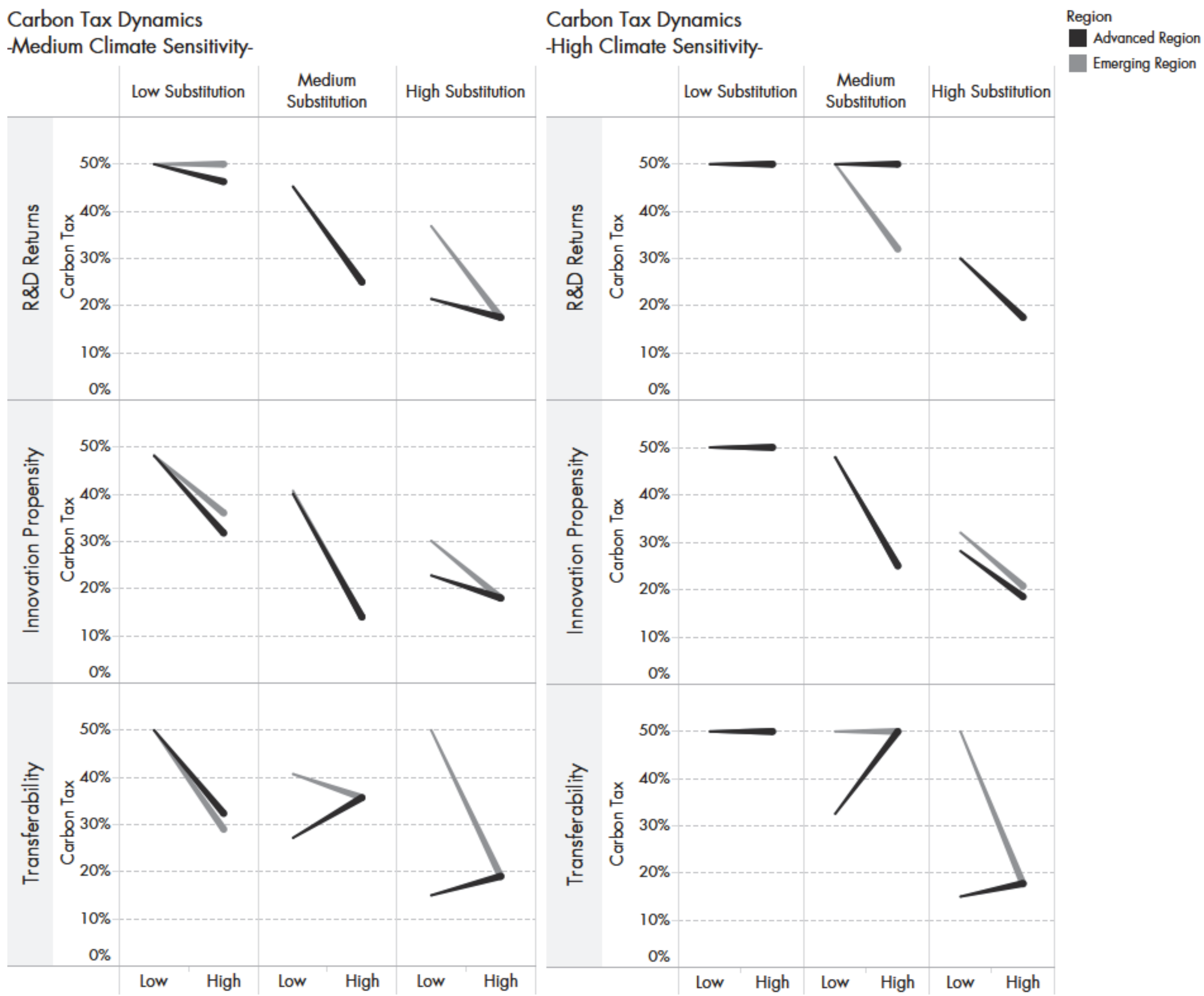
For illustrative purposes, I compare these changes across two policy regimes: the independent comprehensive policy case (i.e. *P2: I. Carbon Tax + I. Tech-R&D[Both])* and the GCF comprehensive policy case (i.e. *P7: H. Carbon Tax + Co-Tech-R&D[GCF]*). This exercise allows me to compare in which way the GCF influences the structure of optimal environmental regulation across the three areas of intervention: 1) carbon taxes, 2) R&D subsidies and 3) technology subsidies.

Carbon Taxes

I focus first on describing changes in the carbon tax rate for the independent comprehensive policy regime (i.e. *P2: I. Carbon Tax + I. Tech-R&D[Both]*). Under this policy regime, both regions implement comprehensive environmental regulation which includes the implementation of carbon taxes, R&D subsidies and technology subsidies. However, under this policy regime, there is no cooperation between regions, such that the level of taxation is set individually to fund their R&D and technology subsidy programs.

Figure 5.9 describes changes in the carbon tax rate for this policy regime across different combinations of technological and climate scenarios. The left panel describes the dynamics of change for medium climate sensitivity scenarios (i.e. $4.0<\beta<5.0$, Table 4.1). The right pane describes changes in the carbon tax rate for high sensitive climate scenarios (i.e. $\beta>5.0$, Table 4.1). Each pane is divided into three columns and three rows. The top three columns describe changes across three types of elasticity of substitution futures: low substitution futures (i.e. $\varepsilon<5.3$), medium substitution futures (i.e. $5.3\leq\varepsilon<7.6$) and high substitution futures (i.e. $\varepsilon\geq7.6$). Each row describes changes across the three different technological properties. The lines track changes in the average carbon tax rate across two sets of futures. The narrower ends mark the results for futures in which the innovation capacities of the SETs sectors are less than the capacities of the FETs sector, the thicker ends mark results for futures in which the innovation capacities of SETs are greater than the innovation capacities of FETs. The top row describes changes from low relative R&D returns futures ($\gamma_{set}/\gamma_{fet}<1.0$) to high relative R&D returns futures $\gamma_{set}/\gamma_{fet}>1.0$), while holding the other technological properties constant (i.e. $\eta_{set}=\eta_{fet}=0.25$ and $\nu_{set}=\nu_{fet}=0.02$). The middle row describes changes from low relative innovation propensity futures ($\eta_{set}/\eta_{fet}<1.0$) to high innovation propensity futures ($\eta_{set}/\eta_{fet}>1.0$), while holding the other technological properties constant (i.e. $\gamma_{set}= \gamma_{fet}=0.25$ and $\nu_{set}= \nu_{fet}=0.02$). Finally, the bottom row tracks changes from low transferability futures ($\nu_{set}/\nu_{fet}<1.0$) to high transferability futures ($\nu_{set}/\nu_{fet}>1.0$), also holding constant the other two technological properties (i.e. $\gamma_{set}= \gamma_{fet}=0.25$ and $\eta_{set}= \eta_{fet}=0.02$). Finally, the dark color lines describe changes in the carbon tax rate in the advanced region, while the grey lines describe changes in the emerging region.

Figure 5.9
Carbon Tax Dynamics Across Technological and Climate Scenarios
P2: I. Carbon Tax + I. Tech-R&D [Both]



NOTES: The lines track changes in the average carbon tax rate for the independent comprehensive policy regime (P2) across two sets of futures. The narrower ends mark the results for futures in which the innovation capacities of the SETs sectors are less than the capacities of the FETs sector, the thicker ends mark results for futures in which the innovation capacities of SETs are greater than the innovation capacities of FETs. The dark color lines describe changes in the carbon tax rate in the advanced region, while the grey lines describe changes in the emerging region. The left panel describes the dynamics of change for medium climate sensitivity scenarios. The right pane describes changes in the carbon tax rate for high sensitive climate scenarios. Each pane is divided into three columns and three rows. The top three columns describe changes across three types of elasticity of substitution futures. Each row describes changes across the three different technological properties.

Figure 5.9 describes comprehensively the dynamics of the carbon tax rate across different futures. It shows that the carbon tax rate is proportional to the level of climate sensitivity: the more sensitive climate scenarios are to CO_2 emissions, the higher the carbon tax rate across both regions. It also shows that the carbon tax rate is inversely proportional to the elasticity of substitution: the more substitutable sustainable energy and fossil energy are, the lower the carbon tax rate in the optimal policy response.

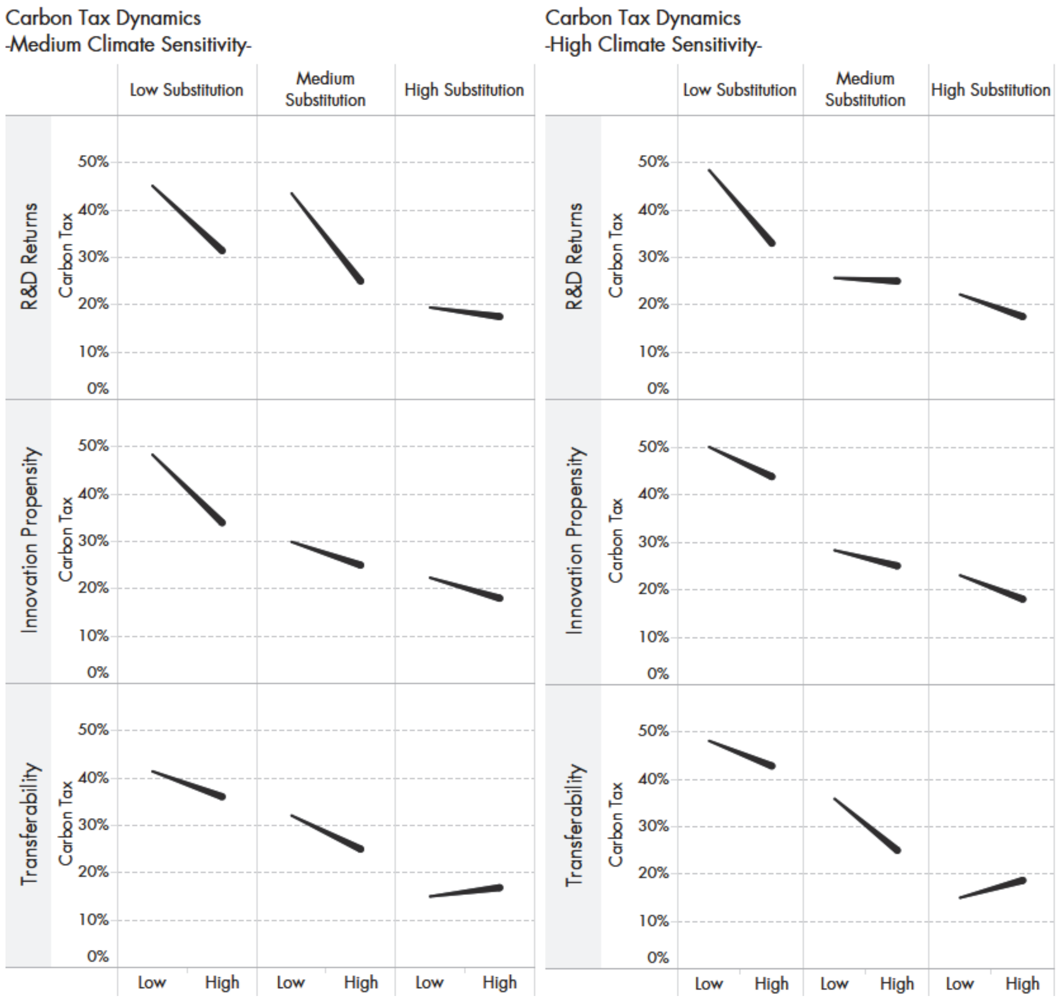
These results also highlight the importance of alternative technological scenarios in shaping the structure of the optimal response across both regions. For instance, the results show that when innovation is less favorable in the SETs sector, then under this policy regime, for these adverse technological scenarios, the carbon tax rate in the emerging region is on average equal or higher than the carbon tax rate in the advanced region. In some scenarios, this difference can be quite large, for example for the high substitution and low transferability scenarios there are approximately 40 percent points difference in the carbon tax rate. The chart also shows for the case of R&D returns and innovation propensity, moving from the low to the high technological scenarios reduces substantially the carbon tax rate in both regions. In the case of transferability, this same pattern occurs across the low substitutability futures; for the medium and high substitutability futures, moving from the low to the high transferability scenarios reduces the carbon tax rate in the emerging region, but it increases in the advanced region. In these futures, it is cost-effective for the advanced region to accelerate the decarbonization of the energy sector because SETs are adopted at a faster rate in the emerging region, which contributes to limiting further temperature rise.

Figure 5.10 shows similar results for the GCF comprehensive policy (i.e. *P7: H. Carbon Tax + Co-Tech-R&D[GCF]*). In this policy regime, the two regions use homogenous carbon taxes and co-fund R&D and technology subsidies in the emerging region through the GCF. Thus the results presented in Figure 5.10 describe changes in the structure of the optimal policy response under a highly cooperative case.

These results depict similar change patterns as the ones described in the previous case. It shows that the carbon tax rate is directly proportional to the level of greenhouse climate sensitivity, and inversely proportional to the degree of substitutability of the two technological sectors. Similarly, moving from the adverse "low" technological scenarios to the more advantageous "high" scenarios reduces the carbon tax rate in both regions. Only for the case of high transferability and high substitution this is not the case.

Comparing change patterns in the carbon tax rate across the two policy regimes is illustrative of the potential influence of the GCF on the structure of optimal environmental regulation. It shows that for the adverse climate scenarios (i.e. high sensitivity) the carbon tax rate under the GCF is on average lower than the tax rate under the non-GCF based policy.

Figure 5.10
Carbon Tax Dynamics Across Technological and Climate Scenarios
P7: H. Carbon Tax + Co-Tech-R&D [GCF]



NOTES: The lines track changes in the average carbon tax rate for the comprehensive GCF based policy regime (P7) across two sets of futures. The narrower ends mark the results for futures in which the innovation capacities of the SETs sectors are less than the capacities of the FETs sector, the thicker ends mark results for futures in which the innovation capacities of SETs are greater than the innovation capacities of FETs. The dark color lines describe changes in the carbon tax rate in the advanced region, while the grey lines describe changes in the emerging region. The left panel describes the dynamics of change for medium climate sensitivity scenarios. The right pane describes changes in the carbon tax rate for high sensitive climate scenarios. Each pane is divided into three columns and three rows. The top three columns describe changes across three types of elasticity of substitution futures. Each row describes changes across the three different technological properties.

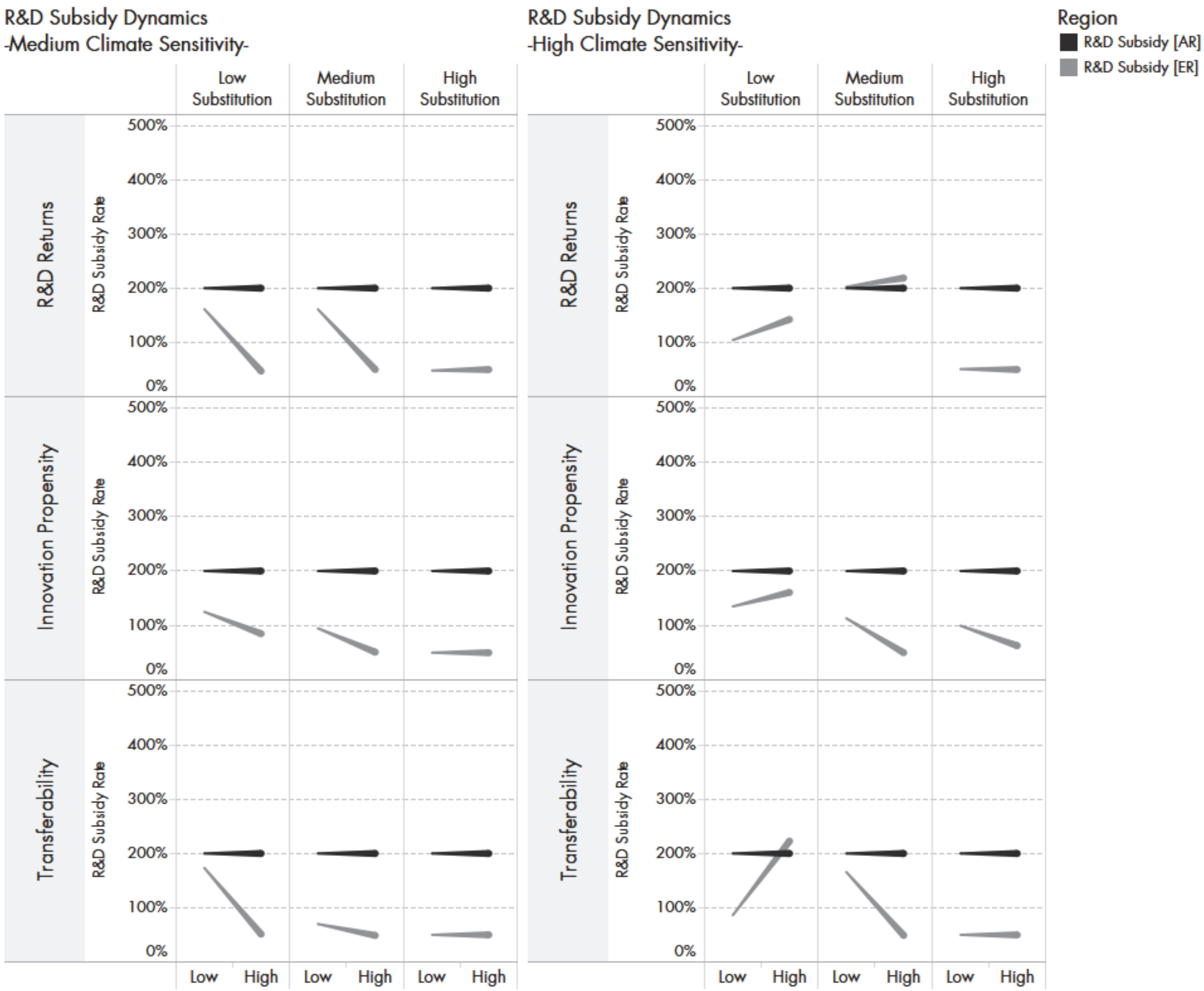
R&D Subsidies

Figure 5.11 describes how the R&D subsidy rate changes across different climate and technological scenarios. In the same fashion as in the previous charts, the lines track changes in the average R&D subsidy rate across two sets of futures. The narrower ends mark the results for futures in which the innovation capacities of the SETs sector are less favorable than the capacities of the FETs sector, the thicker ends mark results for futures in which the innovation capacities of SETs are greater than the innovation capacities of FETs. The dark lines track changes across the advanced region, while the grey lines track changes across the emerging region. The results show that the optimal level of R&D subsidies in the advanced region is set at 200% regardless of the elasticity of substitution, climate or technological conditions. In the emerging region, the R&D subsidy rate displays a slighter dynamic behavior. For instance, it is more responsive to alternative technological scenarios than to alternative climate and elasticity of substitution scenarios. In technological scenarios less favorable to SETs, the R&D subsidy rate tends to be higher than in technological scenarios that are more favorable for SETs innovation. The exception to this trend is the set of futures that combine high climate sensitivity and low substitution conditions (i.e. worst case scenario), in which the R&D subsidy rate in the emerging region increases for the more favorable technological scenarios.

Figure 5.12 presents a similar set of results but for the case of the GCF comprehensive policy (i.e. *P7: H. Carbon Tax + Co-Tech-R&D[GCF]*). Similarly, each cell describes changes in the R&D subsidy rate across different combination of technological, substitution and climate conditions. The dark lines describe changes in the R&D subsidy rate in the advanced region, while the grey lines describe changes in the R&D subsidy rate in the emerging region. Note, that in this GCF case, the R&D subsidy rate in the emerging region represents the co-funded R&D subsidy rate (i.e. equation *e34*). The chart shows once more that the R&D subsidy rate in the advanced region remains at the same level (i.e. 200%) regardless of the technological, substitution and climate conditions. In the emerging region, similarly as in the previous case, the R&D subsidy rate remains fairly stable at 100% for the medium and high substitution scenarios, regardless of the technological and climate conditions. However, for the low substitution scenarios, it possible to see that the R&D subsidy rate in the emerging region changes more drastically across different technological and climate change condition. Compared to the case in which the GCF is not in place, this change pattern is quite different. In these futures, the R&D subsidy rate in the emerging region is always higher than the R&D subsidy rate in the advanced region. In fact, for the low transferability case, the R&D subsidy rate in the emerging region is 2.5 times higher than the subsidy rate in the advanced region.

