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An Evolutionary Model of Industry Transformation and the Political Sustainability of Emission Control Policies

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Prepared for the National Science Foundation

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Preface

Markets are tools for resource allocation but may also contribute to or even trigger significant changes in values, technology, and institutions. These ancillary transformations are important elements of policies that have been advocated as solutions to many issues we face today. Yet our current analytic tools often provide inadequate support to policymakers in framing and assessing market-based policies that might promote such transformations. Better understanding of the interacting socioeconomic mechanisms and processes involved in market-induced transformations would be an important tool for effective policy and decision making.

The problems climate change raises and the potential policy interventions to limit its effects present a case in point. In this technical report, we describe a computational model that tracks the evolution of an industry sector while also accounting for transformations in the political realm that arise from market-mediated outcomes and the effects of these transformations, in turn, on a national government's choice of regulatory policy. This report provides a technical description of the model and a guide to its behavior and capabilities. Later publications will focus on the analytical results from utilizing this model to examine alternative carbon emission reduction policies.

This research is part of a series of studies produced by the RAND Corporation's "Market Creation as a Policy Tool for Transformational Change" project. The project was supported by the National Science Foundation as part of its Human and Social Dynamics program.

The RAND Environment, Energy, and Economic Development Program

The research reported here was conducted in the RAND Environment, Energy, and Economic Development Program, which addresses topics relating to environmental quality and regulation, water and energy resources and systems, climate, natural hazards and disasters, and economic development, both domestically and internationally. Program research is supported by government agencies, foundations, and the private sector.

This program is part of RAND Justice, Infrastructure, and Environment, a division of the RAND Corporation dedicated to improving policy and decisionmaking in a wide range of policy domains, including civil and criminal justice, infrastructure protection and homeland security, transportation and energy policy, and environmental and natural resource policy.

Questions or comments about this report should be sent to the project leaders, Robert Lempert (lempert@rand.org) and Steven W. Popper (swpopper@rand.org). For more information about the Environment, Energy, and Economic Development Program, see http://www.rand.org/energy or contact the director at eeed@rand.org.

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Summary

Limiting the extent and effects of climate change requires the transformation of energy and transportation systems. Holding global atmospheric concentrations of greenhouse gases (GHGs) below what appear to be unreasonably dangerous levels will require the carbon intensity of these systems to drop more rapidly over the coming decades than it has in the past.

Market-based policies should prove useful in promoting such transformations. But studying which policies might be most effective toward that end is more difficult because, while standard economic theory provides an excellent understanding of the efficiency-enhancing potential of markets, it sheds less insight on their transformational implications. In particular, the introduction of markets often also leads to significant changes in society's values, technology, and institutions, and these types of market-induced transformations are generally not well understood. Our current analytic tools are often inadequate for comparing and evaluating policies that might promote such transformations. Therefore, a better understanding of the interacting socioeconomic mechanisms and processes involved in market-induced transformations would be important for effective policy and decisionmaking.

This technical report focuses on such issues in the context of climate change. The document describes a model that tracks the evolution of an industry sector and its market and tests the outcomes under different carbon emission control policies. The model is a tool to support the design of a government's regulatory policy by examining how measures intended to reduce emissions of climate-changing GHGs may give rise to market-induced transformations that in turn may ease or hinder the government's ability to maintain its policy. This technical report focuses on a description of this model; as we discuss later, the model contains novel features among simulations designed for the assessment of climate change policies. Later publications will focus on the results of policy analyses using the model.

The simulation in this volume examines how the choice of the initial design of GHG emission reduction policies affects how the policies evolve over time. In the spirit of effective long-term policy analysis, we are interested in how the choice of an initial, near-term policy architecture affects the long-term path to zero emissions over many decades. Political scientists have studied the long-term trajectories of initial policy choices in such areas as social protection and deregulation. In particular, Patashnik (2003) has studied cases in which new legistation is put into place during a brief period of focused public concern, and notes the conditions that do or do not lead the policy reform to persist over time after the public concern dissipates. The author found that new policies are more likely to persist when they create supportive and enduring constituencies.

Following this framework, we envision that policymakers have a brief window of opportunity for implementing policies with the ultimate goal of eliminating GHG emissions

(e.g., by passing legislation). Once implemented, policies will evolve along paths no longer under the control of the initial policymakers. In this report, we examine how policymakers might use their window of opportunity to choose a set of initial actions and means that increases the chances of achieving their long-term goal, in part by causing transformations that will yield future conditions supportive of these goals. This general framework seems relevant to the challenge policymakers interested in limiting the magnitude of future climate change face, but no such framework has been widely treated, if at all, in previous model-based climate policy studies.