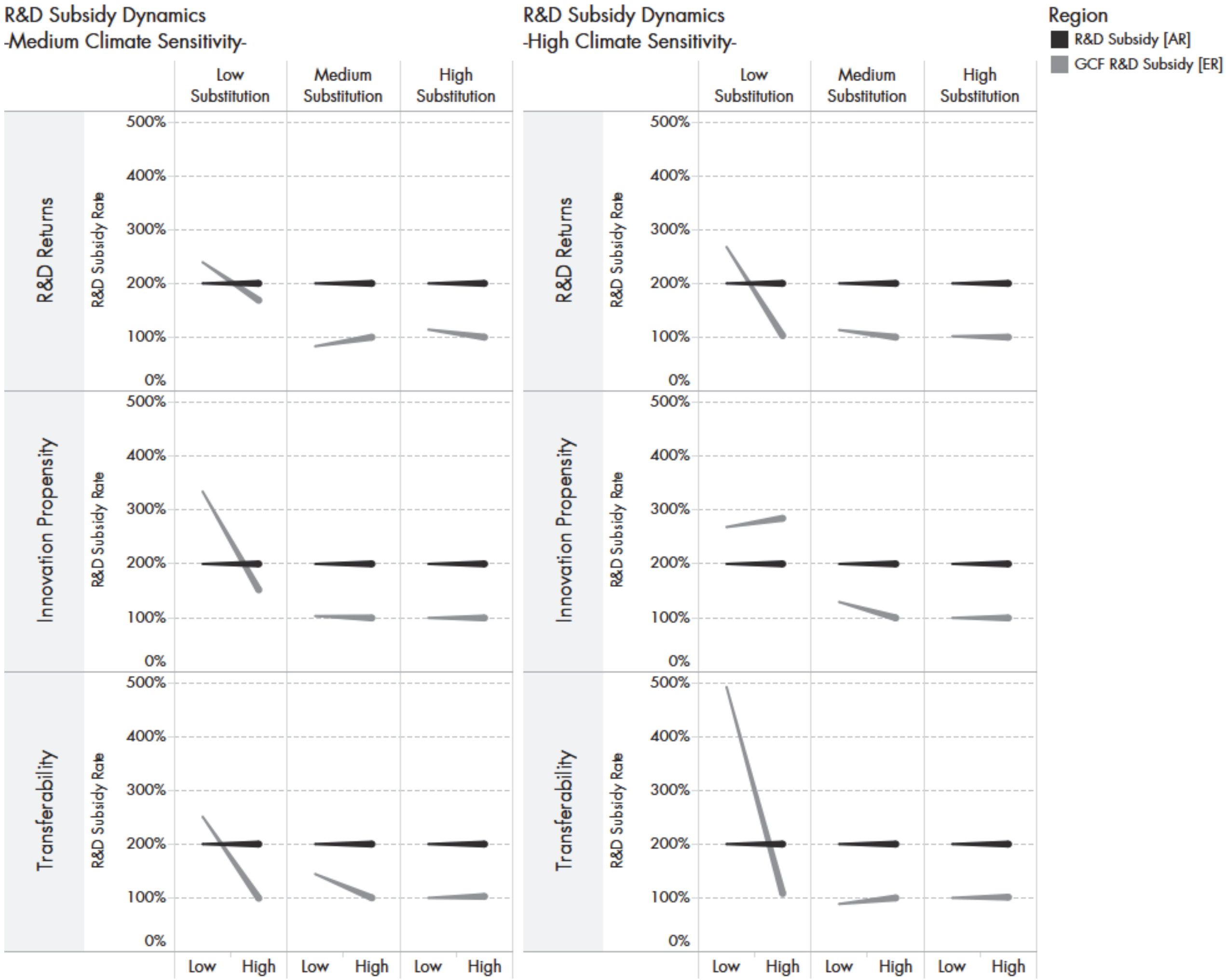
This outcome highlights the role of the GCF in changing the structure of the optimal comprehensive environmental regulation. In the independent comprehensive policy regime, this level of R&D investment in the emerging is not optimal because it would surpass the emerging region's budget constraint. Yet, when co-funding is possible through the GCF, this higher level of investment becomes feasible for the emerging region and it is optimal for both regions. However, by comparing both sets results, it is also possible to see that for the more favorable technological and climate conditions, the GCF R&D subsidy rate in the emerging region is higher compared to the non-GCF comprehensive policy, which may indicate that in these scenarios the GCF commitment is more onerous than the independent comprehensive policy.

Figure 5.11
R&D Subsidy Rate Dynamics Across Technological and Climate Scenarios
P2: I. Carbon Tax + I. Tech-R&D [Both]



NOTES: The lines track changes in the average R&D subsidy rate for the independent comprehensive policy regime (P2) across two sets of futures. The narrower ends mark the results for futures in which the innovation capacities of the SETs sectors are less than the capacities of the FETs sector, the thicker ends mark results for futures in which the innovation capacities of SETs are greater than the innovation capacities of FETs. The dark color lines describe changes in the carbon tax rate in the advanced region, while the grey lines describe changes in the emerging region. The left panel describes the dynamics of change for medium climate sensitivity scenarios. The right pane describes changes in the carbon tax rate for high sensitive climate scenarios. Each pane is divided into three columns and three rows. The top three columns describe changes across three types of elasticity of substitution futures. Each row describes changes across the three different technological properties.

Figure 5.12
R&D Subsidy Rate Dynamics Across Technological and Climate Scenarios
P7: H. Carbon Tax + Co-Tech-R&D [GCF]



NOTES: The lines track changes in the average R&D subsidy rate for the comprehensive GCF based policy regime (P7) across two sets of futures. The narrower ends mark the results for futures in which the innovation capacities of the SETs sectors are less than the capacities of the FETs sector, the thicker ends mark results for futures in which the innovation capacities of SETs are greater than the innovation capacities of FETs. The dark color lines describe changes in the carbon tax rate in the advanced region, while the grey lines describe changes in the emerging region. The left panel describes the dynamics of change for medium climate sensitivity scenarios. The right pane describes changes in the carbon tax rate for high sensitive climate scenarios. Each pane is divided into three columns and three rows. The top three columns describe changes across three types of elasticity of substitution futures. Each row describes changes across the three different technological properties.

Technology Subsidies

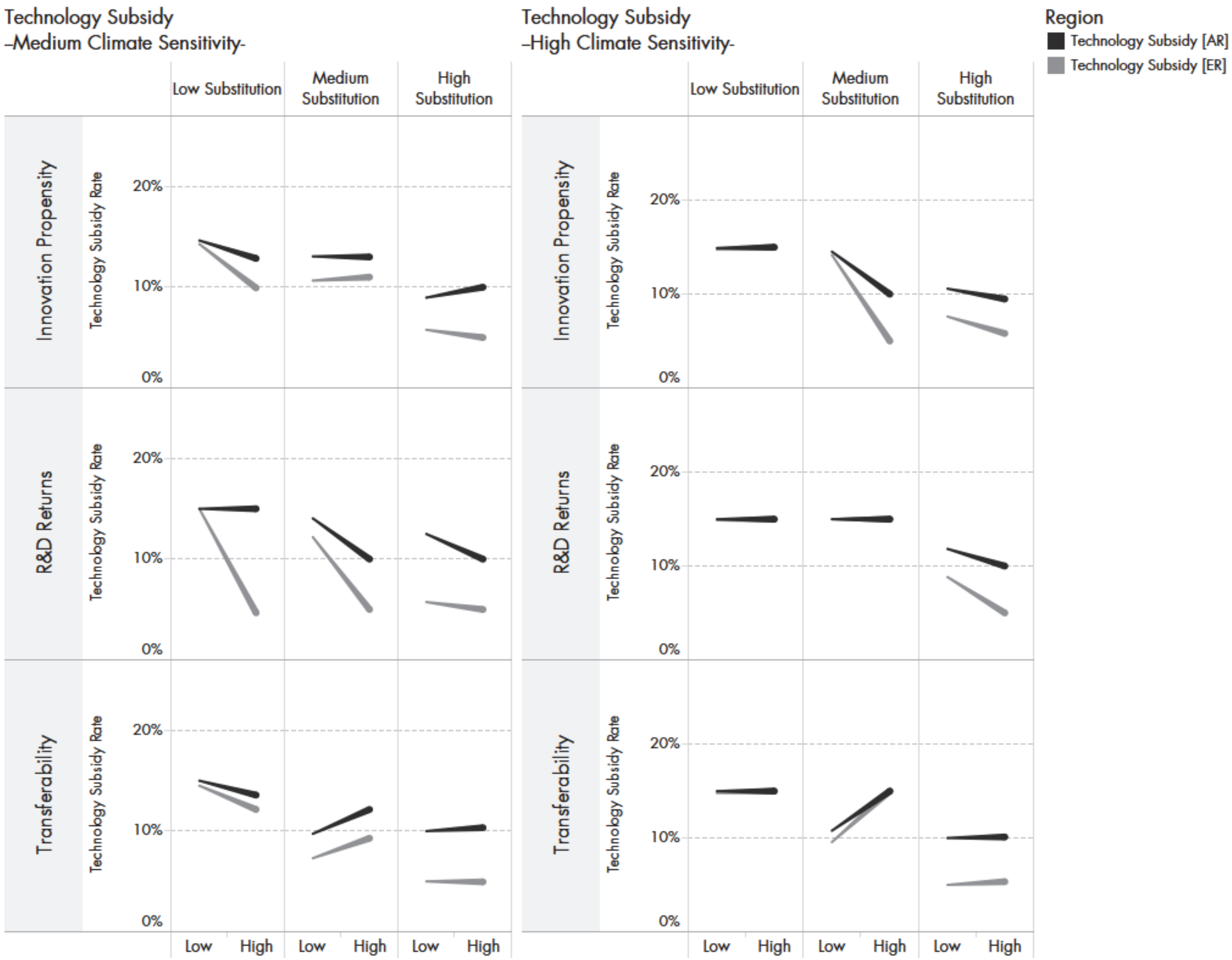
Figure 5.13 describes the technology subsidy rate change patterns across the different climate and technological scenarios. In the same way as in previous cases, the lines track changes in the average R&D subsidy rate across two sets of futures. The narrower ends mark the results for more adverse technological futures for SETs, and the thicker ends mark results for more favorable futures for SETs. Dark lines describe changes in the technology subsidy rate in the advanced region and the grey lines describe changes in the technology subsidy rate in the emerging region.

These change patterns show that the optimal technology subsidy rate is more sensitive to alternative substitution scenarios and to alternative technological scenarios than it is to different climate scenarios. In particular, it shows that the technology subsidy rate changes more drastically across different scenarios in the emerging region than in the advanced region, and that the technology subsidy rate in the advanced region is always higher than the technology subsidy rate in the emerging region.

Figure 5.14 describes the dynamics of the technology subsidy rate across the different futures for the comprehensive GCF policy regime (i.e. *P7: H. Carbon Tax + Co-Tech-R&D[GCF]*. It shows that under the GCF the technology subsidy rate is less sensitive to medium and high substitution scenarios and to different climate scenarios. Specifically, under the medium and high substitution scenarios it displays a tendency towards convergence across regions. However, similarly to the R&D subsidy rate, for the low substitution scenarios it shows that the optimal technology subsidy rate in the emerging region is higher than the technology subsidy rate in the advanced region. By comparing these results against the non-GCF comprehensive policy regime it is possible to see that also in this case the GCF enables a higher technology subsidy rate in the emerging region than in case in which comprehensive climate policy is funded individually.

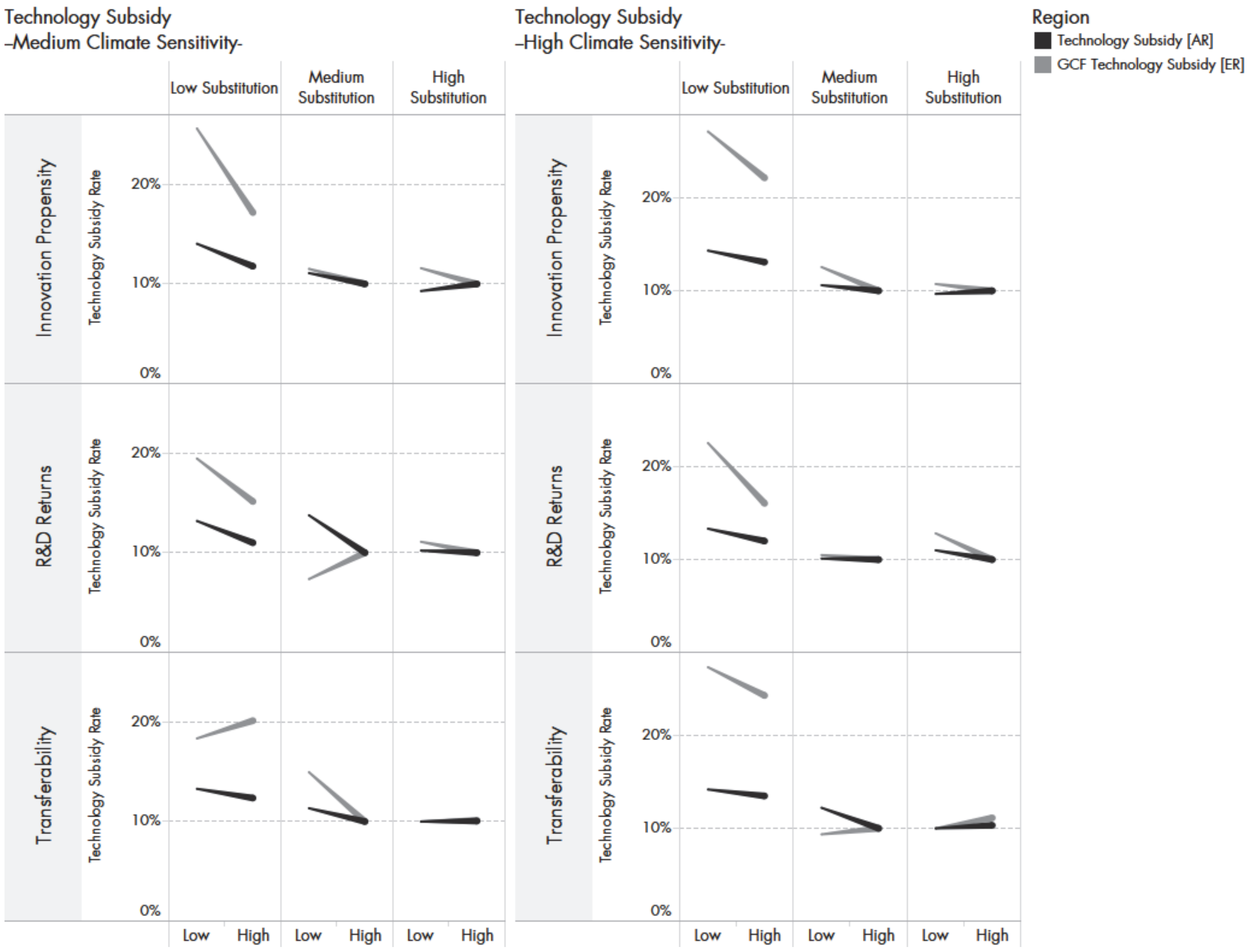
Comparing the structure of optimal environmental regulation across these two policy regimes shows that the GCF clearly influences the structure of the optimal policy response. The results presented in this section show that in the most adverse futures, the GCF enables a stronger policy response in the emerging region that would not be possible in the comprehensive non-GCF policy. However, at the same time it shows that for the less adverse futures, in comparison with the non-GCF policy, the comprehensive GCF policy results in stronger policy efforts. This may an indication that in the less adverse scenarios, cooperation across all sectors may not be required and that policy architectures that use a more flexible form of cooperation may be more cost-effective alternatives.

Figure 5.13
Technology Subsidy Rate Dynamics Across Technological and Climate Scenarios
P2: I. Carbon Tax + I. Tech-R&D [Both]



NOTES: The lines track changes in the average technology subsidy rate for the independent comprehensive policy regime (P2) across two sets of futures. The narrower ends mark the results for futures in which the innovation capacities of the SETs sectors are less than the capacities of the FETs sector, the thicker ends mark results for futures in which the innovation capacities of SETs are greater than the innovation capacities of FETs. The dark color lines describe changes in the carbon tax rate in the advanced region, while the grey lines describe changes in the emerging region. The left panel describes the dynamics of change for medium climate sensitivity scenarios. The right pane describes changes in the carbon tax rate for high sensitive climate scenarios. Each pane is divided into three columns and three rows. The top three columns describe changes across three types of elasticity of substitution futures. Each row describes changes across the three different technological properties.

Figure 5. 14
R&D Subsidy Rate Dynamics Across Technological and Climate Scenarios
P7: H. Carbon Tax + Co-Tech-R&D [GCF]



NOTES: The lines track changes in the average technology subsidy rate for the comprehensive GCF policy regime (P7) across two sets of futures. The narrower ends mark the results for futures in which the innovation capacities of the SETs sectors are less than the capacities of the FETs sector, the thicker ends mark results for futures in which the innovation capacities of SETs are greater than the innovation capacities of FETs. The dark color lines describe changes in the carbon tax rate in the advanced region, while the grey lines describe changes in the emerging region. The left panel describes the dynamics of change for medium climate sensitivity scenarios. The right pane describes changes in the carbon tax rate for high sensitive climate scenarios. Each pane is divided into three columns and three rows. The top three columns describe changes across three types of elasticity of substitution futures. Each row describes changes across the three different technological properties.

V.4 Scenario Discovery Using High-Dimensional Stacking

In this section I combine scenario discovery (Bryant and Lempert, 2010) with high-dimensional stacking methods (Suzuki, Stern and Manzocchi, 2015; Taylor et al., 2006; LeBlanc, Ward and Wittels, 1990) to study under which climate and technological conditions the different policy regimes considered meet the CO_2 stabilization targets and/or the temperature rise targets.

This expansion of the traditional scenario discovery methods is motivated by the high number of uncertainty dimensions considered in this experimental design (i.e. 12 climate scenarios, 6 technological parameters and 1 economic parameter). Initially, I analyzed the experiments' database using the traditional scenario discovery approach (Bryant and Lempert, 2010), but the results yielded several high dimensional scenario boxes, which hindered both the interpretability and usefulness of the results. As an alternative, I implemented also the expanded version of scenario discovery with orthogonal rotations (Dalal et al., 2013). In this latter case, it was possible to reduce the resulting number of scenario boxes and to describe these boxes through fewer dimensions. However, the resulting boxes and principal components were too abstract to be policy relevant in this context.

As an alternative to these traditional methods I combine high-dimensional stacking with the scenario discovery framework. In scenario discovery with dimensional stacking, similar to (Suzuki, Stern and Manzocchi, 2015), the process starts by decomposing each uncertainty dimension into more basic categorical levels. Then these transformed uncertainty dimensions are combined into "scenario cells" that represent the most basic element of the uncertainty space. These scenario cells are then combined iteratively with other cells, yielding a final map that represents a scenario map of various scenario cells. Following the scenario discovery approach and in similar way to Taylor et al. (2006), coverage and density statistics are estimated for each scenario cell such that only high density and high coverage cells can be visualized. Finally, for each axis in the scenario map, the stacking order is determined using principal component analysis. Uncertainty dimensions that can be associated into a principal component are stacked in consecutive order.

The elasticity of substitution and climate sensitivity bins are defined as follows:

$$Elasticity\ of\ Substitution: \begin{cases} low: & \varepsilon < 5.3 \\ medium: & 5.3 \leq \varepsilon < 8.0 \\ high: & \varepsilon \geq 8.0 \end{cases}$$

$$Climate\ Sensitvity\ to\ GHG: \begin{cases} low: & \beta < 4.0 \\ medium: & 4.0 \leq \beta < 5.0 \\ high: & \beta \geq 8.0 \end{cases}$$

Since SETs and FETs are competing technological sectors, the technological uncertainty bins are defined one relative to the other, such that:

$$Relative\ R\&D\ Returns: \begin{cases} low: \dfrac{\gamma_{set}}{\gamma_{fet}} < 1.0 \\ high: \dfrac{\gamma_{set}}{\gamma_{fet}} \geq 1.0 \end{cases}$$

$$Relative\ Innovation\ Propensity: \begin{cases} low: \dfrac{\eta_{set}}{\eta_{fet}} < 1.0 \\ high: \dfrac{\eta_{set}}{\eta_{fet}} \geq 1.0 \end{cases}$$

$$Relative\ Transferability: \begin{cases} low: \dfrac{\nu_{set}}{\nu_{fet}} < 1.0 \\ high: \dfrac{\nu_{set}}{\nu_{fet}} \geq 1.0 \end{cases}$$

In the following sections I use this technique for describing the conditions under which different policy regimes meet the two climate policy objectives of interest for this study.

V.4.1 Analyzing the End-of-Century CO_2 Stabilization Target

I focus first on using scenario discovery with high dimensional stacking to understand the futures in which end-of-century CO_2 stabilization at 2 °C is no met. These are futures in which CO_2 stabilization is not achieved and in which end-of-century temperature rise is above 2 °C. From a policy perspective, these vulnerable futures are relevant because these can illuminate the vulnerabilities of the optimal policy response in meeting the most ambitious climate change policy target.

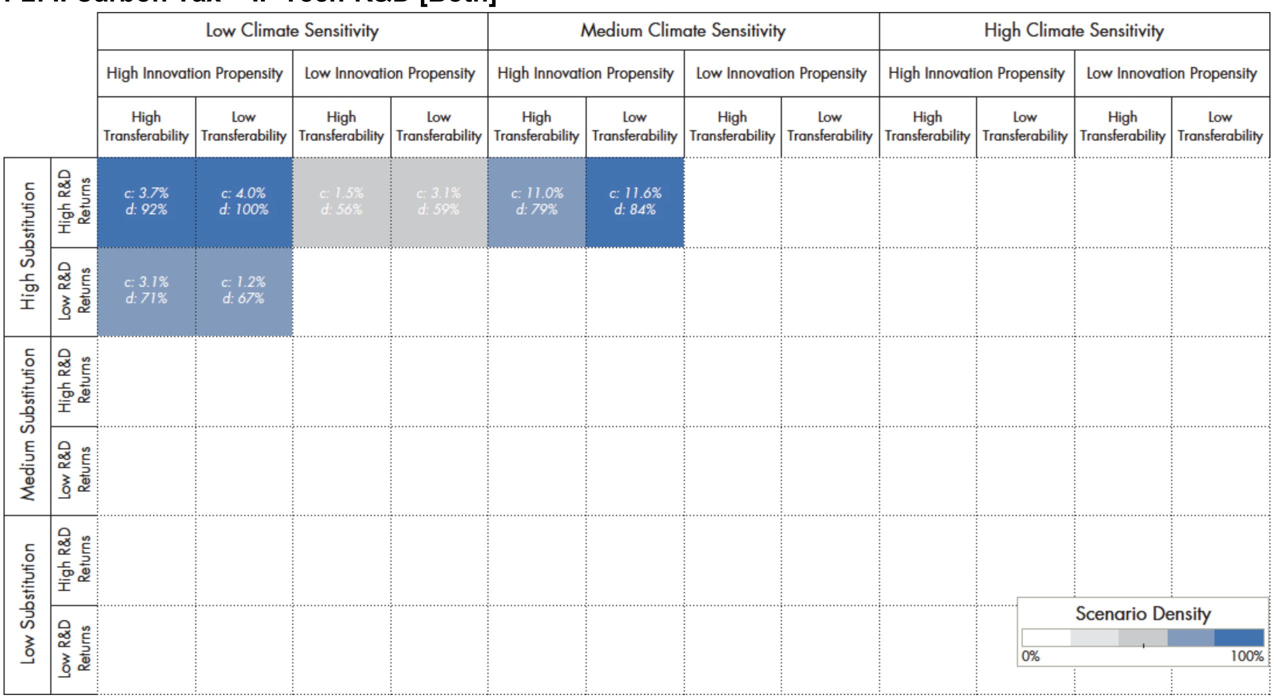
Figure 5.15 describes the performance of the independent comprehensive policy “P2: I. Carbon Tax + I. Tech-R&D [Both]” using scenario discovery with high dimensional stacking. In this uncertainty map each scenario cell represents the set of futures that fall into the discrete combination of the different uncertainty bins. In the horizontal axis, the first order montage in the horizontal axis describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution bins: low, medium and high, and the second order montage describes two R&D returns bins: high and low.

In line with traditional scenario discovery methods, within each scenario cell, I classify simulation outcomes into two groups: 1) future scenarios in which the policy target is met and 2) future scenarios in which the policy target is not met. Coverage and density statistics are calculated and noted for each scenario cell focusing on the futures that meet the CO_2 stabilization target. The color legend denotes scenario cells' density.

Figure 5.15 shows that by combining scenario discovery with high-dimensional stacking it is possible to map the performance of this policy regime across the entire uncertainty space using a two dimensional map. As expected, the results show that under this policy regime, the objective of stabilizing CO_2 emissions before the end of the century is only met under very favorable climate and technological circumstances.

Four scenario clusters describe the vulnerability space: 1) low-medium elasticity of substitution futures, 2) high climate sensitivity futures, 3) low relative R&D returns combined with high substitution and medium climate sensitivity futures and 4) low relative R&D returns combined with low innovation propensity.

Figure 5.15
Scenario Discovery with High-Dimensional Stacking for Analyzing the CO_2 Stabilization Target P2: I. Carbon Tax + I. -Tech-R&D [Both]

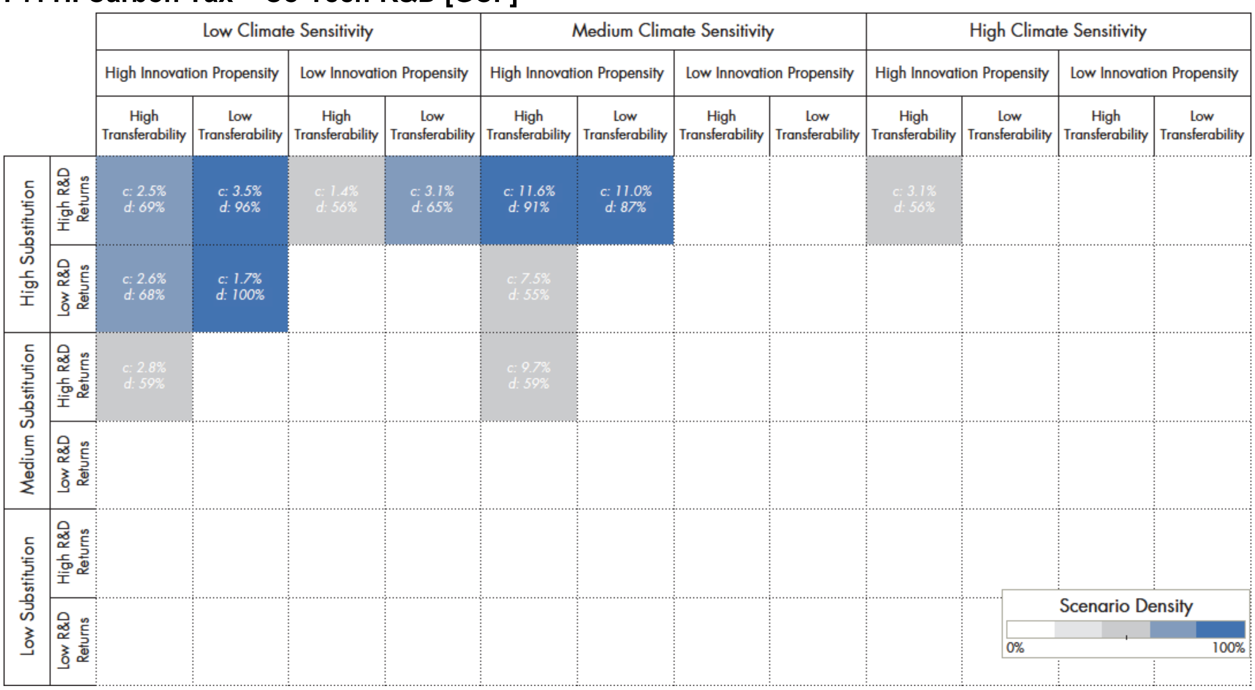


NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The blue legend denotes scenarios cells' density.

As found in chapter four, these results show that the elasticity of substitution and climate sensitivity are key determinants of CO_2 stabilization vulnerability. However, these results also show that technologically adverse scenarios in which the SET's R&D returns are lower than FETs' R&D returns or in which the FETs' innovation propensity is higher than SETs' innovation propensity also result in vulnerable futures.

Alternative policy regimes behave differently across the uncertainty space. Figure 5.16 describes scenario discovery results for the GCF policy regime (P7: H. Carbon Tax + Co-Tech-R&D [GCF]). As in the case of the independent comprehensive policy, these results show that CO_2 stabilization before the end of the century is achieved only under favorable climate and technological conditions. However, there are additional scenario cells under which the CO_2 stabilization objective is met. For instance, under the high climate sensitivity futures it is possible to see that full GCF cooperation leads to CO_2 stabilization in the scenario cell that combines the most favorable technological futures: high substitution, high R&D returns, high innovation propensity and high transferability. Similar scenario boxes are found across the medium substitution scenario cells.

Figure 5.16
Scenario Discovery with High-Dimensional Stacking for Analyzing the CO_2 Stabilization Target P7: H. Carbon Tax + Co-Tech-R&D [GCF]



NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The blue legend denotes scenarios cells' density.

By comparing the performance of these two policy regimes it can be seen that the GCF expands the possibilities of meeting the CO_2 stabilization target into more adverse substitution and climate scenarios. This occurs because under this policy regime (i.e. P7) the co-funding of R&D and technology subsidies allow for a stronger policy response in the emerging region, which it is not possible under the independent comprehensive policy regime (i.e. P2).

V.4.2 Analyzing the End-of-Century 2 °C Temperature Rise Target

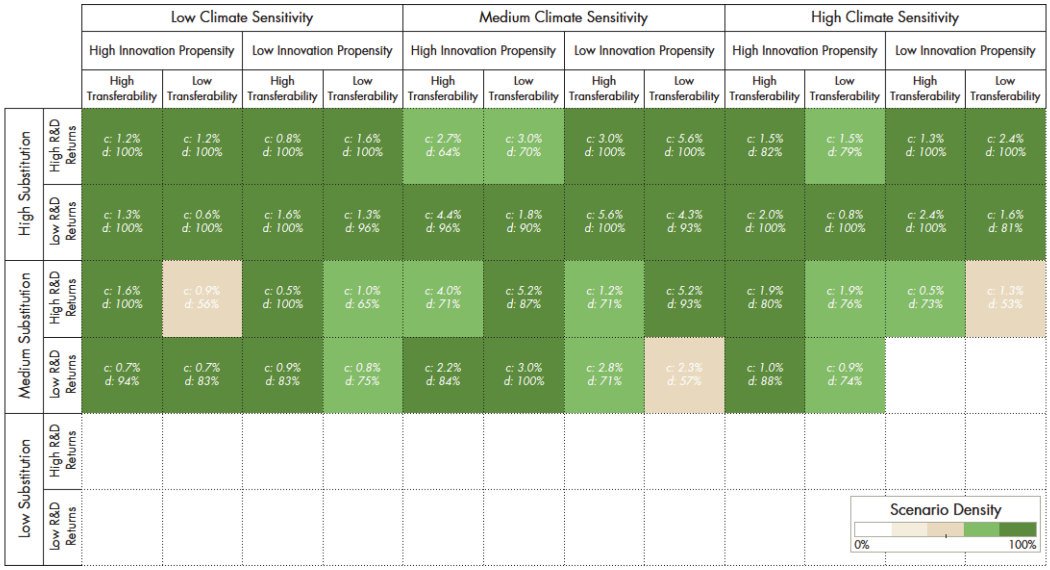
In this section I describe a similar analysis for understanding under which conditions the two degrees Celsius target is met across different policy regimes. For illustrative purposes, I describe results for only three different policy regimes, the independent carbon tax policy regime (i.e. *"P1:I. Carbon Tax [Both]")* the comprehensive independent policy regime (i.e. *"P2: I. Carbon Tax + I. -Tech-R&D [Both*]") and the comprehensive GCF based policy regime (i.e. *"P7: H. Carbon Tax + Co-Tech-R&D [GCF]"*).

Figure 5.17 presents the results of using scenario discovery with high-dimensional stacking for analyzing the vulnerability conditions of the independent carbon tax policy regime (i.e. *"P1:I. Carbon Tax [Both*). The results show that two scenario clusters describe the vulnerability of this policy regime: 1) low substitution and 2) the combination of medium substitution with high climate sensitivity, low relative innovation propensity and low relative R&D returns.

Similarly, Figure 5.18 and Figure 5.19 display scenario discover results for the independent comprehensive policy regime (i.e. *"P2: I. Carbon Tax + I. -Tech-R&D [Both*]") and for the GCF comprehensive policy regime (i.e. *"P7: H. Carbon Tax + Co-Tech-R&D [GCF]"*) respectively. These results show that the optimal policy response under each policy regime works better under different areas of the uncertainty space. For instance, the optimal policy response under the independent comprehensive policy regime is more effective in meeting the temperature rise target in the high climate sensitivity futures, while the optimal policy response under the comprehensive GCF policy regime is more effective in the low elasticity of substitution futures.

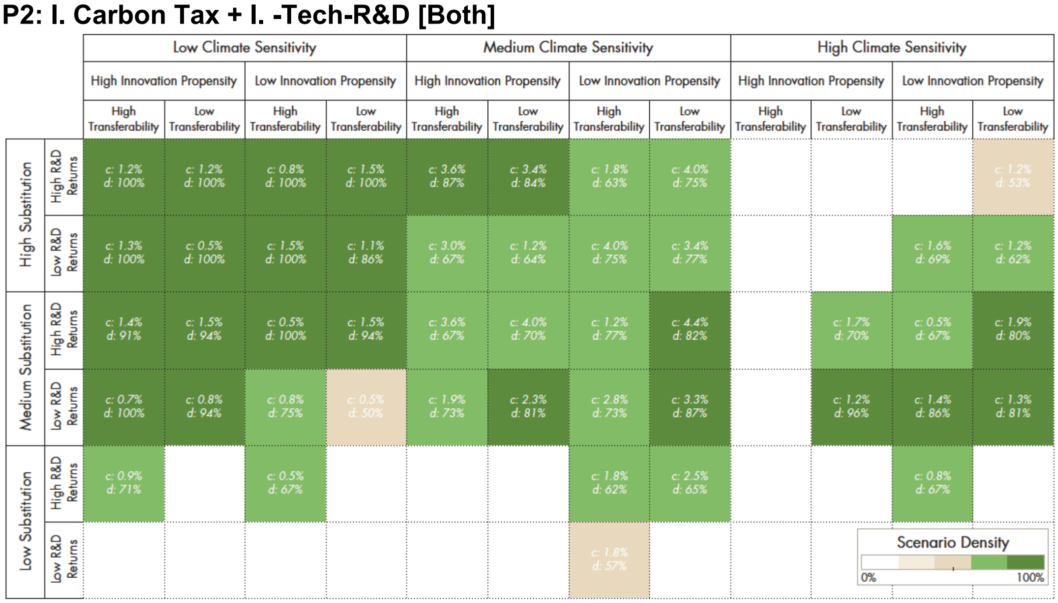
Comparing the scenario discovery results across the three policy regimes yields two observations: 1) different policy regimes are more effective under different combinations of the uncertainty space and 2) for various scenario cells it is possible to meet the temperature rise target though different policy regimes. It follows from these observations that the next analytical step is to understand under which conditions one policy regime is preferred over the others.

Figure 5.17
Scenario Discovery with High-Dimensional Stacking for Analyzing the 2 °C Temperature Rise Target, P1: I. Carbon Tax [Both]



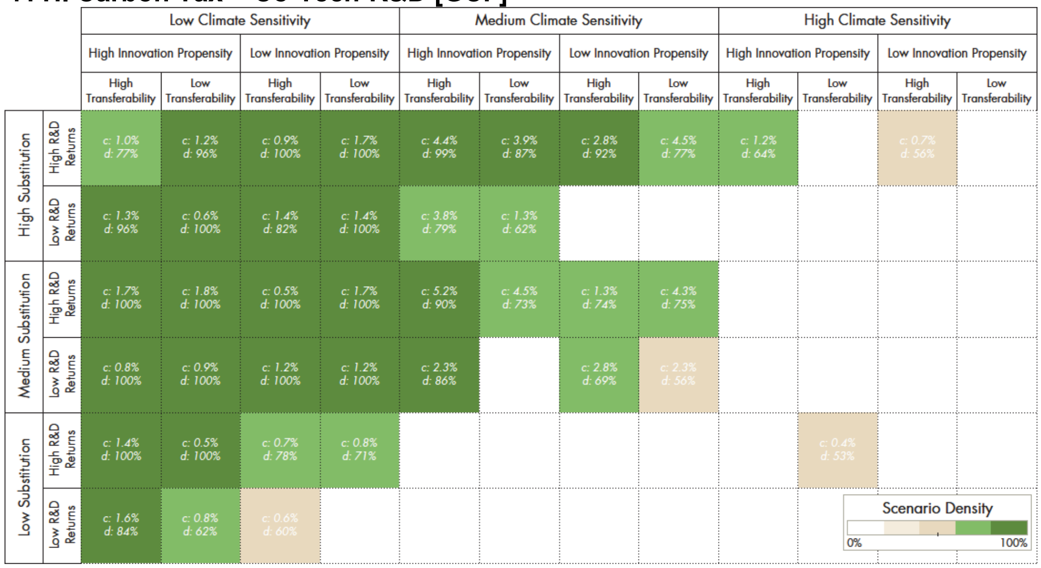
NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The green legend denotes scenarios cells' density.

Figure 5.18
Scenario Discovery with High-Dimensional Stacking for Analyzing the 2 °C Temperature Rise Target, P2: I. Carbon Tax + I. -Tech-R&D [Both]



NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The green legend denotes scenarios cells' density.

Figure 5.19
Scenario Discovery with High-Dimensional Stacking for Analyzing the 2 °C Temperature Rise Target, P7: H. Carbon Tax + Co-Tech-R&D [GCF]



NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The green legend denotes scenarios cells' density

V.4.3 Robust Mapping of Cost-Effective Optimal Environmental Regulation

In this section I apply the same robust mapping procedure described in section IV.4. For this mapping process I use the regret function described in equation *(e46)* and the value function specified in equation *(e47)* such that for each scenario cell the policy regime selected is the architecture than minimizes the level of environmental and economic cost regret.

Figure 5.20 depicts the results of this mapping process. Similarly as with high-dimensional stacking, each cell represents the set of futures that fall into combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. The label and the color legend denote the corresponding least regret policy for each scenario cell. The greener cells refer to the GCF based policy architectures (i.e. P3-P7), while the clearer cells denote the independent policy architectures (i.e. P1 and P2).

Figure 5.20
Robust Mapping of Least-Regret Optimal Environmental Regulation

		Low Climate Sensitivity				Medium Climate Sensitivity				High Climate Sensitivity			
		High Innovation Propensity		Low Innovation Propensity		High Innovation Propensity		Low Innovation Propensity		High Innovation Propensity		Low Innovation Propensity	
		High Transferability	Low Transferability	High Transferability	Low Transferability	High Transferability	Low Transferability	High Transferability	Low Transferability	High Transferability	Low Transferability	High Transferability	Low Transferability
High Substitution	High R&D Returns	P2	P6	P6	P7	P6	P3	P7	P5	P7	P1	P7	P2
	Low R&D Returns	P6	P2	P7	P3	P4	P4	P2	P4	P1	P1	P6	P2
Medium Substitution	High R&D Returns	P5	P2	P2	P4	P7	P7	P7	P7	P1	P6	P6	P6
	Low R&D Returns	P2	P3	P7	P7	P7	P4	P4	P7	P1	P6	P5	P6
Low Substitution	High R&D Returns	P2	P4	P2	P5	P6	P3	P4	P6	P3	P7	P6	
	Low R&D Returns	P4	P7	P7		P3		P4					

NOTES: Each scenario cell represents the set of futures that fall into combinations of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. The label and the color legend denote the corresponding least regret policy for each scenario cell.

The map displayed in Figure 5.20 shows that there is not one single policy regime that dominates over the entire uncertainty space. Rather, more importantly this map shows that by combining different types of policy architectures it is possible meet one or the two climate change policy targets in a larger set of futures.

The policy regimes considered in this analysis describe different forms in which technology policy can be implemented alongside carbon taxation, and also different ways by which the GCF can support the implementation of complementary technology policy in the emerging region. Thus the results depicted in Figure 5.20 also demonstrate that optimal environmental regulation for mitigating climate change does not required to be same across the entire uncertainty space, but rather that depending on the unfolding climate and technological conditions different policy regimes are better suited for meeting the climate change policy objectives.

The results discussed thus far show that the CO_2 stabilization target can only be met under the most favorable climate and technological conditions, which is expected. Yet, the map presented in Figure 5.20 shows that the two degrees Celsius temperature rise target can be met in a large number of futures, including various cases that display markedly unfavorable climate or technological conditions. To a certain extent, this is a counterintuitive result because the two degrees Celsius target is by its own merit an ambitious objective.

As described in section V.2.2, in these adverse conditions the optimal policy response is strong because it is cost-effective to implement high carbon taxes and high R&D and technology subsidies in order to avoid the environmental damage caused by high temperature rise levels. In particular, under these circumstances the GCF funding expands the budget constraint in the emerging region allowing for a stronger policy intervention across both regions. This shows that optimal environmental regulation is not a static concept, but rather a dynamic one, and that the architecture of cooperation changes depending on the unfolding technological and climate conditions.

From a policy perspective it is also important to judge the performance of different policy regimes in light of well-defined cost thresholds that can illustrate to decision makers and interested parties the importance that the technological and climate context have not only on defining the structure and effectiveness of policy intervention, but ultimately on the cost of optimal environmental regulation.

Figure 5.21 shows the results of re-running the preceding analysis adding a 10% cost threshold to the vulnerability criteria. Thus the non-vulnerable futures in this case are those in which the optimal environmental policy achieves the CO_2 stabilization target or the two degrees Celsius temperature rise target at an implementation cost below 10%. Since the cost of policy intervention is the percent difference in consumption levels between the policy intervention case and the future without action case (i.e. laissez-faire economy), these non-vulnerable futures represent the best combination of economic and environmental outcomes. In a real policy setting this cost threshold would be defined by decision makers in climate negotiations. In fact, in this case, it is likely that policy makers would find it useful to explore these results across various different policy cost thresholds such that this could support deliberation. Thus, it should be understood that for this example I have arbitrarily chosen this 10% threshold to highlight that comprehensive climate policy that uses carbon taxes and complementary technology policy can lead to both advantageous economic and environmental outcomes.