The new simulation tool involves three key components. At its core is an evolutionary economics model (Nelson and Winter, 1982) that focuses on how the structure of an economic sector evolves as firms make investment decisions in production and new emissions-reducing technologies. An evolutionary economics formalism is ideal for our purposes because its focus on the diffusion of innovation and on firm entry and exit directly addresses processes of transformation in technology and industry structure. This approach not only allows us to simulate agent behavior and market outcomes but also provides a laboratory for testing the linkages that give rise to the observed behavior. Our model builds on recent work by Dosi et al. (Dosi, Fagiolo, and Roventini, 2006, and Dosi, Fagiolo, and Roventini, 2010).

As a second key component, we modified the Dosi et al. model. The most significant modification involved developing a generalized version of the game theoretic "protection for sale" model from the trade economics literature (Grossman and Helpman, 1994), which Polborn (2010) applied to GHG regulatory regimes. This component of the simulation represents the process firms use to attempt to influence the stringency of future GHG regulations as the competitive landscape changes under the influence of innovation (which is driven in part by a firm's research and development [R&D] investment decisions), expectations about future regulatory policy, and changing industry structure. Some firms may find more-stringent regulations beneficial, while others may find them less so. The influence of both sets of firms on government decisions may importantly affect any transition to a low-carbon economy. We have added a simple representation of the economy's interaction with a changing climate to Dosi's model and included carbon intensity as a factor that firms may improve through innovative activities.

As the third component, we embedded this simulation in a set of methods and supporting analytic tools called *robust decision making* (RDM) (Lempert, Popper and Bankes, 2003; Lempert et al., 2006; Lempert and Collins, 2007). RDM seeks strategies that are robust, that is they exhibit adequate performance when compared to the alternatives over a wide range of plausible futures under conditions of deep uncertainty, defined here as the situation in which decisionmakers do not know or do not agree on the structure of the model relating actions to consequences, the probability distributions describing key inputs to the model(s), or the criteria for assessing model outcomes. In this report, we use RDM to compare the consequences of alternative near-term decisions regarding the design of market-based policy architectures for reducing GHG emissions. As the case study work associated with this project emphasized,[1] the available evidence poorly constrains many of the processes expected to prove most important to the comparison of such policy architectures. RDM appears particularly useful for this project because it is designed to provide policy-relevant conclusions under such conditions of deep uncertainty.

This evolutionary, agent-based simulation model and the RDM framework for exercising it are intended to serve as a laboratory for examining how the choice of the initial design of GHG emission reduction policies may affect how the policies evolve over time and the extent to which intended goals are achieved. Initial experiments reported here have generated both expected and surprising results. We explored the model's behavior with over 20,000 different sets of assumptions about future states of the world. We found, as expected, that assumptions about the potential for significant advances in carbon emission reducing technology are key drivers of both the economy's overall decarbonization rate and the strength of the high-carbon-price lobby. In general, decarbonization is fast and the high-carbon-price lobby is strong when opporunities for carbon reducing R&D are strong compared to opportunities for labor-reducing R&D. As an example of the richness of the model's behavior, we also found some situations in which, despite a lack of low-carbon R&D opportunities, a strong high-carbon-price lobby nonethless pursues a high carbon tax to remain competitive with firms with much higher labor productivity.

Initial experiments with a grandfathering policy, in which incumbent firms do not have to pay the full carbon tax on any current capital, suggest that, contrary to our initial expectations, such a policy may have little effect on the decarbonization rate. We had expected that grandfathering would reduce the initial strength of the low-carbon lobby by reducing the incentive for established firms to advocate for a low carbon price. But, on average, this effect is countered by new entrants' increased need for a low carbon price to remain competitive with established firms.

In the next steps of our work, we will continue to explore the effects of alternative policies and the specific types of circumstances in which policies, such as grandfathering, may prove more or less effective. Overall, it is our intention to apply this model to an examination of how the interaction between firms and the government may affect government choices about how to design market-based regulatory policies to improve their prospects of catalyzing potential carbon-reducing transformations of the economy. The current model is clearly a first step, but its combination of elements, combined with the means for exercising it, provide a unique platform for addressing such issues.