The results presented in Figure 5.2 show that some uncertainty dimensions are key for meeting this more ambitious target. As expected, this new map shows that the elasticity of substitution of the technological sectors and climate sensitivity are key drivers of this vulnerability type. However, it also highlights the important role of some of the technological uncertainty dimensions. For instance, the map shows that for the majority of scenario cells that display low relative transferability it is not possible to meet cost and climate targets, regardless of the other uncertainty dimensions. This exemplifies the importance that the pace of development SETs in the emerging region has for reducing the costs of optimal environmental regulation. Similarly, SETs' R&D returns are also shown to be an important driver of vulnerability.

Figure 5.21
Robust Mapping of Least-Regret Optimal Environmental Regulation
Policy Cost Threshold=10%

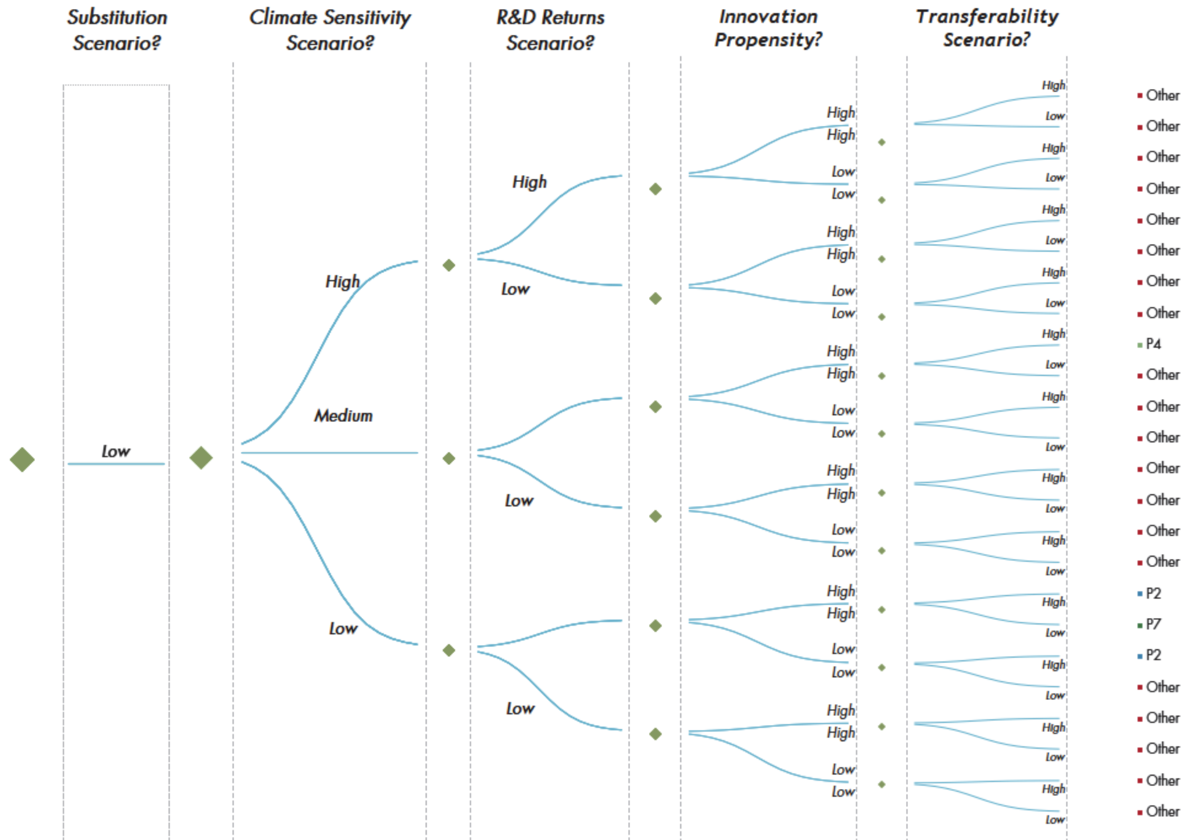
		Low Climate Sensitivity				Medium Climate Sensitivity				High Climate Sensitivity			
		High Innovation Propensity		Low Innovation Propensity		High Innovation Propensity		Low Innovation Propensity		High Innovation Propensity		Low Innovation Propensity	
		High Transferability	Low Transferability	High Transferability	Low Transferability	High Transferability	Low Transferability	High Transferability	Low Transferability	High Transferability	Low Transferability	High Transferability	Low Transferability
High Substitution	High R&D Returns	P2	P6	P6		P6	P3	P7		P7		P4	
	Low R&D Returns	P6				P4	P4						
Medium Substitution	High R&D Returns	P5	P2	P2		P7	P7	P7				P6	
	Low R&D Returns	P2				P7							
Low Substitution	High R&D Returns	P2	P7	P2		P4							
	Low R&D Returns												

NOTES: Each scenario cell represents the set of futures that fall into combinations of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. The label and the color legend denote the corresponding least regret policy for each scenario cell.

It is possible to transform this type of uncertainty maps into futures' trees that can be later used to conduct further statistical analysis such as Classification and Regression Tree (CART) Analysis (Lawrence and Wright, 2001) or for developing adaptive strategies.

Figure 5.22 provides an example of this transformation process for a subset of the scenario cells described in Figure 5.21. Each branch of this futures' tree describes a combination of different uncertainty conditions across the different dimensions considered (i.e. elasticity of substitution, climate sensitivity, R&D returns, innovation propensity and transferability). Thus for different policy regimes it is possible look for patterns across the tree branches that describe the conditions that lead to the use of one policy regime over the other.

Figure 5.22
Example of Futures' Tree for Low Elasticity of Substitution Futures



NOTES: This futures' tree describes each scenario cell as one branch in tree; the final part of each branch denotes the least cost regret policy for that combination of future conditions.

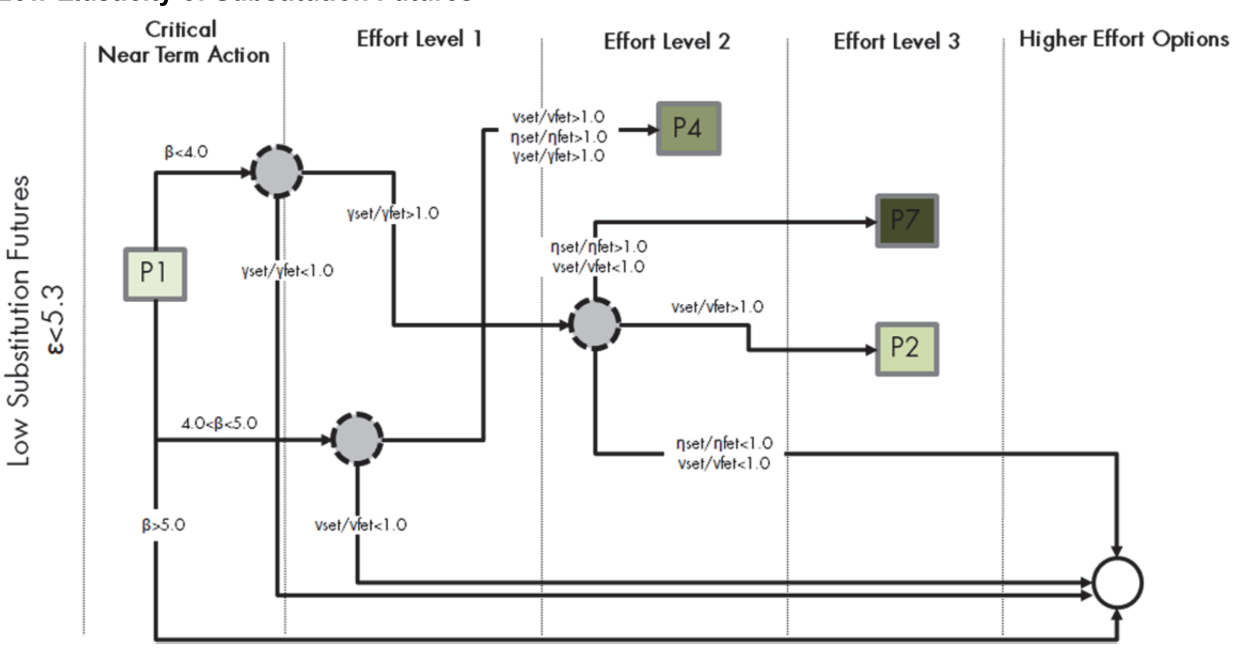
V.5 A Dynamic Architecture for Low Cost Decarbonization

Recent applications of RDM have focused on expanding the suit of methods of exploratory modeling and scenario discovery to develop strategies that adapt to new information or to changing conditions of the decision context. For instance Bloom (2015) describes an expansion of the RDM analysis cycle that is suited for providing planners' decision support for developing adaptive strategies. This approach uses a naïve-Bayes' model to assist planners in integrating new information in their decision-making process such that they can identify which new information can lead to changes in their plans and the tradeoffs of doing so. Kalra et al. (2015) use RDM methods and portfolio optimization to develop an adaptive decision tree for designing an adaptive investment plan for a water utility company in Peru. In this latter case, the adaptive plan evolves as new information about climate conditions, budget availability and water demand unfold. Haasnoot et al. (2013) use exploratory modeling to develop adaptation pathways which are a sequence of possible actions that are recommended after a tipping point has been reached.

It is possible to combine these adaptive planning approaches with the results depicted in Figure 5.21 and Figure 5.22 to develop a dynamic architecture for decarbonization. For this process I trace commonalities among the futures tree's branches in order to identify the combinations of uncertainties that signal a move from one policy regime to another. These moves between policy regimes describe increasing levels of effort or cooperation across the different sectors. For instance, for the independent carbon tax policy "P1", valid moves are: P1→P2, P1→P3, P1→P4, P1→P5, P1→P6 and P1→P7. For the policy regime "P3", valid moves are: P3→P5, P3→P7; for policy regime "P4", valid moves are: P4→P6, P4→P6. Finally for policy regimes "P5" and "P6", the valid moves are: P5→P7 and P6→P7 respectively.

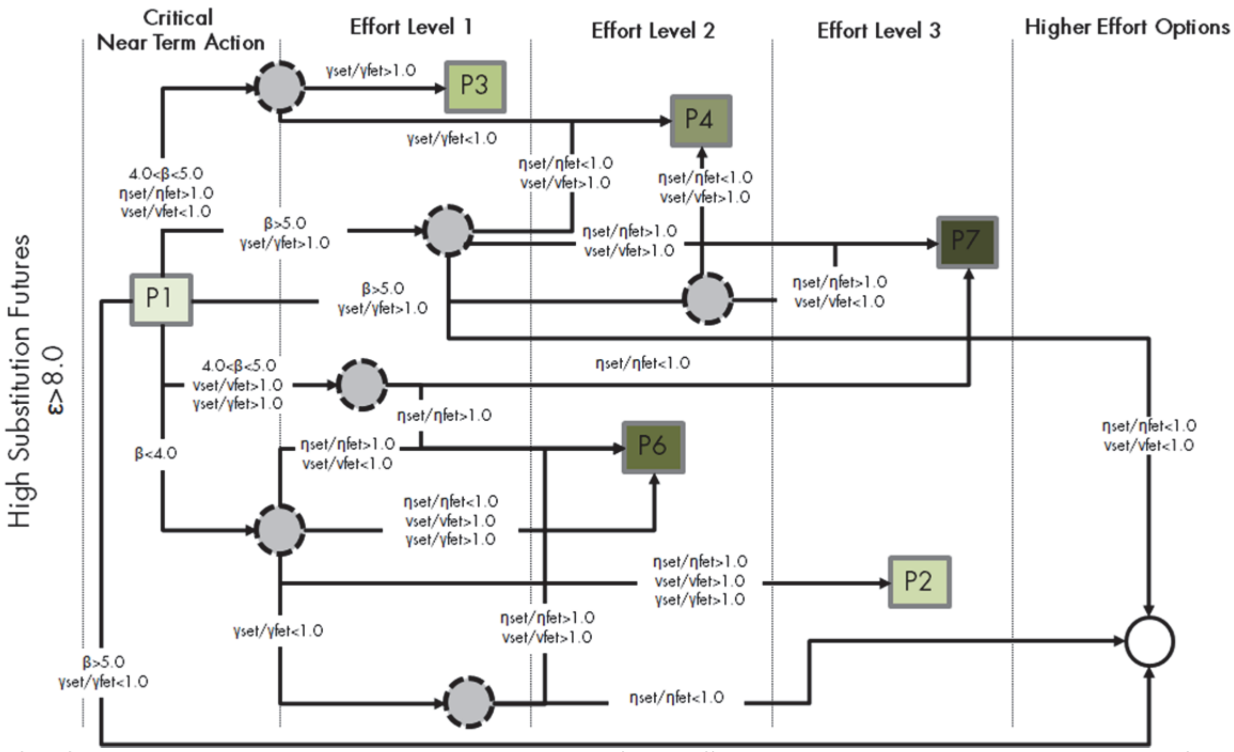
Figure 5.23 and Figure 5.24 illustrate how this analytical process can be used to develop a dynamic architecture for decarbonization. In both figures, lines describe pathways towards one of the different policy regimes. Labels describe the future conditions shared by individual pathways and nodes indicate the conditions that split common pathways into individual ones.

Figure 5.23
Dynamic Architecture for Decarbonization
Low Elasticity of Substitution Futures



NOTES: Each line describes a pathway towards one of the different policy regimes; labels describe the future conditions shared by individual pathways; nodes indicate the conditions that split common pathways into individual ones. Column names indicate the level of effort associated with each policy regime.

Figure 5.24
Dynamic Architecture for Decarbonization
High Elasticity of Substitution Futures



NOTES: Each line describes a pathway towards one of the different policy regimes; labels describe the future conditions shared by individual pathways; nodes indicate the conditions that split common pathways into individual ones. Column names indicate the level of effort associated with each policy regime.

The pathways depicted in Figure 5.23 and 5.24 show that it is possible to represent the results of scenario discovery with high-dimensional stacking as a dynamic architecture that adapts to changing climate and technological conditions. In this case, both pathways begin with carbon taxation as a critical near term action. In the EDIAM modeling framework, carbon taxation directs economics agent's efforts towards the sustainable energy sector and it is also necessary to fund the complementary technology policy programs in both regions. Then in subsequent phases different pathways are triggered depending on the unfolding climate and technological conditions. Note that these pathways show that subsequent phases of technological cooperation are sometimes triggered by simple dimensional conditions. For instance, Figure 5.23 show that for the low elasticity futures, high climate sensitivity leads directly to the consideration of high effort options for which the cost of policy intervention is above the 10% cost threshold.

These pathways illustrate clearly that optimal environmental regulation in the context of climate change mitigation is not a static concept, but rather a dynamic one that adapts to changing climate and technological conditions. This analysis also shows that different cooperation regimes under the GCF are better suited for different combinations of climate and technological conditions, such that it is possible to combine these different architectures into a dynamic framework for technological cooperation.

V.6 Summary

This chapter describes an RDM study that focuses on understanding the role that climate change and technological deep uncertainty have on the structure and effectiveness of optimal environmental regulation across advanced and emerging regions.

The EDIAM model is used as the scenario generator in this RDM study. The scope of the computational experiment in this study considers an ample set of climate and technological scenarios. These scenarios combine five sources of uncertainty: climate change, elasticity of substitution and three different sources of technological uncertainty (i.e. R&D returns, innovation propensity and technological transferability). The performance of eight different policy regimes is evaluated in terms of end-of-century conditions. In particular, the analysis focuses on understanding under which circumstances the stabilization of CO_2 emissions and/or the two degrees Celsius targets are met. The scope of the analysis considers 3,600 different futures across eight policy regimes, yielding a total of 28,800 thousand simulation cases.

Comparing the structure of optimal environmental regulation across GCF based policy regimes and non-GCF policy regimes shows that the GCF clearly influences the structure of the optimal policy response. In particular, I find that the structure of optimal environmental regulation is strongly influenced by the GCF, such that in the most adverse climate and technological futures, the GCF enables a stronger policy response in the emerging region which would not be possible otherwise. Yet, I also find that under the most favorable scenarios, comprehensive GCF cooperation may lead to higher policy intervention costs.

I combine traditional scenario discovery methods (Bryant and Lempert, 2010) with high-dimensional stacking methods (Suzuki, Stern and Manzocchi, 2015; Taylor et al., 2006; LeBlanc, Ward and Wittels, 1990) for describing the vulnerability conditions of different policy regimes. The results show that the objective of stabilizing CO_2 emissions before the end of the century is met under a limited number of futures that describe favorable climate and technological conditions. In contrast the two degrees Celsius target (without CO_2 stabilization) can be met in a greater number of futures.

I also find that different policy regimes are more effective under different uncertainty conditions and that for various scenarios it is possible to meet the climate change targets through more than one policy regime. I use robustness criteria to map the least-cost regret policy response across the uncertainty space. This mapping process shows that that there is not one single policy regime that dominates over the entirety of the uncertainty space. On the contrary, these results show that by combining different types of policy architectures (i.e. GCF based and non-GCF based) it is possible meet one or the two climate change policy targets in a greater number of futures.

Finally, I describe a method by which it is possible to combine the results of scenario discovery and of the robust mapping analysis to construct a dynamic architecture of low cost technological cooperation. This dynamic architecture consists of adaptive pathways (Haasnoot et al., 2013) which begin with carbon taxation across both regions as a critical near term action. Then in subsequent phases different forms of cooperation are triggered depending on the unfolding climate and technological conditions.

These pathways demonstrate that under the EDIAM and other IAMs modeling frameworks optimal environmental regulation is not a static concept, but rather a dynamic one which adapts to changing climate and technological conditions. In this respect, the analysis presented in this chapter shows that different cooperation regimes under the GCF are better suited for different combinations of climate and technological conditions, such that it is possible to combine these different architectures into a dynamic framework for low cost technological cooperation that expands the possibilities of success across the uncertainty space.

CHAPTER VI

Conclusions

VI.1 Contributions to Existing Scientific Literature

The analysis presented in this dissertation contributes primarily to the scientific literature dealing with climate change mitigation and with international environmental technological change.

From a methodological perspective, the analysis presented in this monograph demonstrates that it is possible to combine Robust Decision Making methods and Integrated Assessment Models (IAMs) to consider jointly the interplay of climate change and technological uncertainty. From this perspective, IAMs can be used as scenario generators in an exploratory analysis setting and RDM scenario discovery data mining and visualization techniques can be used to study the resulting database.

As discussed in chapters one and two many aspects associated with climate change policy and international environmental technological change discussed in this monograph have been studied the past. Thus many of the results presented in this study echo previous findings in the scientific literature. As Nordhaus (2011), I find that international carbon taxation can induce a global transition towards sustainable energy technologies and avoid environmental collapse. Similar to Acemoglu et al. (2012) I find that complementing carbon taxation with technology policies can accelerate this transition and reduce the costs of climate change mitigation. Also, similarly to Fischer and Sterner (2012) this dissertation shows that climate change uncertainty influences the structure of the optimal policy response and as Bosetti and Tavoni (2009) I find that uncertainty about technological change also affects the structure and effectiveness of the optimal policy response. Finally, as Di Maria and Smulders (2004) I find that differences between advanced and emerging nations also influence noticeable the structure of optimal environmental regulation.

Thus the innovative aspect of this dissertation is that it combines the research scope of these previous studies into one modeling framework that I apply to study climate change co-financing through the GCF across an ample set of climate and technological scenarios. In doing so, I show that there is not one single policy regime that dominates over the entire uncertainty space. Rather, this dissertation shows that that it is possible to combine these different architectures into a dynamic framework for technological cooperation across regions that can be adapted to unfolding climate and technological conditions. This leads to a greater rate of success in meeting the end-of-century climate change objectives.

VI.2 Implications for Climate Change Policy and the Green Climate Fund

VI.2.1 Investing Carbon Taxes Revenues into Complementary Technology Policies is a Robust Option

This dissertation shows that the implementation of an international carbon tax can induce an international transition towards sustainable energy technologies. However, I find that across many climate change and technological conditions this international carbon tax by itself fails to induce this transition at a rate that can successfully stabilize CO_2 emissions before the end of the century.

Similarly to Isley et al. (2015) I find that in an international context investing carbon tax revenues into complementary technology policies increases noticeable the rate of success in meeting the end-of-century climate change policy objectives. In fact, from the perspective of optimal environmental regulation, I find that in many climate and technological conditions it is optimal for both regions to use carbon tax revenues for financing GCF efforts.

VI.2.2 There Are Candidate Shaping Actions for Accelerating International Decarbonization

As in Acemoglu (2002) this study shows that the elasticity of substitution between the sustainable and fossil energy sectors is a key factor for determining the success of optimal environmental regulation. In addition to the elasticity of substitution, I find that sustainable energy technologies' R&D returns and the rate at which these technologies are absorbed by emerging nations are key factors in determining the success and costs of the optimal policy response. In particular these technological dimensions are found to be important for achieving low cost decarbonization.

From the perspective of assumption based planning, these uncertainties can be viewed as candidate shaping actions (Dewar, 2002). This implies that these key uncertainties can be viewed as policy levers and moving the system towards the favorable spectrum of these uncertainties dimensions can reduce vulnerabilities of the GCF efforts.

These technological uncertainties describe the institutional environment supporting innovative activity in the sustainable energy and fossil energy sectors, and although the evolution of these institutions across advanced and emerging nation is deeply uncertain. The analysis presented in this monograph shows that if these institutions evolve such that they enhance the innovative activity in the sustainable energy sector across both regions, it is possible to accelerate international decarbonization and reduce the cost of policy intervention.

VI.2.3 A Flexible Green Climate Fund Architecture Can Lead to Low Cost Decarbonization

This study shows that the architecture of the Green Climate Fund (GCF) can become more robust to climate and technological uncertainty if it is designed dynamically such that it can adapt to unfolding climate and technological conditions.

I find that using the GCF for financing jointly sustainable energy projects (i.e. technology subsides) and the development of technological capacities (i.e. R&D subsidies) in the emerging nations is not always the most cost-effective financing strategy, as in various alternative circumstances more targeted financing schemes are more effective for inducing low cost decarbonization.

VI.2.4 Monitoring the Evolution of Sustainable Energy and Fossil Energy Technologies Is Important for Climate Change Policy

Frequently climate change policy discussions focus solely on the evolution and rate of improvement of sustainable energy technologies to assess the progress of climate change mitigation efforts. However, this study shows that the technological evolution of both sustainable energy technologies and fossil energy technologies strongly influences the structure, effectiveness and costs of optimal environmental regulation under the GCF. Thus, it appears relevant for future research to develop a framework that can help monitoring the progress of sustainable energy technologies with respect to fossil energy technologies.

VI.3 Limitations and Suggestions for Future Research

This monograph represents an initial effort to combine exploratory modeling, RDM methods and IAMs for considering jointly climate and technological uncertainty into climate change policy assessment studies. Thus additional research efforts could refine and improve the study presented in this monograph in various forms.

VI.3.1 Geographical Disaggregation

The EDIAM modeling framework presented in this study remains highly aggregated and abstract. Future research can focus on expanding this modeling framework such that it can depict more economic regions. This would improve the policy usefulness of this analysis as it would make it more relevant to specific regions.

Further geographical disaggregation can also lead to a more detailed and accurate description of GCF financing such that more specific recommendations regarding the structure of the GCF can be provided.

VI.3.2 Technological Disaggregation

The technological sectors described in the EDIAM framework are highly abstract. Future refinements of this modeling framework should focus on providing a more detailed description of the competing technological sectors. This expansion of the modeling framework can also lead to more relevant and specific policy recommendations.

One important limitation of this study is that it does not consider the evolution of carbon removal and sequestration technologies such as carbon capture and storage (CSS). The inclusion of this type of technologies can substantially change the adaptive pathways describe in this study and can potentially illuminate new avenues for climate change policy cooperation.

VI.3.3 Considering Additional Uncertainties

There are several structural expansions that can be added to the EDIAM modeling framework which can yield new insights in this context. For instance, currently the EDIAM framework does not consider the implications of trade among regions. In future expansions of this framework including the effects of energy trade among regions can highlight new forms in which climate and technological uncertainty affect the structure and effectiveness of optimal environmental regulation.

In its current version, the damage function in the EDIAM framework assumes that the impacts of climate change affect equally advanced and emerging nations. However, this is not necessarily true as it appears that the impacts of climate change will be greater in emerging and developing nations. Thus an illustrative expansion of this analysis would include the consideration of alternative climate change damage scenarios.

VI.3.4 Structural and Analytical Expansions

In its current form the EDIAM framework only considers the case in which new technologies developed in advanced nations are imitated by emerging nations. In this respect, two additional cases are relevant for expanding the EDIAM framework: 1) the case in which emerging nations also develop new technologies such that these can also be adopted in advanced nations and 2) the case in which new technologies are developed jointly by the two regions.

Currently the EDIAM framework does not account for economic damages resulting from increase temperatures. In subsequent expansions it would be important to include this cost element in the performance metrics such that it can be considered. The inclusion of this cost element will significantly impact the performance of the future without action reference case.

Finally in subsequent expansions of the model it would be necessary to test EDIAM's behavior against previous IAMs studies. Given the exploratory nature of the EDIAM framework it would enhance the usefulness of the model to be able to replicate the results and behavior of other IAMs studies. It would also be useful for this study to provide a more detailed and systematic comparison of the reference case runs against the SRES socioeconomic pathways.

References

Acemoglu, Daron, "Directed technical change," *The Review of Economic Studies,* Vol. 69, No. 4, 2002, pp. 781-809.

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous, "The Environment and Directed Technical Change," *American Economic Review,* Vol. 102, No. 1, 2012, pp. 131-166.

Achtnicht, Martin, Georg Bühler, and Claudia Hermeling, "The impact of fuel availability on demand for alternative-fuel vehicles," *Transportation Research Part D: Transport and Environment,* Vol. 17, No. 3, 5//, 2012, pp. 262-269.

Aghion, Philippe, and Peter Howitt, *Endogenous growth theory*: MIT press, 1998.

Arthur, W. Brian, *The Nature of Technology: What It Is and How It Evolves*: Penguin UK, 2009.

Baker, Erin, and Kwame Adu-Bonnah, "Investment in risky R&D programs in the face of climate uncertainty," *Energy Economics,* Vol. 30, No. 2, 3//, 2008, pp. 465-486.

Baker, John, "New technology and possible advances in energy storage," *Energy Policy,* Vol. 36, No. 12, 12//, 2008, pp. 4368-4373.

Bankes, Steve "Exploratory Modeling for Policy Analysis," *Operations Research,* Vol. 41, No. 3, 1993, pp. 435-449.

Barrett, S., "Climate treaties and "breakthrough" technologies," *American Economic Review,* Vol. 96, No. 2, May, 2006, pp. 22-25.

Blackman, Allen, and Arne Kildegaard, "Clean technological change in developing-country industrial clusters: Mexican leather tanning," *Environmental economics and policy studies,* Vol. 12, No. 3, 2010, pp. 115-132.

Bloom, Evan, *Changing Midstream: Providing Decision Support for Adaptive Strategies using Robust Decision making: Applications in the Colorado River Basin*, Pardee RAND Graduate School, 2015.

Bosetti, V., C. Carraro, M. Galeotti, E. Massetti, and M. Tavoni, "WITCH - A World Induced Technical Change Hybrid model," *Energy Journal*, 2006, pp. 13-37.

Bosetti, Valentina, and Massimo Tavoni, "Uncertain R&D, backstop technology and GHGs stabilization," *Energy Economics,* Vol. 31, Supplement 1, //, 2009, pp. S18-S26.

Bryant, Benjamin P, and Robert J Lempert, "Thinking inside the box: a participatory, computer-assisted approach to scenario discovery," *Technological Forecasting and Social Change,* Vol. 77, No. 1, 2010, pp. 34-49.

Cabo, Francisco, Guiomar Martin-Herran, and Maria P. Martinez-Garcia, "Global Warming and R&D-based Growth in a Trade Model between Environmentally Sensitive and Environmentally Neglectful Countries," *The Oxford Handbook of the Macroeconomics of Global Warming*: Oxford University Press, 2014.

Coe, David T, Elhanan Helpman, and Alexander W Hoffmaister, "International R&D spillovers and institutions," *European Economic Review,* Vol. 53, No. 7, 2009, pp. 723-741.

———, "North-South R&D Spillovers," *The Economic Journal,* Vol. 107, No. 440, 1997, pp. 134-149.

Comin, Diego, and Bart Hobijn, *The CHAT dataset*, National Bureau of Economic Research, 2009.

———, "Cross-country technology adoption: making the theories face the facts," *Journal of Monetary Economics,* Vol. 51, No. 1, 2004, pp. 39-83.

———, "An Exploration of Technology Diffusion," *American Economic Review,* Vol. 100, No. 5, 2010, pp. 2031-2059.

Comin, Diego, Bart Hobijn, and Emilie Rovito, *Five facts you need to know about technology diffusion*, National Bureau of Economic Research, 2006.

Cui, Lian-biao, Lei Zhu, Marco Springmann, and Ying Fan, "Design and analysis of the green climate fund," *Journal of Systems Science and Systems Engineering,* Vol. 23, No. 3, 2014, pp. 266-299.

Dalal, S., B. Han, R. Lempert, A. Jaycocks, and A. Hackbarth, "Improving scenario discovery using orthogonal rotations," *Environmental Modelling & Software,* Vol. 48, 10//, 2013, pp. 49-64.

Dasgupta, Partha, and Joseph Stiglitz, "Uncertainty, industrial structure, and the speed of R&D," *The Bell Journal of Economics*, 1980, pp. 1-28.

De Coninck, Heleen, Carolyn Fischer, Richard G Newell, and Takahiro Ueno, "International technology-oriented agreements to address climate change," *Energy Policy,* Vol. 36, No. 1, 2008, pp. 335-356.

Dechezlepretre, A., M. Glachant, and Y. Meniere, "The clean development mechanism and the international diffusion of technologies: An empirical study," *Energy Policy,* Vol. 36, No. 4, Apr, 2008, pp. 1273-1283.

Dechezleprêtre, Antoine, Matthieu Glachant, Ivan Haščič, Nick Johnstone, and Yann Ménière, "Invention and transfer of climate change–mitigation technologies: a global analysis," *Review of Environmental Economics and Policy,* Vol. 5, No. 1, 2011, pp. 109-130.

Deser, Clara, Adam Phillips, Vincent Bourdette, and Haiyan Teng, "Uncertainty in climate change projections: the role of internal variability," *Climate Dynamics,* Vol. 38, No. 3-4, 2012, pp. 527-546.

Dewar, James A, *Assumption-based planning: A tool for reducing avoidable surprises*: Cambridge University Press, 2002.

Di Maria, Corrado, and Sjak A. Smulders, "Trade Pessimists vs Technology Optimists: Induced Technical Change and Pollution Havens," *Advances in Economic Analysis & Policy,* Vol. 4, No. 2, 2004, pp. 1-25.

Di Maria, Corrado, and Edwin Van der Werf, "Carbon leakage revisited: unilateral climate policy with directed technical change," *Environmental and Resource Economics,* Vol. 39, No. 2, 2008, pp. 55-74.

EIA, "International Energy Statistics ", edited by U.S. Energy Information Administration, EIA, http://www.eia.gov/, 2015.

Engwerda, Jacob, "Prospects of Tools from Differential Games in the Study of Macroeconomics of Climate Change," *The Oxford Handbook of the Macroeconomics of Global Warming*: Oxford University Press, 2014.

Evenson, Robert E, and Larry Westphal, "Technological change and technological strategy," *Handbook of development economics,* Vol. 3, No. 1, 1995, pp. 2209-2299.

Fischbach, Jordan R, Robert J Lempert, Edmundo Molina-Perez, Abdul Ahad Tariq, Melissa L Finucane, and Frauke Hoss, "Managing Water Quality in the Face of Uncertainty," RAND Corporation, 2015.

Fischer, C., and R. G. Newell, "Environmental and technology policies for climate mitigation," *Journal of Environmental Economics and Management,* Vol. 55, No. 2, Mar, 2008, pp. 142-162.

Fischer, Carolyn, "Emissions pricing, spillovers, and public investment in environmentally friendly technologies," *Energy Economics,* Vol. 30, No. 2, 2008, pp. 487-502.

Fischer, Carolyn, and Thomas Sterner, "Climate Policy, Uncertainty, and the Role of Technological Innovation," *Journal of Public Economic Theory,* Vol. 14, No. 2, 2012, pp. 285-309.

Fisher-Vanden, K., and M. S. Ho, "Technology, development, and the environment," *Journal of Environmental Economics and Management,* Vol. 59, No. 1, Jan, 2010, pp. 94-108.

Friedman, Jerome H, and Nicholas I Fisher, "Bump hunting in high-dimensional data," *Statistics and Computing,* Vol. 9, No. 2, 1999, pp. 123-143.

Golombek, Rolf, and Michael Hoel, "Unilateral emission reductions and cross-country technology spillovers," *Advances in Economic Analysis & Policy,* Vol. 3, No. 2, 2004.

Greiner, Alfred, "Climate Change and Second-best Abatement in a Multiregion World with Endogenous Growth," *The Oxford Handbook of the Macroeconomics of Global Warming*: Oxford University Press, 2014.

Grossman, Gene M, and Elhanan Helpman, "Innovation and Growth in the Global Economy," *MIT Press Books,* Vol. 1, 1993.

Groves, D, E Bloom, JR Fischbach, and Debra Knopman, "Adapting to a Changing Colorado River: Making Future Water Deliveries More Reliable Through Robust Management Strategies," *AGU Fall Meeting Abstracts*, 2013, p. 1407.

Groves, David G, Jordan R Fischbach, Debra Knopman, David R Johnson, and Kate Giglio, *Strengthening Coastal Planning: How Coastal Regions Could Benefit from Louisiana's Planning and Analysis Framework*: Rand Corporation, 2014.

Groves, David G., David Yates, and Claudia Tebaldi, "Developing and applying uncertain global climate change projections for regional water management planning," *Water Resources Research,* Vol. 44, No. 12, 2008, p. W12413.

Grübler, Arnulf, Nebojša Nakićenović, and David G. Victor, "Dynamics of energy technologies and global change," *Energy Policy,* Vol. 27, No. 5, 5//, 1999, pp. 247-280.

Haasnoot, Marjolijn, Jan H. Kwakkel, Warren E. Walker, and Judith ter Maat, "Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world," *Global Environmental Change,* Vol. 23, No. 2, 4//, 2013, pp. 485-498.

Helm, Carsten, and Stefan Pichler, "Climate Policy with Technology Transfers and Permit Trading," *Environmental and Resource Economics,* Vol. 60, No. 1, 2015/01/01, 2015, pp. 37-54.

Howitt, Peter, "Endogenous Growth and Cross-Country Income Differences," *The American Economic Review,* Vol. 90, No. 4, 2000, pp. 829-846.

IPCC, *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, 2013a.

———, "Summary for Policymakers," in Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P.M. Midgley, eds., *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, 2013b, pp. 1–30. www.climatechange2013.org

Isley, Steven C., Robert J. Lempert, Steven W. Popper, and Raffaele Vardavas, "The effect of near-term policy choices on long-term greenhouse gas transformation pathways," *Global Environmental Change,* Vol. 34, 9//, 2015, pp. 147-158.

Jacobsson, Staffan, and Anna Johnson, "The diffusion of renewable energy technology: an analytical framework and key issues for research," *Energy Policy,* Vol. 28, No. 9, 7/31/, 2000, pp. 625-640.

Keller, W., "International technology diffusion," *Journal of Economic Literature,* Vol. 42, No. 3, Sep, 2004, pp. 752-782.

———, "Absorptive capacity: On the creation and acquisition of technology in development," *Journal of development economics,* Vol. 49, No. 1, 1996, pp. 199-227.

———, "Chapter 19 - International Trade, Foreign Direct Investment, and Technology Spillovers," in Bronwyn, H. Hall and Rosenberg Nathan, eds., *Handbook of the Economics of Innovation*: North-Holland, 2010, pp. 793-829.

Kwakkel, Jan H., Marjolijn Haasnoot, and Warren E. Walker, "Developing dynamic adaptive policy pathways: a computer-assisted approach for developing adaptive strategies for a deeply uncertain world," *Climatic Change,* Vol. 132, No. 3, 2014, pp. 373-386.

Lanjouw, Jean Olson, and Ashoka Mody, "Innovation and the international diffusion of environmentally responsive technology," *Research Policy,* Vol. 25, No. 4, 1996, pp. 549-571.

Lawrence, Rick L, and Andrea Wright, "Rule-based classification systems using classification and regression tree (CART) analysis," *Photogrammetric engineering and remote sensing,* Vol. 67, No. 10, 2001, pp. 1137-1142.

LeBlanc, Jeffrey, Matthew O Ward, and Norman Wittels, "Exploring n-dimensional databases," *Proceedings of the 1st conference on Visualization'90*, 1990, pp. 230-237.

Lempert, Robert, David G. Groves, Steven Popper, and Steve Bankes, "A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios," *Management Science,* Vol. 52, No. 4, 2006, pp. 514-528.

Lempert, Robert J, "Climate targets: Values and uncertainty," *Nature Climate Change,* Vol. 5, No. 10, 2015, pp. 914-915.

Lempert, Robert J, and David G Groves, "Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west," *Technological Forecasting and Social Change,* Vol. 77, No. 6, 2010, pp. 960-974.

Lempert, Robert, Steven Popper, and Steven Bankes, *Shaping the next one hundred years: new methods for quantitative, long-term policy analysis*: Rand Corporation, 2003.

Marangoni, Giacomo, and Massimo Tavoni, "The Clean energy R&D strategy for 2°C," *Climate Change Economics,* Vol. 05, No. 01, 2014, p. 1440003.

Maurer, Edwin P, "Uncertainty in hydrologic impacts of climate change in the Sierra Nevada, California, under two emissions scenarios," *Climatic Change,* Vol. 82, No. 3-4, 2007, pp. 309-325.

Mercure, J. F., H. Pollitt, U. Chewpreecha, P. Salas, A. M. Foley, P. B. Holden, and N. R. Edwards, "The dynamics of technology diffusion and the impacts of climate policy instruments in the decarbonisation of the global electricity sector," *Energy Policy,* Vol. 73, Oct, 2014, pp. 686-700.

Newell, Richard G, "International climate technology strategies," *Harvard Project on International Climate Agreements Discussion Paper*, No. 2008-12, 2008.

Nordhaus, W. D., "The architecture of climate economics: Designing a global agreement on global warming," *Bulletin of the Atomic Scientists,* Vol. 67, No. 1, Jan-Feb, 2011, pp. 9-18.

OECD Stat, Extracts, "Organisation for Economic Co-operation and Development," *Access mode: http://stats.oecd.org*, 2015.
http://stats.oecd.org/index.aspx?DatasetCode=POP_FIVE_HIST

Papageorgiou, Chris, Marianne Saam, and Patrick Schulte, "Elasticity of substitution between clean and dirty energy inputs-a macroeconomic perspective," *ZEW-Centre for European Economic Research Discussion Paper*, No. 13-087, 2013.

Popp, D., "ENTICE: endogenous technological change in the DICE model of global warming," *Journal of Environmental Economics and Management,* Vol. 48, No. 1, Jul, 2004, pp. 742-768.

———, "International innovation and diffusion of air pollution control technologies: the effects of NOx and SO2 regulation in the US, Japan, and Germany," *Journal of Environmental Economics and Management,* Vol. 51, No. 1, Jan, 2006a, pp. 46-71.

———,, "R&D subsidies and climate policy: is there a “free lunch”?," *Climatic Change,* Vol. 77, No. 3-4, 2006b, pp. 311-341.

———, "Climate-Friendly Technological Change for Developing Countries," *The Oxford Handbook of the Macroeconomics of Global Warming*: Oxford University Press, 2014.

Popp, David, Richard G. Newell, and Adam B. Jaffe, "Chapter 21 - Energy, the Environment, and Technological Change," in Bronwyn, H. Hall and Rosenberg Nathan, eds., *Handbook of the Economics of Innovation*: North-Holland, 2010, pp. 873-937.

Pottier, Antonin, Jean-Charles Hourcade, and Etienne Espagne, "Modelling the redirection of technical change: The pitfalls of incorporeal visions of the economy," *Energy Economics,* Vol. 42, 3//, 2014, pp. 213-218.

Reitz, Rolf D., "Directions in internal combustion engine research," *Combustion and Flame,* Vol. 160, No. 1, 1//, 2013, pp. 1-8.

Rivera-Batiz, Luis A, and Paul M Romer, "Economic Integration and Endogenous Growth," *The Quarterly Journal of Economics,* Vol. 106, No. 2, 1991, pp. 531-555.

Rizzi, Francesco, Nees Jan van Eck, and Marco Frey, "The production of scientific knowledge on renewable energies: Worldwide trends, dynamics and challenges and implications for management," *Renewable Energy,* Vol. 62, 2//, 2014, pp. 657-671.

Roberts, David, "The "uncertainty loop" haunting our climate models," in *Energy and Environment*, edited by Vox, 2015. http://www.vox.com/2015/10/23/9604120/climate-models-uncertainty

Rosendahl, K. E., "Cost-effective environmental policy: implications of induced technological change," *Journal of Environmental Economics and Management,* Vol. 48, No. 3, Nov, 2004, pp. 1099-1121.

Schalatek, Liane, Smita Nakhooda, and Neil Bird, "The Green Climate Fund," *Overseas Development Institute and Heinrich Böll Stiftung North America*, 2012.