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[1] Eric L. Kravitz and Edward A. Parson, "Markets as Tools for Environmental Protection," *Annual Review of Environment and Resources*, Vol. 38, 2013

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Abbreviations

DSGE	dynamic, stochastic, general equilibrium
GDP	gross domestic product
GHG	greenhouse gas
GtC	gigatonnes of carbon
HCP	high carbon price
IPCC	Intergovernmental Panel on Climate Change
LCP	low carbon price
NPD	net present damage
R&D	research and development
RDM	robust decision making
SCC	social cost of carbon
SREX	IPCC Special Report on Extreme Events
XLRM	exogenous uncertainties (X), policy levers (L), relationships or models (R), and metrics (M)

1. Introduction

Standard economic theory provides an excellent understanding of the efficiency-enhancing potential of markets. However, the introduction of markets often also leads to significant changes in society's values, technology, and institutions, and these types of market-induced transformations are generally not well understood. This presents a significant limitation because potential policy solutions to many problems require transformations in various sectors of society, such as energy, transportation, and housing. Our current analytic tools are often inadequate for comparing and evaluating policies that might promote such transformations. Therefore, a better understanding of the interacting socioeconomic mechanisms and processes involved in market-induced transformations would be an important tool for effective policy- and decisionmaking.

The problems climate change raises and the potential policy interventions to limit its effects present a case in point. This technical report describes a model that tracks the evolution of an industry sector and its market while testing the outcomes under different carbon emission control policies. The model is a tool to support the design of a government's regulatory policy by examining how measures intended to reduce emissions of climate-changing greenhouse gases (GHGs) may give rise to market-induced transformations that, in turn, may ease or hinder the government's ability to maintain its policy. This report contains a detailed description of the model, which introduces several novel features to the family of simulations designed for the assessment of climate change policies. Later publications will focus on the results of policy analyses using the model.

Limiting the extent and effects of climate change requires transforming energy and transportation systems. A recent Intergovernmental Panel on Climate Change (IPCC) report on extreme events defines transformation as "the altering of fundamental attributes of a system (including values systems; regulatory, legislative, or bureaucratic regimes; financial institutions; and technological or biological systems)" (IPCC, 2011). To hold global atmospheric concentrations of GHGs below what appear to be unreasonably dangerous levels will require the carbon intensity of these systems to drop more rapidly over the coming decades than they have in the past.

Our simulation examines how the choice of the initial design of GHG emission reduction policies affects how the policies evolve over time. In the spirit of effective, long-term policy analysis (Lempert, Popper and Bankes, 2003), we are interested in how the choice of an initial, near-term choice of policy architecture affects the long-term path to zero emissions over many decades. Patashnik (2003) has studied the long-term trajectories of initial policy choices in such areas as social protection and deregulation. In particular, he has examined cases in which new legislation was put into place during a brief period of focused public concern, noting the conditions that do or do not lead the policy reform to persist over time after public concern dissipates. He found that new policies are more likely to persist when they create supportive and enduring constituencies.

Following this framework, we envision that policymakers have a brief window of opportunity for implementing policies with the ultimate goal of eliminating GHG emissions (e.g., pass legislation). Once implemented, policies will evolve along paths no longer under the control of the initial policymakers. In this report, we examine how policymakers might use their window of opportunity to choose a set of initial actions and means that increases the chances of achieving their long-term goal, in part by causing transformations that will yield future conditions supportive of these goals. This general framework seems relevant to the challenge policymakers interested in limiting the magnitude of future climate change face, but no such framework has been treated widely, if at all, in previous model-based climate policy studies.

The new simulation tool involves three key components. At its core is an evolutionary economics model that focuses on how the structure of an economic sector evolves as firms make investment decisions in production and new emissions-reducing technologies.[2] An evolutionary economics formalism is ideal for our purposes because its focus on the diffusion of innovation and on firm entry and exit directly addresses processes of transformation in technology and industry structure. This approach not only allows us to simulate agent behavior and market outcomes but also provides a laboratory for testing the linkages that give rise to the observed behavior. Our model builds on recent work by Dosi et al. (Dosi, Fagiolo, and Roventini, 2006, and Dosi, Fagiolo, and Roventini, 2010).

As a second key component, we modified Dosi et al.'s model. The most significant modification involved developing a generalized version of the game theoretic "protection for sale" model from the trade economics literature (Grossman and Helpman, 1994), which Polborn (2010) applied to GHG regulatory regimes. This component of the simulation represents the competition among firms as they attempt to influence the stringency of future GHG regulations as the competitive landscape changes under the influence of innovation (which is driven in part by a firm's research and development [R&D] investment decisions), expectations about future regulatory policy, and changing industry structure. Some firms may find more stringent regulations beneficial, while others may find them less so. The influence of both sets of firms on government decisions may importantly affect any transition to a low-carbon economy. We have added a simple representation of the economy's interaction with a changing climate to Dosi's model and included carbon intensity as a factor that firms may improve through innovative activities. Our model differs from rational expectation theory and instead assumes that each firm uses an innovation strategy that results from a learning and adaptation process. Firms therefore build a diverse set of expectations that are based on past outcomes and how these affected them.

[2] See Nelson and Winter, 1982; Silverberg and Verspagen, 1994; Ciarli et al., 2010; and Saviotti and Pyka, 2004, for notable examples.