Siedschlag, Iulia, Donal Smith, Camelia Turcu, and Xiaoheng Zhang, "What determines the location choice of R&D activities by multinational firms?," *Research Policy,* Vol. 42, No. 8, 9//, 2013, pp. 1420-1430.

Solomon, Susan, Gian-Kasper Plattner, Reto Knutti, and Pierre Friedlingstein, "Irreversible climate change due to carbon dioxide emissions," *Proceedings of the National Academy of Sciences,* Vol. 106, No. 6, February 10, 2009, 2009, pp. 1704-1709.

Suzuki, Satomi, Dave Stern, and Tom Manzocchi, "Using Association Rule Mining and High-Dimensional Visualization to Explore the Impact of Geological Features on Dynamic Flow Behavior," *SPE Annual Technical Conference and Exhibition*, 2015.

Taylor, Adam L, Timothy J Hickey, Astrid A Prinz, and Eve Marder, "Structure and visualization of high-dimensional conductance spaces," *Journal of Neurophysiology,* Vol. 96, No. 2, 2006, pp. 891-905.

Taylor, Karl E, Ronald J Stouffer, and Gerald A Meehl, "An overview of CMIP5 and the experiment design," *Bulletin of the American Meteorological Society,* Vol. 93, No. 4, 2012, pp. 485-498.

Train Kenneth, E, "Discrete choice methods with simulation," Cambridge: Cambridge University Press, 2003.

van Kerkhoff, Lorrae, Imran Habib Ahmad, Jamie Pittock, and Will Steffen, "Designing the green climate fund: how to spend $100 billion sensibly," *Environment,* Vol. 53, No. 3, 2011, pp. 18-31.

Wheeler, David, and Kevin Ummel, "Another inconvenient truth: a carbon-intensive south faces environmental disaster, no matter what the north does," *No Matter What the North Does (December 3, 2007)*, 2007.

Wilson, C., A. Grubler, N. Bauer, V. Krey, and K. Riahi, "Future capacity growth of energy technologies: are scenarios consistent with historical evidence?," *Climatic Change,* Vol. 118, No. 2, 2013/05/01, 2013, pp. 381-395.

Working Group on Coupled Modelling, "Coupled Model Intercomparison Project 5 (CMIP5)," edited by Programme, World Climate Research, 2015. https://pcmdi9.llnl.gov/projects/cmip5/

Worrell, Ernst, Rene van Berkel, Zhou Fengqi, Christoph Menke, Roberto Schaeffer, and Robert O. Williams, "Technology transfer of energy efficient technologies in industry: a review of trends and policy issues," *Energy Policy,* Vol. 29, No. 1, 1//, 2001, pp. 29-43.

APPENDIX A

Derivation of Intertemporal Equilibrium Conditions For the EDIAM Model

This section describes the derivation of the intertemporal equilibrium conditions listed in section III.2.5 and which are used for programming the model.

A.1 Equilibrium Levels of Primary Energy

The maximization problem of the producers of secondary energy is as follows:

$$Max\left(Y_{set}^{\frac{\varepsilon-1}{\varepsilon}}+Y_{fet}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}-p_{set}*Y_{set}-p_{fet}*(1+\tau)*Y_{fet}$$

Setting FOCs with respect to Y_{fe}

$$\frac{\varepsilon}{\varepsilon-1}\left(Y_{set}^{\frac{\varepsilon-1}{\varepsilon}}+Y_{fet}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}-1}\frac{\varepsilon-1}{\varepsilon}*Y_{fet}^{\frac{\varepsilon-1}{\varepsilon}-1}=p_{fet}*(1+\tau)$$

$$\left(Y_{set}^{\frac{\varepsilon-1}{\varepsilon}}+Y_{fet}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{1}{\varepsilon-1}}Y_{fet}^{\frac{-1}{\varepsilon}}=p_{fet}*(1+\tau)$$

Then

$$\frac{Y_{se}(t)}{Y_{fe}(t)}=\left(\frac{p_{fe}(t)*(1+\tau)}{p_{se}(t)}\right)^{\varepsilon}$$

A.2 The Equilibrium Prices of Technologies

First we derive the demand for technologies

Using *e3* and the maximization problem faced by the producers of intermediary inputs:

$$Max_{L_{jt},x_{jit}}\ p_{jt}L_{jt}^{1-\alpha}\int_0^1 A_{jit}^{1-\alpha}x_{jit}^{\alpha}di-wL_{jt}-\int_0^1(1-t_s)p_{jit}x_{jit}di$$

$$s.t.$$

$$L_{fet} + L_{set} \leq 1$$

Setting the FOCs with respect to the demand for technology:

$$\frac{\partial}{\partial x_{jit}} p_{jt} L_{jt}^{1-\alpha} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha} di - wL_{jt} - \int_0^1 (1-t_s) p_{jit} x_{jit} di$$

$$= p_{jt} L_{jt}^{1-\alpha} \frac{\partial}{\partial x_{jit}} [\int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha} di] - \frac{\partial}{\partial x_{jit}} [\int_0^1 (1-t_s) p_{jit} x_{jit} di]$$

Then

$$= p_{jt} L_{jt}^{1-\alpha} \frac{\partial}{\partial x_{jit}} A_{jit}^{1-\alpha} x_{jit}^{\alpha} - \frac{\partial}{\partial x_{jit}} (1-t_s) p_{jit} x_{jit}$$

$$= p_{jt} L_{jt}^{1-\alpha} A_{jit}^{1-\alpha} \alpha x_{jit}^{\alpha-1} - (1-t_s) p_{jit}$$

Solving for the optimal level of technology demand:

$$p_{jt} L_{jt}^{1-\alpha} A_{jit}^{1-\alpha} \alpha x_{jit}^{\alpha-1} - (1-t_s) p_{jit} = 0$$

$$x_{jit} = \left(\frac{\alpha p_{jt}}{(1-t_s) p_{jit}}\right)^{\frac{1}{1-\alpha}} L_{jt} A_{jit} \quad \text{...a1}$$

In addition, considering the optimization problem faced by the producers of technology:

$$max \quad (p_{jit} - \psi) x_{jit}$$

Using a1:

$$max_{\{p_{jit}\}} (p_{jit} - \psi) \left(\frac{\alpha p_{jt}}{(1-t_s) p_{jit}}\right)^{\frac{1}{1-\alpha}} L_{jt} A_{jit}$$

Setting FOCs:

$$\frac{d\, \pi_{jit}^m}{d p_{jit}} = \left(\frac{\alpha p_{jt}}{(1-t_s)}\right)^{\frac{1}{1-\alpha}} L_{jt} A_{jit} \left[(p_{jit} - \psi) \frac{d}{d p_{jit}} \left(\frac{1}{p_{jit}}\right)^{\frac{1}{1-\alpha}} + \left(\frac{1}{p_{jit}}\right)^{\frac{1}{1-\alpha}} \frac{d}{d p_{jit}} (p_{jit} - \psi) \right]$$

$$(p_{jit} - \psi) \frac{-1}{1-\alpha} (p_{jit})^{\frac{-1}{1-\alpha} - 1} + (p_{jit})^{\frac{-1}{1-\alpha}} = 0$$

$$\psi = p_{jit} \alpha$$

$$p_{jit} = \frac{\psi}{\alpha} \ldots\text{a2}$$

Substituting a2 into a1, we obtain

$$x_{jit} = \left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{1}{1-\alpha}} L_{jt}A_{jit} \ldots\text{a3}$$

A.3 Equilibrium Research Profits

Monopoly profits of technology developers are given by:

$$\pi_{jit} = (p_{jit} - \psi_j)x_{jit}$$

Using the result in a2, we can write:

$$\pi_{jit} = \psi_j\left(\frac{1-\alpha}{\alpha}\right)x_{jit}$$

Using a3, then profits are given by:

$$\pi_{jit} = \psi_j\left(\frac{1-\alpha}{\alpha}\right)\left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{1}{1-\alpha}} L_{jt}A_{jit}$$

Accounting for R&D subsidies:

$$\pi_{jit} = (1+q_{se})\psi_j\left(\frac{1-\alpha}{\alpha}\right)\left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{1}{1-\alpha}} L_{jt}A_{jit}$$

Considering the probability of success in innovation:

$$E[\pi_{jit}] = \eta_j(1+q_{se})\psi_j\left(\frac{1-\alpha}{\alpha}\right)\left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{1}{1-\alpha}} L_{jt}A_{jit}$$

Then average profits per sector are given by:

$$\Pi_{jt} = \int_0^1 \eta_j(1+q_{se})\psi_j\left(\frac{1-\alpha}{\alpha}\right)\left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{1}{1-\alpha}} L_{jt}A_{jit}di$$

Using assumption

$$A_{jt} \equiv \int_0^1 A_{jit}di$$

Then, in the discrete form we obtain:

$$\Pi_{jt} = \eta_j(1+q_{se})\psi_j\left(\frac{1-\alpha}{\alpha}\right)\left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{1}{1-\alpha}} L_{jt}A_{jt}$$

Therefore the profit ratio across sectors:

$$\frac{\Pi_{se}}{\Pi_{fe}} = (1+q_{se}) * \frac{\eta_{se}}{\eta_{fe}} * \frac{1}{(1-t_s)^{\frac{1}{1-\alpha}}} * \left(\frac{\psi_{fe}}{\psi_{se}}\right)^{\frac{\alpha}{1-\alpha}} * \left(\frac{p_{se}}{p_{fe}}\right)^{\frac{1}{1-\alpha}} * \frac{L_{se}}{L_{fe}} * \frac{A_{se}}{A_{fe}}$$

A.4 Equilibrium Prices of Primary Energy

Taking into account the first order conditions with respect to labor of the producers of intermediate inputs:

$$max_{L_{jt},x_{jit}}\ p_{jt}L_{jt}^{1-\alpha}\int_0^1 A_{jit}^{1-\alpha}x_{jit}^{\alpha}di - wL_{jt} - \int_0^1(1-t_s)p_{jit}x_{jit}di$$

$$\frac{\partial}{\partial L_{jt}} p_{jt}L_{jt}^{1-\alpha}\int_0^1 A_{jit}^{1-\alpha}x_{jit}^{\alpha}di - wL_{jt} - \int_0^1(1-t_s)p_{jit}x_{jit}di$$

$$= (1-\alpha)p_{jt}L_{jt}^{-\alpha}\int_0^1 A_{jit}^{1-\alpha}x_{jit}^{\alpha}di = w$$

Substituting the demand function $x_{jit} = \left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{1}{1-\alpha}} L_{jt}A_{jit}$ …a3

$$(1-\alpha)\left(\frac{\alpha^2}{(1-t_s)\psi_j}\right)^{\frac{\alpha}{1-\alpha}} p_{jt}{}^{\frac{1}{1-\alpha}}\int_0^1 A_{jit}di = w$$

Using assumption 1: $A_{jt} \equiv \int_0^1 A_{jit}di$

Then:

$$p_{jt} \quad = w^{(1-\alpha)}(1-\alpha)^{-(1-\alpha)}A_{jt}{}^{-(1-\alpha)}\left(\alpha^2(1-t_s)^{-1}\psi_j{}^{-1}\right)^{-\alpha}$$

Therefore the ratio of prices:

$$\frac{p_{set}}{p_{fet}} = \left(\frac{A_{fet}}{A_{set}}\right)^{(1-\alpha)} \left(\frac{(1-t_s)\psi_c}{\psi_d}\right)^{\alpha} \quad \text{...a4}$$

We use this result to determine prices for each sector. Taking the final good as the numeraire:

$$\left[p_{set}^{1-\varepsilon} + p_{fet}^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} = 1$$

$$p_{set}^{1-\varepsilon} + p_{fet}^{1-\varepsilon} = 1$$

Using a4:

$$\frac{p_{set}}{p_{fet}} = \left(\frac{A_{set}}{A_{fet}}\right)^{-(1-\alpha)} \left(\frac{\psi_d}{(1-t_s)\psi_c}\right)^{-\alpha} = Rp$$

Then

$$p_{set} = \frac{Rp}{(Rp^{1-\varepsilon}+1)^{\frac{1}{1-\varepsilon}}}$$

A.5 Equilibrium Levels of Labor

Using result *(e35)*: $\frac{p_{set}}{p_{fet}} = (1+\tau) * \left(\frac{Y_{set}}{Y_{fet}}\right)^{-\frac{1}{\varepsilon}}$ And the production function *(e6)*, then :

$$\frac{p_{set}}{p_{fet}} = (1+\tau) * \left(\frac{L_{set}^{1-\alpha}\int_0^1 A_{cit}^{1-\alpha} x_{cit}^{\alpha} di}{L_{fet}^{1-\alpha}\int_0^1 A_{dit}^{1-\alpha} x_{dit}^{\alpha} di}\right)^{-\frac{1}{\varepsilon}}$$

Substituting *(e37):*

$$x_{jit} = \left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{1}{1-\alpha}} L_{jt} A_{jit}$$

Then, the price ratio is given by:

$$\frac{p_{set}}{p_{fet}} = (1+\tau) * \left(\frac{L_{set}\left(\frac{\alpha^2 p_{set}}{(1-t_s)\psi_c}\right)^{\frac{\alpha}{1-\alpha}} \int_0^1 A_{cit}^1\, di}{L_{fet}\left(\frac{\alpha^2 p_{fet}}{\psi_d}\right)^{\frac{\alpha}{1-\alpha}} \int_0^1 A_{dit}^1 di}\right)^{-\frac{1}{\varepsilon}}$$

Using assumption:

$$A_{jt} \equiv \int_0^1 A_{jit} di$$

Then, relative labor is given by:

$$\frac{L_{set}}{L_{fet}} = \frac{(1-t_s)^{\frac{\alpha}{1-\alpha}}}{(1+\tau)^{-\varepsilon}} * \left(\frac{\psi_c}{\psi_d}\right)^{\frac{\alpha}{1-\alpha}} \left(\frac{p_{fet}}{p_{set}}\right)^{-\frac{(1-\alpha)(1-\varepsilon)-1}{1-\alpha}} \frac{A_{fet}}{A_{set}}$$

Considering *(e39)*:

$$\frac{p_{set}}{p_{fet}} = \left(\frac{A_{fet}}{A_{set}}\right)^{(1-\alpha)} \left(\frac{(1-t_s)\psi_c}{\psi_d}\right)^{\alpha}$$

Using the inverse of equilibrium prices of intermediate inputs, then:

$$\frac{L_{set}}{L_{fet}} = (1+\tau)^{\varepsilon} \left(\frac{(1-t_s)\psi_c}{\psi_d}\right)^{\alpha(1-\varepsilon)} \left(\frac{A_{set}}{A_{fet}}\right)^{-(1-\alpha)(1-\varepsilon)}$$

A.6 Equilibrium Levels of Production

Equilibrium levels of production, considering initially e6:

$$Y_{jt} = L_{jt}^{1-\alpha} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha} di$$

Substituting a3:

$$x_{jit} = \left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{1}{1-\alpha}} L_{jt} A_{jit}$$

Then

$$Y_{jt} = L_{jt}^{1-\alpha} \left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{\alpha}{1-\alpha}} L_{jt}^{\alpha} \int_0^1 A_{jit}^{1-\alpha} A_{jit}^{\alpha} di$$

Using assumption

$$A_{jt} \equiv \int_0^1 A_{jit} di$$

Then:

$$Y_{jt} = \left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{\alpha}{1-\alpha}} L_{jt} A_{jt}$$

A.7 Determination of Initial Conditions

Using data on energy production across developed and developing countries it is possible to estimate the corresponding initial levels of productivity for both regions.

From a3, it is known that:

$$Y_{jt} = \left(\frac{\alpha^2 p_{jt}}{(1-t_s)\psi_j}\right)^{\frac{\alpha}{1-\alpha}} L_{jt} A_{jt}$$

From a5, relative labor is given by:

$$\frac{L_{set}}{L_{fet}} = (1+\tau)^{\varepsilon}(1-t_s)^{\frac{\alpha}{1-\alpha}} \left(\frac{\psi_c}{\psi_d}\right)^{\frac{\alpha}{1-\alpha}*(1-\alpha)(1-\varepsilon)} \left(\frac{A_{set}}{A_{fet}}\right)^{-(1-\alpha)(1-\varepsilon)}$$

And from a4, relative prices are given by:

$$\frac{p_{set}}{p_{fet}} = \left(\frac{A_{set}}{A_{fet}}\right)^{-(1-\alpha)} \left(\frac{\psi_d}{(1-t_s)\psi_c}\right)^{-\alpha} = Rp$$

The objective is to express a3 in terms of the productivity of the two sectors. For this, it is necessary to express individually pc and pd. From aX, it is know that:

$$p_{set}^{1-\varepsilon} + p_{fet}^{1-\varepsilon} = 1$$

Then, using a4 and assuming that in the initial stage of the system, no policy is being implemented, then:

$$p_{fet} = \left(\frac{A_{set}}{A_{fet}}\right)^{(1-\alpha)} p_{set}$$

Resulting in:

$$p_{set} = \frac{{A_{fet}}^{\frac{\varphi}{1-\varepsilon}}}{\left({A_{fet}}^{\varphi} + {A_{set}}^{\varphi}\right)^{\frac{1}{1-\varepsilon}}}$$

Similarly, for relative labor:

$$\frac{L_{set}}{L_{fet}} = \left(\frac{A_{set}}{A_{fet}}\right)^{-(1-\alpha)(1-\varepsilon)}$$

$$L_{set} = \left(\frac{A_{set}}{A_{fet}}\right)^{-(1-\alpha)(1-\varepsilon)} L_{fet}$$

From e7:

$$L_{set} + L_{fet} = \rho$$

For L_{set}:

$$L_{set} = \left(\frac{A_{set}}{A_{fet}}\right)^{-(1-\alpha)(1-\varepsilon)} (\rho - L_{set})$$

$$L_{set} = \rho \frac{{A_{fet}}^{\varphi}}{{A_{set}}^{\varphi} + {A_{fet}}^{\varphi}}$$

For L_{fet}:

$$L_{fet} = \rho \left(\frac{{A_{set}}^{\varphi}}{{A_{set}}^{\varphi} + {A_{fet}}^{\varphi}}\right)$$

Then plugging this back into the equation for production, we see that scale factor has a monotonic impact on the production functions:

$$Y_{se} = \rho * \left(A_{set}^{\varphi} + A_{fet}^{\varphi}\right)^{-\frac{\alpha+\varphi}{\varphi}} A_{set} A_{fet}^{\alpha+\varphi} \quad \ldots\text{a21}$$

$$Y_{fe} = \rho * \left(A_{set}^{\varphi} + A_{fet}^{\varphi}\right)^{-\frac{\alpha+\varphi}{\varphi}} A_{set}^{\alpha+\varphi} A_{fet} \quad \ldots\text{a22}$$

Finally, using:

$$Y = \left(Y_{se}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{fe}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

And substituting L_{set} and L_{fet}:

$$Y = \left(\left(\rho * \left(A_{set}^{\varphi} + A_{fet}^{\varphi}\right)^{-\frac{\alpha+\varphi}{\varphi}} A_{set} A_{fet}^{\frac{\alpha+\varphi}{\varphi}}\right)^{\frac{\varepsilon-1}{\varepsilon}} + \left(\rho * \left(A_{set}^{\varphi} + A_{fet}^{\varphi}\right)^{-\frac{\alpha+\varphi}{\varphi}} A_{set}^{\frac{\alpha+\varphi}{\varphi}} A_{fet}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

$$= \rho \quad * \left(A_{set}^{\varphi} + A_{fet}^{\varphi}\right)^{-\left(\frac{1}{(1-\alpha)(1-\varepsilon)}\right)} A_{set} A_{fet} \text{ .. 1.3b}$$

Finally using 1.3b and a1:

$$A_{set} = A_{fet} \left(\frac{Y_{se}}{Y_{fe}}\right)^{\frac{1}{1-\alpha-\varphi}} \text{..r1}$$

Then I can write:

$$\left(Y_{se}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{fe}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} = \rho \left(A_{fet}^{\varphi} \left(\frac{Y_{se}}{Y_{fe}}\right)^{\frac{\varphi}{1-\alpha-\varphi}} + A_{fet}^{\varphi}\right)^{-\frac{1}{\varphi}} A_{fet} \left(\frac{Y_{se}}{Y_{fe}}\right)^{\frac{1}{1-\alpha-\varphi}} A_{fet}$$

Solving for A_{fet}

$$A_{fet} = \frac{1}{\rho} \frac{\left(Y_{se}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{fe}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}}{\left(1 + \left(\frac{Y_{se}}{Y_{fe}}\right)^{\frac{-\varphi}{1-\alpha-\varphi}}\right)^{-\frac{1}{\varphi}}}$$

Then the initial condition for A_{fet} is given by:

$$A_{fet,0} = \frac{1}{\rho} \left(Y_{se,0}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{fe,0}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} \left(1 + \left(\frac{Y_{fe,0}}{Y_{se,0}}\right)^{\frac{\varphi}{1-\alpha-\varphi}}\right)^{\frac{1}{\varphi}}$$

And the initial condition for A_{set} is given by:

$$A_{set,0} = \frac{1}{\rho}\left(Y_{se,0}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{fe,0}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}\left(1 + \left(\frac{Y_{se,0}}{Y_{fe,0}}\right)^{\frac{\varphi}{1-\alpha-\varphi}}\right)^{\frac{1}{\varphi}}$$

where: $\varphi = (1-\alpha)(1-\varepsilon)$

APPENDIX B

Game Theory Analysis of the No-Regret Policy

Figure B.1 describes the strategic context in which the social planners of both regions consider simultaneously three strategies: 1) commit to the no-regret policy, 2) free riding on the efforts of the other region (i.e. "lower effort" strategy) and 3) increase the efforts to climate change mitigation (i.e. "higher effort" strategy).