As the third component, we embedded this simulation in a set of methods and supporting analytic tools called robust decision making (RDM) (see Lempert, Popper and Bankes, 2003; Lempert and Collins, 2007; and Lempert et al., 2006). RDM seeks strategies that are robust, that is, perform well compared to the alternatives over a wide range of plausible futures under conditions of deep uncertainty, defined here as the situation in which decisionmakers do not know or do not agree upon the structure of the model relating actions to consequences, the probability distributions describing key inputs to the model(s), or the criteria for assessing model outcomes.[3] As described in more detail later, we use RDM here to compare the consequences of alternative near-term decisions regarding the design of market-based policy architectures for reducing GHG emissions. As the case study work associated with this project emphasized (Kravitz and Parson, 2013), the available evidence poorly constrains many of the processes expected to prove most important to the comparison of such policy architectures. RDM appears particularly useful for this project because it is designed to provide policy-relevant conclusions under such conditions of deep uncertainty.

To help envision how this simulation might work, consider two potential future paths. In both cases, the government initially implements a small carbon tax. Some firms invest in low-emitting production capital and lobby the government to increase the carbon tax to favor their investments. Other firms lobby to keep the carbon tax low. In each case, the combination of initial policy design, technology opportunities, and the government's response to lobbying leads to a rise in carbon taxes. In the first case, the increase is sufficient to catalyze a beneficial transformation. In the second, however, the increase is slight, so high carbon intensities, and high emissions, continue indefinitely.

We designed our model to examine the types of policy architectures surrounding the initial carbon tax that may, in general, produce outcomes like the first case when it results in a net social benefit and avoid such outcomes when it does not result in net social benefit. Such questions appear highly relevant to the types of issues policymakers concerned with climate change face but are beyond the reach of most current integrated assessment models. The current model is clearly a first step, but its combination of elements, combined with the means for exercising it, provide a unique platform for addressing such issues.

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[3] That is, it may be the case that all members of society wish to have a healthy, sustainable environment and high economic growth. There may be significant differences over what weights to assign to these two desirable, but possibly antithetical outcomes.

2. Design of Robust Decision Making Analysis

Our simulation model displays characteristics that make it useful for our purposes, while making it difficult to employ the traditional tools of policy analysis. Addressing an important issue of interest in this project, the model can display properties that the complex systems literature calls *emergence* and a dynamics shaped by self-referential expectations in the presence of imperfect information. Such features can generate regions of extreme sensitivity to particular assumptions yet can, at the same time, exhibit important regularities of macroscopic behavior. Traditional policy analytic tools, which employ a probabilistic representation of uncertainty and rank alternative strategies according to expectations contingent on these probabilities, can prove ineffective when used with such simulations (Lempert, 2002). In contrast, our RDM approach can use the information contained in such simulations more effectively.

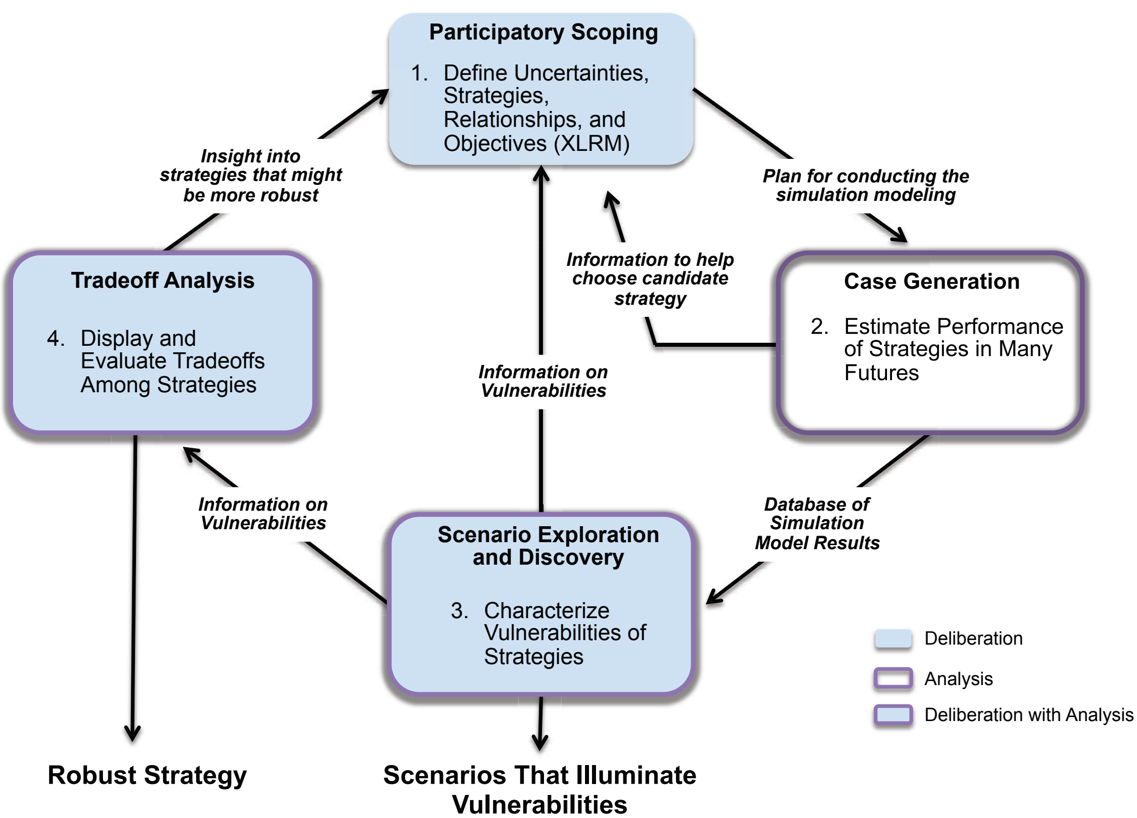
Bankes (1993) differentiates between what it calls "consolidative" and "exploratory" models. The former can be validated and provides an accurate representation of the real world. For instance, engineers creating a new airplane might use a consolidative model in lieu of a wind tunnel or flight tests to compare alternative aircraft designs, confident that the model accurately predicts the performance of each proposed aircraft configuration. In contrast, an exploratory model provides a mapping of assumptions to consequences without privileging one set of assumptions over another. For instance, an exploratory model might show the implications of various feedbacks occurring between the future economy and climate, without any claim that they *will* occur.

RDM provides a means of conducting a systematic and meaningful policy analysis using such exploratory models. RDM involves running a simulation over many (sometimes hundreds of thousands) of cases to create a database of model results. Each entry in the database records some specific set of assumptions about the future state of the world and the resulting estimate of how a proposed policy would perform (Banks, 1993). The ensemble of cases in the database maps a wide range of assumptions to their consequences. The analysis then aims to find policy-relevant patterns in that mapping.

For example, an RDM analysis for Israel's Ministry of National Infrastructure compared alternative strategies for integrating natural gas into the country's energy mix (Popper, 2009). Analysts ran simulation models projecting the performance of each strategy for each of many cases reflecting a wide range of assumptions about future costs, demand, and the security of alternative sources of supply. A "scenario discovery" cluster analysis on the resulting database then summarized the common characteristics of the cases in which one type of strategy performs consistently better than another (Bryant, 2010; Lempert et al., 2006). We have similarly used our evolutionary economics simulation to project the long-term evolution of alternative market-based policy architectures over many cases reflecting a wide range of assumptions about potentially relevant processes. We then used visualization tools and scenario discovery analyses on the resulting database to identify the types of policy architectures that most reliably lead to beneficial transformations and the conditions that best explain when and how different policy choices lead to different long-term consequences.

As Figure 2.1 shows, the RDM process begins with a scoping activity that defines the objectives and metrics of the decision problem, strategies that could be used to meet these objectives, the uncertainties that could affect the success of these strategies, and the relationships that govern how strategies would perform with respect to the metrics (Step 1). This scoping activity often uses a framework called "XLRM" (described later) and provides the information needed to organize the simulation modeling. RDM is designed to facilitate a structured process of stakeholder engagement by aligning its steps with the "deliberation with analysis" decision support process recommended by the U.S. National Research Council (2009). This report does not include any stakeholder involvement, and the scoping process was conducted entirely by the authors of this report and their colleagues. However, as discussed below, we hope that the iterative RDM process, combined with the design of our model, facilitates an ongoing progression of model refinement and improvement.

Figure 2.1. Iterative Steps of a Robust Decision Making Analysis



In Step 2, analysts use the simulation model or models to evaluate the strategy or strategies in each of many plausible futures. This step in the analysis generates a large database of simulation model results. In Step 3, analysts and decisionmakers use visualizations and "scenario discovery" cluster analysis to explore the data and identify the key combinations of future conditions where one or more candidate strategy might not meet its objectives. For example, a policy architecture for emission reduction might fail to meet its goals if the rate of technology innovation is low and the effects of climate change are particularly severe. Combinations of such conditions can describe a scenario (e.g., slow innovation and severe climate) that illuminates the vulnerabilities of the policy architecture.