Figure B.1 presents this game on its normal form. The payoffs noted in each cell are based on the objective function of the optimal policy response described in equation (e43). Each cell compares the payoffs of each strategy with respect to the no-regret policy. Note that because of the no-regret strategy is the optimal policy response it guarantees that even in the case in which both regions decide to implement a higher effort policy the payoffs will be less than the optimal. In this case, the higher economic cost of the policy response reduces its payoffs when compared to the no-regret policy.

The analysis shows that there is only one Nash-equilibrium in the game which is that both regions implement the no-regret policy. Thus, this shows unambiguously that the no-regret policy is the policy that would be preferred by the social planners of both regions and that none of the regions has an incentive to free ride or increase efforts of climate change mitigation.

Figure B.1
Normal Form of Game Theory Analysis of The No-Regret Policy

		Emerging Region		
		Lower effort	No-regret policy	Higher effort
Advanced Region	Lower effort	$V_{AR} \ll V_{AR}^*$ $V_{ER} \ll V_{ER}^*$	$V_{AR} < V_{AR}^*$ $V_{ER} < V_{ER}^*$	$V_{AR} = V_{AR}^*$ $V_{ER} \ll V_{ER}^*$
	No-regret policy	$V_{AR} < V_{AR}^*$ $V_{ER} < V_{ER}^*$	$\underline{V_{AR}^*}$ $\underline{V_{ER}^*}$	$V_{AR} > V_{AR}^*$ $V_{ER} < V_{ER}^*$
	Higher effort	$V_{AR} \ll V_{AR}^*$ $V_{ER} = V_{ER}^*$	$V_{AR} < V_{AR}^*$ $V_{ER} > V_{ER}^*$	$V_{AR} < V_{AR}^*$ $V_{ER} < V_{ER}^*$

NOTES: Each cell compares the payoffs of each strategy with respect to the no-regret policy. Note that because of the no-regret strategy is the optimal policy response it guarantees that even in the case in which both regions decide to implement a higher effort policy the payoffs will be less than the optimal. In this case, the higher economic cost of the policy response reduces its payoffs when compared to the no-regret policy.

APPENDIX C
Calibrating EDIAM's Climate Change Parameters Using the CMIP5 Data Ensemble

This appendix describes the process followed to calibrate the climate change parameters in the EDIAM model to existing CMIP5 climate projections.

First, I estimate parameters β, $CO_{2,0}$ $CO_{2,disaster}$ in equation *(e3)* individually for each CMIP5 model using OLS in the following regression model:

$$T_{t,m} = c + \beta_m * ln\left(co_2[ppm]_{t,m}\right)$$

where "$T_{t,m}$" denotes temperature observations at each time period "t" for each model "m";"c" is the constant parameter in the linear model and the term $co_2[ppm]_{t,m}$ denotes co_2 atmospheric concentrations in parts per million at each time "t" for each model "m".

Then using the parameter β_m I estimate the parameters $CO_{2,0}$ and $CO_{2,disaster}$ using the following approach:

$$CO_{2,base} = e^{-1\frac{c}{\beta_m}}$$

$$CO_{2,disaster,m} = CO_{2,base} * e^{\frac{\Delta T_{disaster}}{\beta_m}}$$

where $\Delta T_{disaster}$ disaster in this model is set to 6 degrees Celsius.

Table C.1 presents a statistical summary this simple OLS fitting process.

For calibrating equation *(e1)* I assume that:

$$\delta = -0.5\frac{\xi\left(Y(t)_{fe}{}^{world}\right)}{S(t-1)}$$

Such that the parameters of equation (e1) can be estimated using the following OLS model:

$$S(t)_m - S(t-1)_m = -0.5\xi\left(Y(t)_{fe}{}^{world}\right)_{historic}$$

where:

$$S(t)_m = CO_{2,disaster,m} - CO(t)_{2,m}$$

Such that combining the historic record of world fossil fuel consumption with CO_2 concentration data in CMIP5 scenarios it is possible to estimate parameters ξ and δ. The results of this fitting process are presented in Table 4.1

Table C.1
OLS Fitting of Climate Parameters in EDIAM

Climate Model	β	c	Adj R^2	c [p value]	β [p value]	$CO_{2,0}$	$CO_{2,disaster}$
MRI-ESM1	4.3	-24.2	1.0	0.0	0.0	288.4	1674.9
MIROC5	4.1	-23.4	0.9	0.0	0.0	291.5	1798.6
MPI-ESM-LR	4.7	-26.4	1.0	0.0	0.0	286.0	1423.3
MPI-ESM-MR	4.7	-26.4	1.0	0.0	0.0	285.9	1426.8
NorESM1-M	4.1	-23.4	1.0	0.0	0.0	291.6	1796.2
NorESM1-ME	4.3	-24.5	1.0	0.0	0.0	287.0	1617.7
MIROC-ESM	5.9	-33.6	1.0	0.0	0.0	286.2	1013.6
MIROC-ESM-CHEM	6.1	-34.7	1.0	0.0	0.0	285.7	970.9
bcc-csm1-1	5.0	-28.3	1.0	0.0	0.0	289.4	1298.2
GFDL-ESM2G	3.2	-18.1	0.9	0.0	0.0	293.1	3076.8
GFDL-ESM2M	3.3	-18.6	1.0	0.0	0.0	285.1	2784.2
GFDL-CM3	6.1	-34.8	0.9	0.0	0.0	298.0	1016.8

NOTES: The table lists the estimated parameters for the 12 CMIP5 climate models included in this study, the parameters of equations (e1) and (e3) are listed for each climate model. These parameters are estimated using CO_2 emission levels' variation across representative concentration pathways (RCPs) for each of the climate models in an autoregressive model.

APPENDIX D

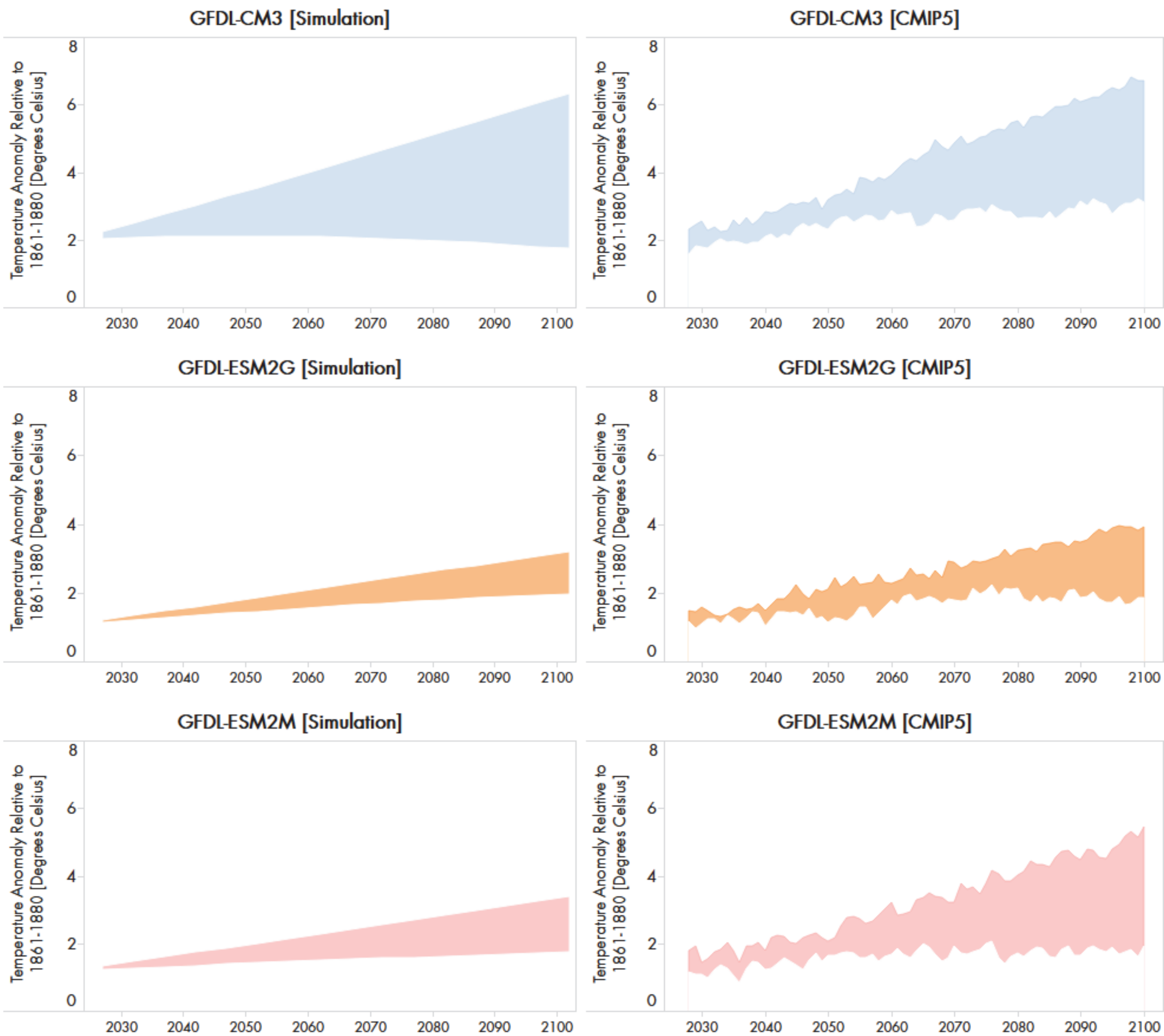
Additional Comparisons between EDIAM Simulated Output and Original CMIP5 Models' Temperature Rise Trajectories and RCP Emissions Scenarios

This appendix provides additional comparisons of EDIAM's behavior against the CMIP5 climate data ensemble and RCP emission scenarios.

Figures D.1, D2 and D.3 compare the behavior of the CMIP5 dataset and the simulated output using the parameters listed in Table 4.1. The right panel shows CMIP5 temperature rise time series for all the GCM models considered in this study that were not described in Chapter IV. For each time step, the upper limit of each envelope denotes the maximum temperature rise level across all RCPs in CMIP5 (i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5), while the lower limit denotes the minimum temperature rise level. Thus, each envelope indicates the range for plausible temperature rise levels for each time step. Similarly, the left panel shows temperature rise levels for a subsample of simulation runs that describe similar emission pathways as the RCPs.

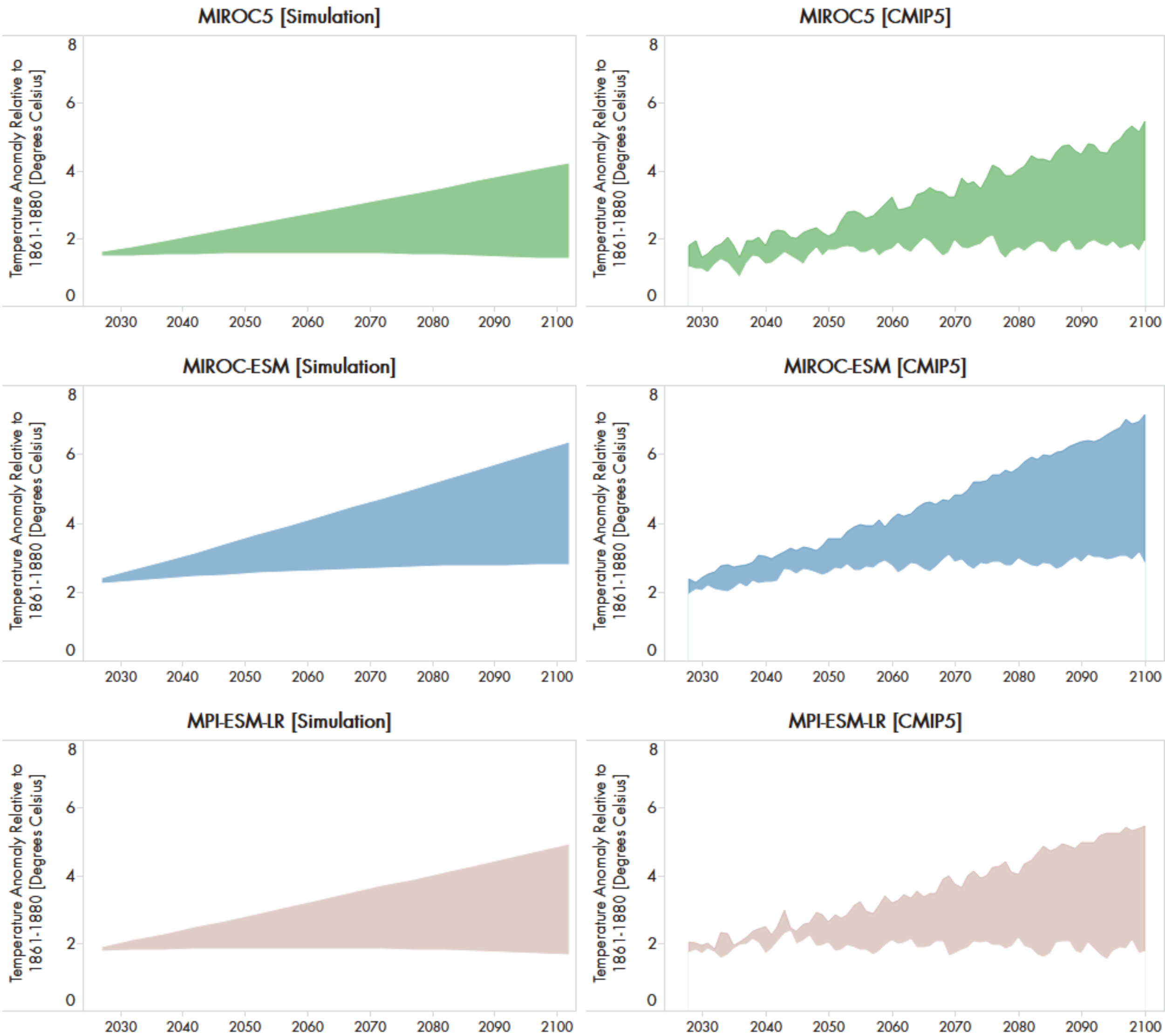
Figure D.4 compares the subset of simulated emissions pathways against the four RCPs used in the CMIP5 data set. The right panel shows emissions time series for all RCPs considered in this study (i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5). For each time step, the left panel shows the subset of emissions scenarios used for comparing CMIP5 and EDIAM's output. The upper limit of the envelope denotes the maximum level of emissions across all scenarios considered. The lower limit denotes the minimum level of emissions across this set of scenarios.

Figure D.1
Comparison between Simulated (Left Panel) versus Original (Right Panel) CMIP5 Models' Temperature Rise Trajectories



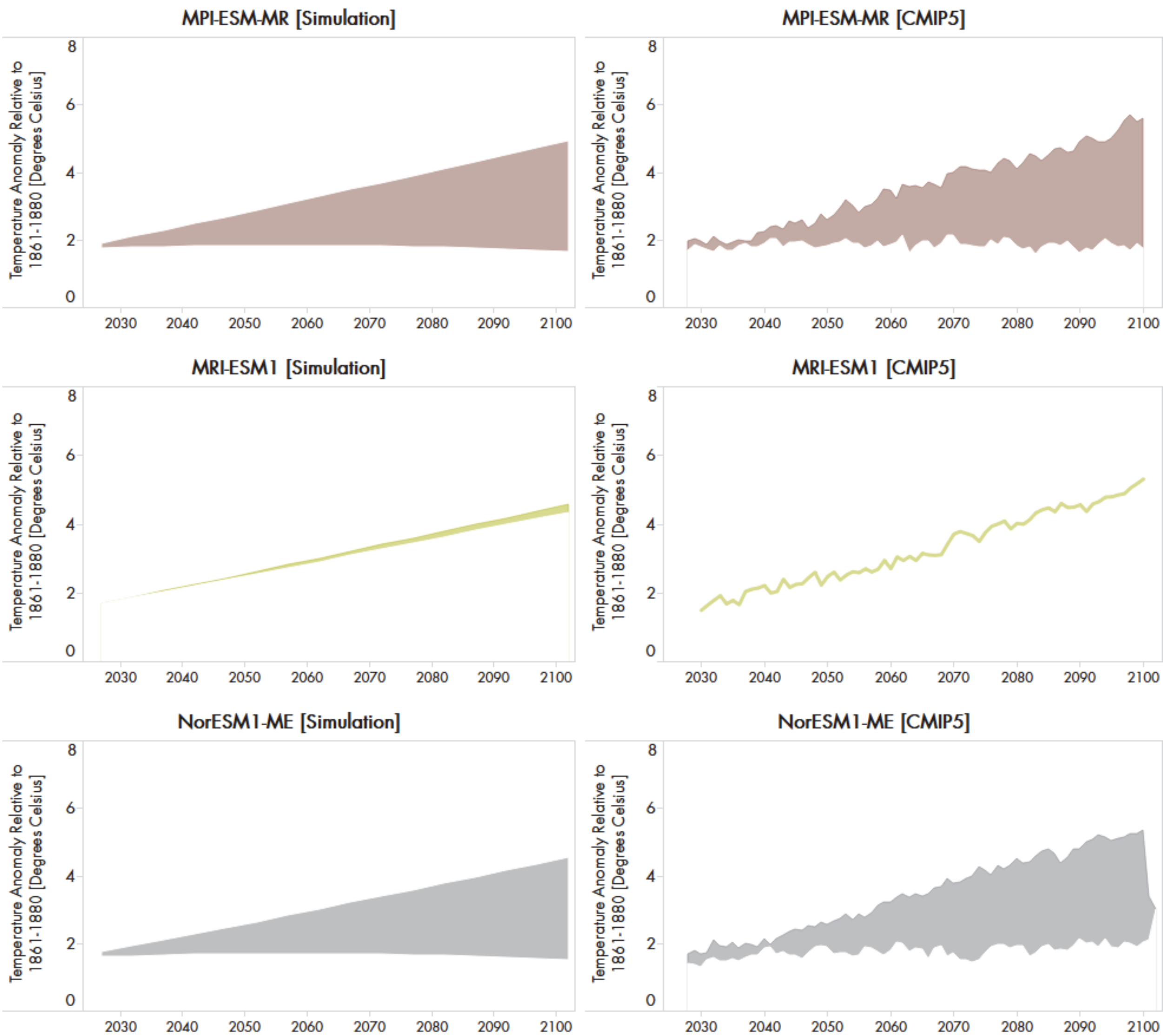
NOTES: The right panel shows CMIP5 temperature rise time series for three models: GFDL-CM3, GFDL-ESM2G and GFDL-ESM2M. For each time step, the upper limit of each envelope denotes the maximum temperature rise level across all RCPs in CMIP5 (i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5), while the lower limit denotes the minimum temperature rise level. Thus, each envelope indicates the range for plausible temperature rise for each time step. Similarly, the left panel shows temperature rise ranges for a subsample of simulation runs that describe similar emission pathways as the RCPs.

Figure D.2
Comparison between Simulated (Left Panel) versus Original (Right Panel) CMIP5 Models' Temperature Rise Trajectories



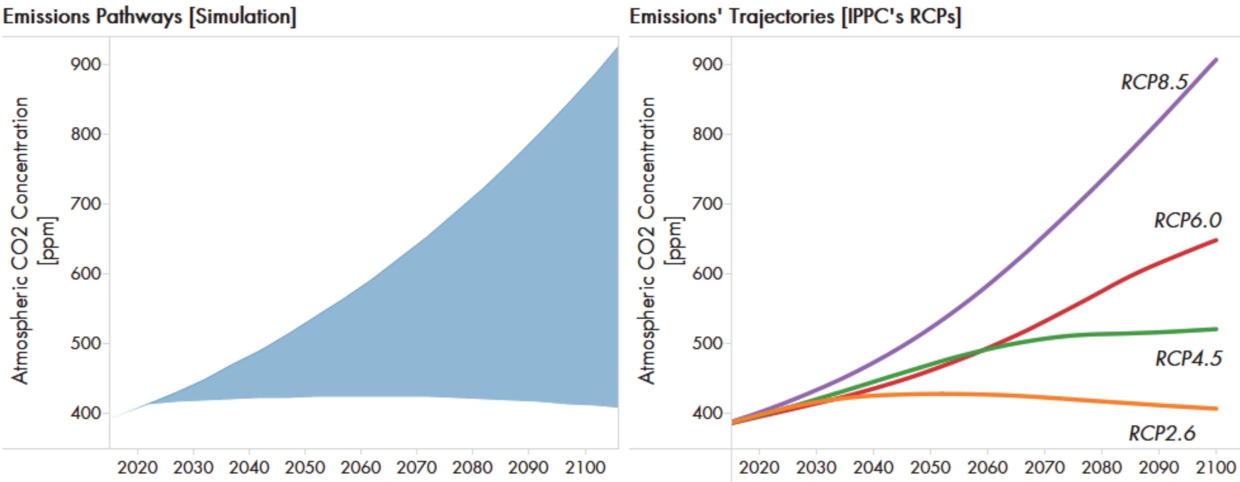
NOTES: The right panel shows CMIP5 temperature rise time series for three models: MIROC5, MIROC-ESM and NMPI-ESM-LR. For each time step, the upper limit of each envelope denotes the maximum temperature rise level across all RCPs in CMIP5 (i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5), while the lower limit denotes the minimum temperature rise level. Thus, each envelope indicates the range for plausible temperature rise for each time step. Similarly, the left panel shows temperature rise ranges for a subsample of simulation runs that describe similar emission pathways as the RCPs.