This information on potential vulnerabilities can prove quite useful, providing the foundation for developing, evaluating, and comparing potential modifications to the alternative strategies that might reduce these vulnerabilities (Step 4). For instance, analysis might suggest that a policy with a higher initial carbon tax than originally considered, combined with grandfathering of existing capital stock, might induce sufficient innovation without opposition from current market incumbents to enable the emissions reductions necessary to forestall the severe climate damages. Having developed a set of alternative strategies, analysts can compare the trade-offs among them, in particular identifying the conditions under which one strategy performs better than another. Given such a trade-off analysis, decisionmakers may decide on a robust strategy. They may instead decide that none of the alternative strategies under consideration proves sufficiently robust and return to the scoping exercise, this time with deeper insight into the strengths and weaknesses of the strategies initially considered.[4]

RDM exercises often employ an "XLRM" framework (Lempert, Popper, and Bankes, 2003) to help organize the participatory scoping step with stakeholders and the subsequent model development and data gathering. The letters X, L, R, and M refer to four categories of factors in an RDM analysis:

- **Policy levers (L)** are near-term actions that decisionmakers want to consider; different groupings of such levers (varying by including some, excluding others, and perhaps using different sequences for application) would constitute the policy alternatives that a government actor might consider employing when crafting a policy architecture.
- **Exogenous uncertainties (X)** are factors that, like climate change, are outside the control of decisionmakers but may affect the ability of near-term actions to achieve long-term goals;
- **Metrics (M)** are the performance standards used to evaluate the policy levers—the quantitative measures of what does and does not constitute a beneficial transformation of the energy system.
- **Relationships or models (R)** are used to analyze how policy levers perform, as measured by the metrics, under the various uncertainties.

[4] There are also other paths through the RDM process. For instance, information in the database of model results may be used to identify the initial candidate strategy. In other situations, information about the vulnerabilities of the candidate strategy may lead directly to another scoping exercise to revisit objectives, uncertainties, or strategies.

In essence, RDM compares the performance of alternative combinations of policy levers, as evaluated by the metrics, over a wide range of uncertain futures using the relationships or models.

The box summarizes the factors considered in the analyses this model is designed to conduct. We will now use this XLRM structure to describe our modeling activities.

Box: Main Groups of Factors to Be Explored in the Full RDM Analysis

<table>
<tr><th>Uncertainties (X)</th><th>Policy Levers (L)</th></tr>
<tr><td>Climate
• Sensitivity to emissions
• Effects of climate change
Government
• Ability to estimate and willingness to deviate from socially optimal carbon price
Consumers
• Maximum acceptable carbon price
• Responsiveness of this price to observed effects
Firms
• Willingness to lobby for favorable carbon price
• Expectations about future carbon prices
• Adjustment of expectations over time
• R&D allocation based on expected carbon price
• Entry and exit conditions
Technology
• Future technology landscape
• Effectiveness of firms' R&D investments
Economy
• Price elasticity of aggregate demand
• Price elasticity of firms' market share
• Exogenous growth rate
• Responsiveness of firm market share to price change</td><td>Phase I:
• Initial stringency of carbon tax
• Grandfathering of existing capital stock
• Frequency with which government updates the carbon tax (e.g., yearly, or every 2, 4, or 10 years)
Phase II:
• Revenue recycling to citizens or to firms for technology subsidies
• Long-term (e.g., 10, 50, and 100 year) emission reduction targets</td></tr>
<tr><th>Relationships (R)</th><th>Measures (M)</th></tr>
<tr><td>Dosi et al. evolutionary economics model, with
• New modules to address
• Governmental decisions
• Climate change
• Modified modules to include
• Two types of R&D (to improve carbon intensity as well as labor productivity)</td><td>Environmental:
• Total emissions
• Impacts of climate change
• Socially optimum carbon price
Economic:
• Consumption growth rate
• Carbon intensity of economy
• Concentration (Herfindahl index)
• Average capital turnover rate
• Carbon price
• Funds spent on affecting policy</td></tr>
</table>

Policy Levers

As described above, the simulation aims to evaluate policymakers' initial choice of policy architecture. We assumed that policymakers have a brief window of opportunity during which to pass GHG control legislation for reducing carbon emissions. While the overall architecture survives subsequent legislative turnover, specific aspects, notably the price of carbon, are subject to modification by future lawmakers.

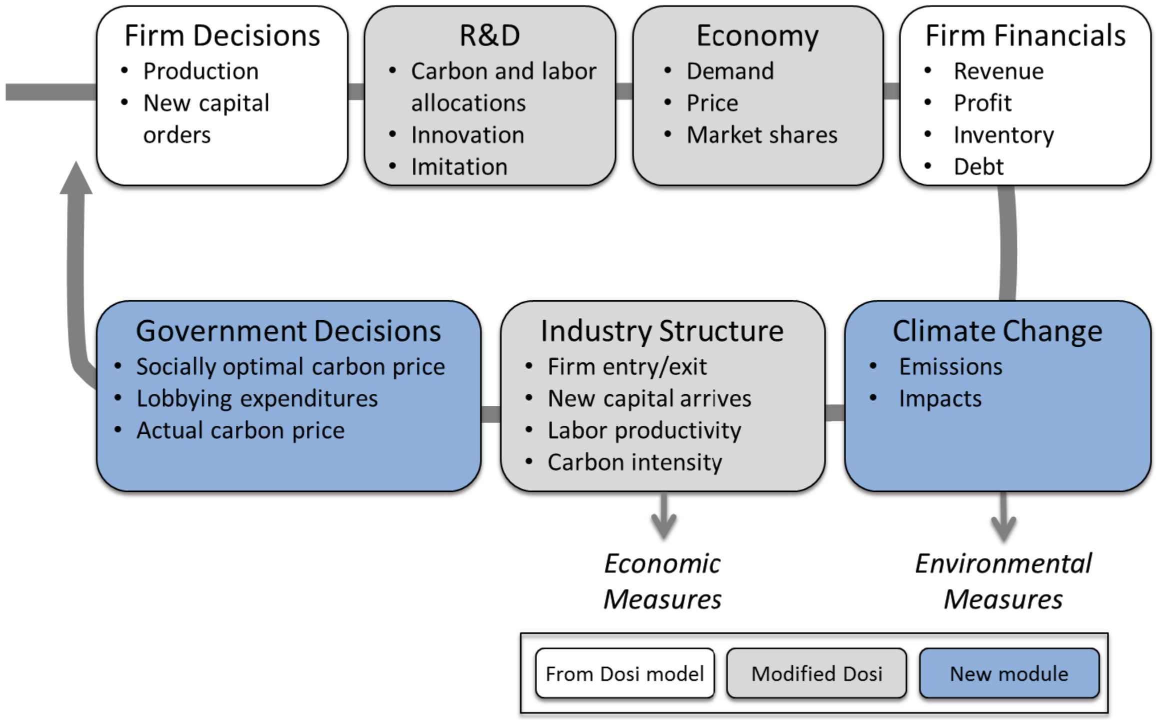
The box on p. 8 lists the various components (policy levers) that make up such an initial architecture. In this report, we first consider architectures that vary the initial stringency and grandfathering of existing capital stock. We will next add consideration of various types of revenue recycling and whether or not the government should use long-term emission reduction targets. Once the architecture is chosen, the simulation focuses on the government's ongoing decisions about more or less stringent emissions reductions. For simplicity, we focus here only on carbon taxes as the price mechanism and assume that, once set, the policy architecture (other than stringency) does not change. This assumption represents a necessary limitation that should nonetheless let us capture much of the interesting dynamics that affect how initial policy designs evolve over time. The government could also pursue innovation policies: R&D, tax credits or subsidies for particular technologies, etc. Rather than model these as explicit decision variables, we assumed the government pursues such policies at a reasonable level, and focused our attention on the ongoing evolution of choices about stringency of carbon taxes.

Relationships

Our simulation model generates the set of cases shown in Step 2 of Figure 2.1. The model evaluates the long-term consequences of the alternative policies focusing on firms and their interaction with the government. The firms compete in selling a single good to consumers, and the government sets the stringency of carbon taxes to limit the effect of climate change on the economy. Firms invest in R&D for new production technologies that may reduce labor requirements or lower GHG emissions. Firms also engage in activities to provide information to the government to promote what they regard as favorable choices about carbon tax rates. Given such distinguishing factors as heterogeneous costs, expectations about future conditions, market share, and R&D success, firms will generally differ in their preference for carbon tax rates; some will find higher carbon taxes a source of competitive advantage.

As shown in Figure 2.1, the simulation proceeds through a series of steps. Each cycle notionally represents one calendar year. White boxes in Figure 2.2 represent processes largely similar to those in the Dosi et al. (2010) model, gray boxes represent modified elements from the Dosi model, and blue boxes represent entirely new processes. At each time step, firms decide how to allocate their financial resources to produce goods for sale, purchase new capital stock, and conduct R&D that might increase the capabilities of any future capital stock investment. In the aggregate, these decisions result in the total supply of consumer goods, a market share for

Figure 2.2. Main Elements of Simulation and the Direction of Model Flows



each firm, and revenues for each firm. Firms sell their final goods to consumers at different prices that reflect their specific production costs. Each unit of capital stock is characterized by its labor productivity and carbon intensity. The latter determines the firm's sensitivity to carbon taxes. Each firm's price is proportional to its production costs, and its market share varies according to its price relative to other firms. Total demand for the final good varies according to an exogenously growing demand curve based on the average price. Firms can reduce costs by investing in capital stock with higher labor productivity and/or lower carbon intensity. Their access to more-efficient capital stock depends on their investments in R&D aimed at new development or imitating competitors. Technology evolves endogenously based on total firms R&D spending and how each firm chooses to allocate funds between carbon and labor enhancing technologies. Firms base their investment decisions on their expectations about future carbon tax rates, which are influenced by their own heterogeneous expectations, the government's declared emission reduction targets (if any), and the government's credibility in meeting past targets. The emissions from production can cause climate change effects that reduce GDP and thus overall demand.