Figure D.3
Comparison between Simulated (Left Panel) versus Original (Right Panel) CMIP5 Models' Temperature Rise Trajectories



NOTES: The right panel shows CMIP5 temperature rise time series for three models: MPI-ESM1, MRI-ESM1 and NorESM1-ME. For each time step, the upper limit of each envelope denotes the maximum temperature rise level across all RCPs in CMIP5 (i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5), while the lower limit denotes the minimum temperature rise level. Thus, each envelope indicates the range for plausible temperature rise for each time step. Similarly, the left panel shows temperature rise ranges for a subsample of simulation runs that describe similar emission pathways as the RCPs. Note that for model MRI-ESM1 only RCP 8.5 is available. The comparison presented in this figure only considers emissions pathways that resemble RCP 8.5.

Figure D.4
Comparison between Simulated (Left Panel) versus Original (Right Panel) RCP Emissions Trajectories



NOTES: The right panel shows emissions time series for all RCPs considered in this study (i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5). For each time step, the left panel shows the subset of emissions scenarios used for comparing CMIP5 and EDIAM's output. The upper limit of the envelope denotes the maximum level of emissions across all scenarios considered. The lower limit denotes the minimum level of emissions across this set of scenarios.

APPENDIX E

Additional Scenario Discovery Results

This section presents additional scenario discovery results for the policy regimes that are not presented in Chapter V. The first section describes results for end-of-century emissions stabilization target. The second section describes results for the 2 °C temperature rise target.

End-of-Century CO2 Stabilization Target

Figure E.1 describes the performance of the independent comprehensive policy “P1” using scenario discovery with high dimensional stacking. In this uncertainty map each scenario cell represents the set of futures that fall into the discrete combination of the different uncertainty bins. In the horizontal axis, the first order montage in the horizontal axis describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution bins: low, medium and high, and the second order montage describes two R&D returns bins: high and low.

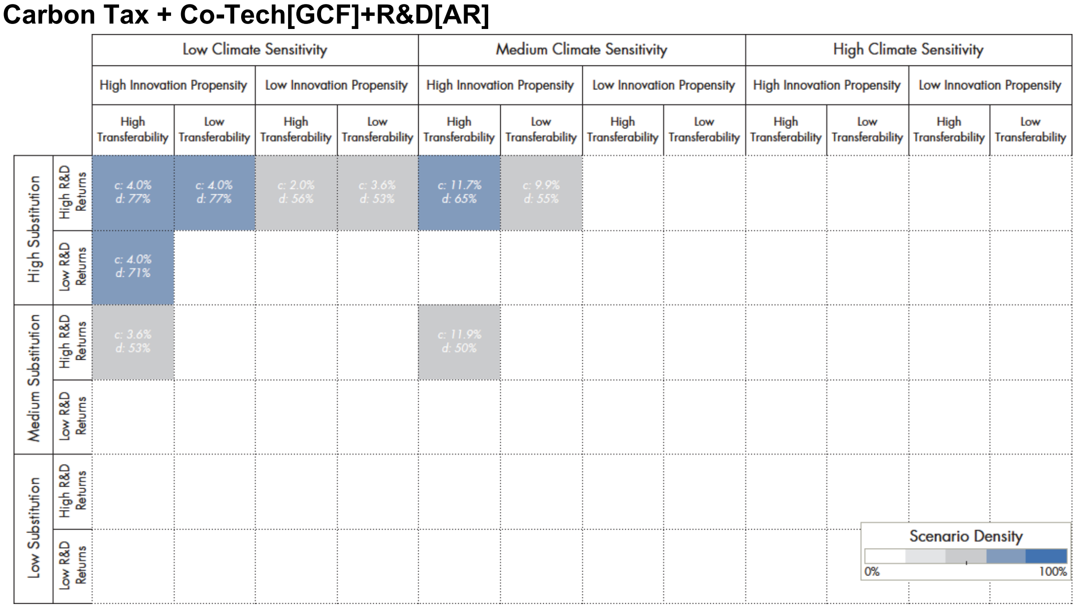
In line with traditional scenario discovery methods, within each scenario cell, I classify simulation outcomes into two groups: 1) future scenarios in which the policy target is met and 2) future scenarios in which the policy target is not met. Coverage and density statistics are calculated and noted for each scenario cell focusing on the futures that meet the CO2 stabilization target. The color legend denotes scenario cells’ density.

Figures E.2-E.5 presents similar results for policy regimes P3, P4, P5 and P6.

Figure E.1
Scenario Discovery with High-Dimensional Stacking for Analyzing the CO_2 Stabilization Target
P1: I. Carbon Tax [Both]

NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The blue legend denotes scenarios cells' density.

Figure E.2
Scenario Discovery with High-Dimensional Stacking for Analyzing the CO_2 Stabilization Target
P3: H. Carbon Tax + Co-Tech[GCF]+R&D[AR]

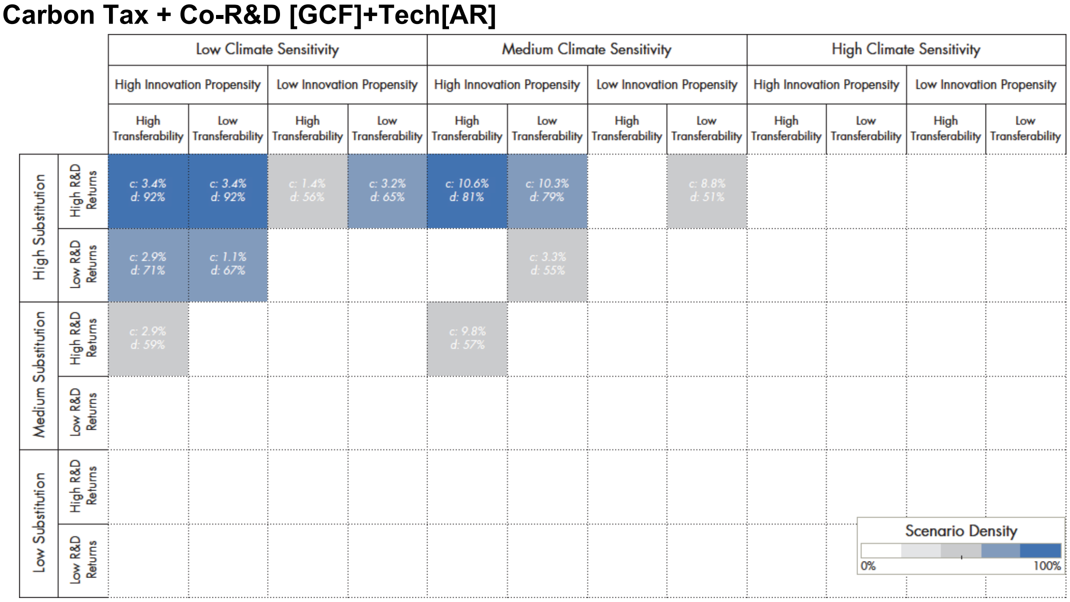


NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The blue legend denotes scenarios cells' density.

Figure E.3
Scenario Discovery with High-Dimensional Stacking for Analyzing the CO_2 Stabilization Target P4: H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both]

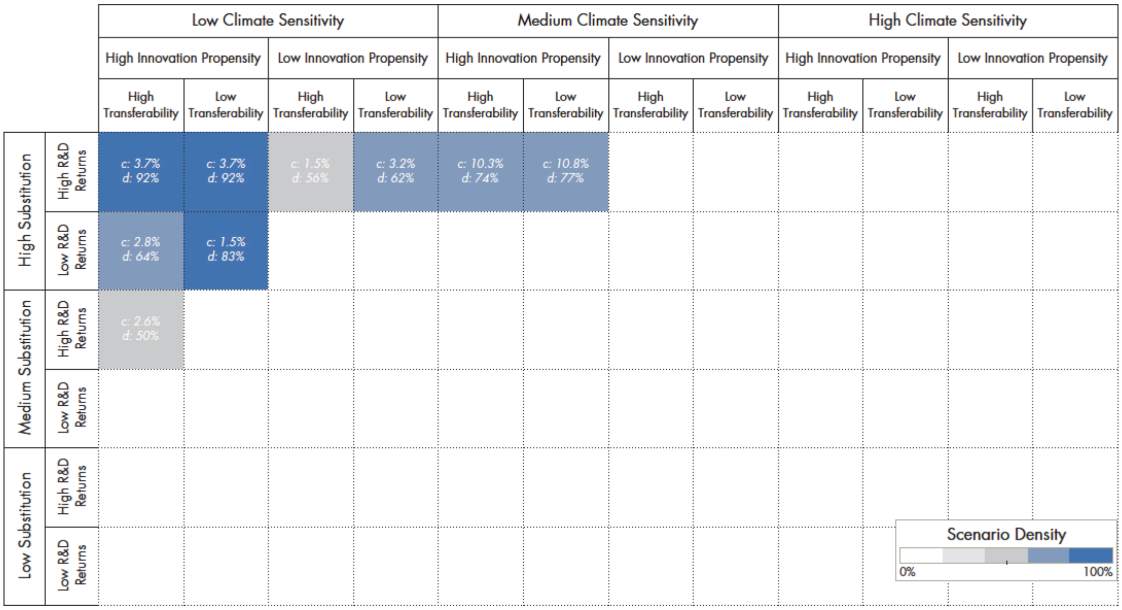
NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The blue legend denotes scenarios cells' density.

Figure E.4
Scenario Discovery with High-Dimensional Stacking for Analyzing the CO_2 Stabilization Target P5: H. Carbon Tax + Co-R&D [GCF]+Tech[AR]



NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The blue legend denotes scenarios cells' density.

Figure E.5
Scenario Discovery with High-Dimensional Stacking for Analyzing the CO_2 Stabilization Target P6: H. Carbon Tax + Co-R&D[GCF]+I. Tech[Both]



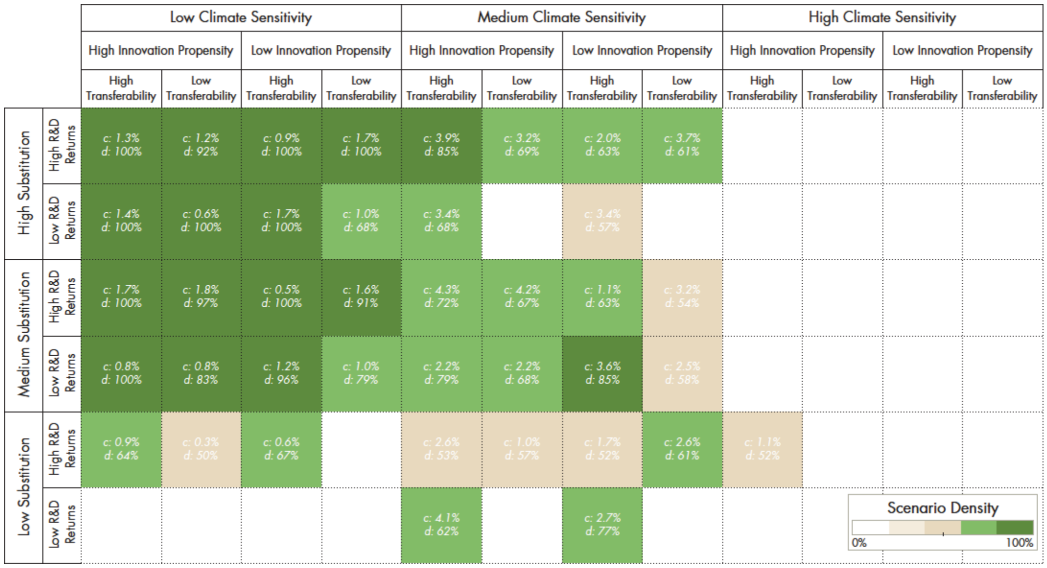
NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The blue legend denotes scenarios cells' density.

End-of-Century 2 °C Temperature Rise Target

This section presents similar results as those described in section IV.4.2 for the policy regimes that were not discussed in detail in the body of this manuscript. Figures E.6-E.9 presents scenario discovery results for policy regimes P3, P4, P5 and P6.

Figure E.6

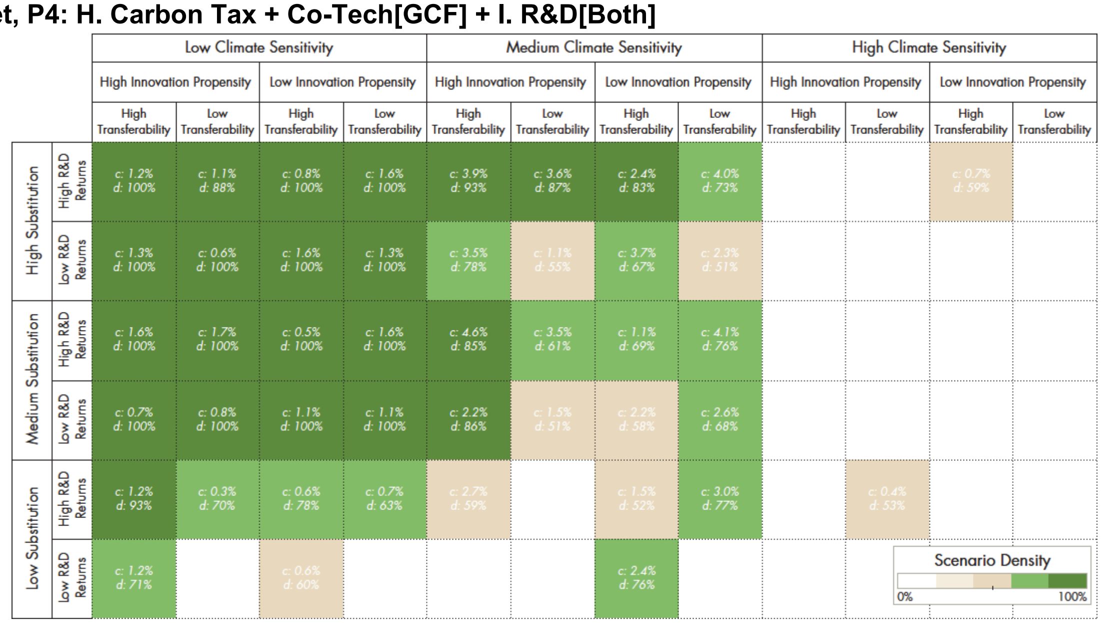
Scenario Discovery with High-Dimensional Stacking for Analyzing the 2 °C Temperature Rise Target, P3: H. Carbon Tax + Co-Tech[GCF]+R&D[AR]



NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The green legend denotes scenarios cells' density.

Figure E.7

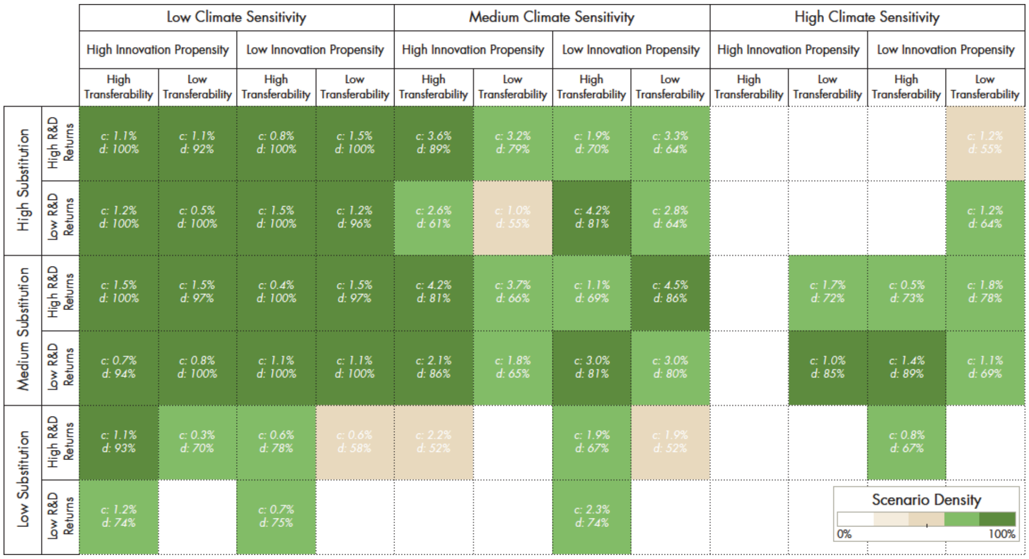
Scenario Discovery with High-Dimensional Stacking for Analyzing the 2 °C Temperature Rise Target, P4: H. Carbon Tax + Co-Tech[GCF] + I. R&D[Both]



NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The green legend denotes scenarios cells' density.

Figure E.8

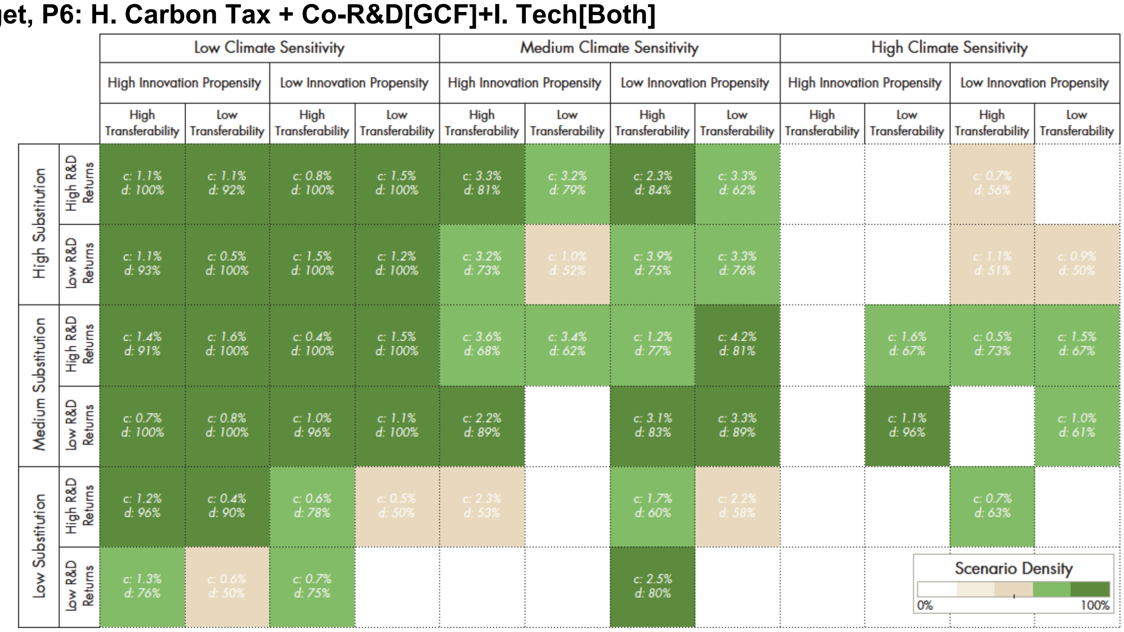
Scenario Discovery with High-Dimensional Stacking for Analyzing the 2 °C Temperature Rise Target, P5: H. Carbon Tax + Co-R&D [GCF]+Tech[AR]



NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The green legend denotes scenarios cells' density.

Figure E.9

Scenario Discovery with High-Dimensional Stacking for Analyzing the 2 °C Temperature Rise Target, P6: H. Carbon Tax + Co-R&D[GCF]+I. Tech[Both]



NOTES: Each scenario cell represents the set of futures that fall into the discrete combination of the uncertainty bins. In the horizontal axis, the first order montage describes three climate sensitivity bins: low, medium and high; the second order montage describes two relative innovation propensity bins: high and low, and the third order montage two relative transferability bins. In the vertical axis, the first order montage describes three substitution levels: low, medium and high, and the second order montage describes two R&D returns bins: high and low. Coverage and density statistics are noted for each scenario cell. The green legend denotes scenarios cells' density.