The choice of initial policy architecture may also influence this evolution. Grandfathering initial capital stocks may increase early emissions but may enhance innovation by reducing lobbying pressure for low carbon prices. If the government sets ambitious emission reduction targets, firms may shift resources toward reducing carbon intensity, but the government may lose credibility if it fails to meet its targets, causing firms to shift R&D away from carbon-reducing investments.

At the end of each period, firms that have exhausted their financial resources or fallen below an exogenously set market share limit are removed from the market. The entrants that replace them have behavioral characteristics similar to the remaining firms with the fastest growing market share.

In a unique and important feature, the simulation considers the interaction between firms and the government in setting the future price of carbon. The government estimates the social cost of carbon based on estimates of future emissions and their likely environmental consequences. Firms divide themselves into two lobbies: one consisting of firms whose profits would increase with a higher carbon tax and one consisting of firms whose profits would benefit from a lower carbon tax. Each lobby is willing to pay an amount based on its resources and expected profits to influence moving the tax in its desired direction. The government is willing to deviate from its prior estimate of the socially optimal tax. We have developed a game theoretic model, based on Grossman and Helpman (1994), that determines the tax rate that emerges from these competing forces. The resulting carbon tax rate will influence future production decisions, GHG emissions, R&D investments, and the profitability of each firm. The initial choices about policy architecture influence this ongoing interaction between the government and firms.

There is a large and growing literature on coalition formation and its effects on climate policy (Hoel and Zeeuw, 2010; Brechet and Eyckmans, 2012; Burger and Kolstad, 2009), much of it focused on several central issues: the conditions under which coalitions form, the stability of coalitions over time, and the incentives for individual members to defect or join coalitions. In addition, much of this literature on climate change focuses on coalitions of nations deciding whether or not to join treaties limiting GHG emissions. Our treatment is consistent with this literature but adopts a different focus. First, we focus on coalitions of firms lobbying their national governments. Second, we assume a firm must join one of the two lobbies and thus neglect potential defections. While chosen for simplicity, this assumption implicitly considers the fruits of lobbying to be not entirely a public good, so that members of a lobby can discourage free-riding by excluding nonmembers from benefits not explicitly considered in our model. However, the rule firms use in our model to decide which lobby to join seems consistent with the finding in the literature that the marginal return of joining a coalition is an important driver of coalition formation. Overall, this study focuses on a particular feedback that is not a central focus of the current coalition-formation literature: the long-term stability of policies that create shifting incentives to join alternative coalitions when the policies may have strong effects on the benefits accruing to different firms, depending in part on the future evolution of policy and their own investment decisions.

Many climate policy studies build on the dynamic, stochastic, general equilibrium (DSGE) formalism in contrast to the evolutionary, agent-based approach used here. DSGE models provide economists their standard view of economic growth and are commonly used to estimate the levels of greenhouse emission reductions that provide the highest levels of consumer welfare over time. DSGE models offer other advantages, including their consistent treatment of agents' uncertain expectations regarding the future and a self-correcting structure that reproduces the degree of order observed in large-scale economies. While DSGE models generally treat uncertainty as well characterized, they have been used to address deep uncertainty using RDM (Lempert et al., 2006; Hall et al., 2012).

Despite these advantages of DSGE models, we used an evolutionary, agent-based approach. The latter best suits our purpose because we focus on how alternative GHG regulatory architectures affect society's ability to adhere closely to the socially optimum path under conditions having significant potential for unexpected improvements in emissions-reducing technology, radical shifts in industry structure, or abrupt increases in the damages from climate change. For our purposes, the standard DSGE formalism seemed too stable, and its agents know too much. In principle, it might prove possible to use a DSGE formalism to model the competition among firms and their government; sudden shifts in knowledge about technology and the physical world; and the irreducible uncertainties, organizational biases, and cognitive imperfections that allow heterogeneous expectations regarding such shifts. In practice, the surgery required to adapt DSGE models to these circumstances would be significant. The evolutionary, agent-based formalism appears a better starting point because it allows us to focus attention on the particular dynamics of interest here, those that in some circumstance can generate endogenous and rapid transformations in industry structure, which in turn may affect the government's ability to maintain support for its regulatory policy. The potential for such transformations may prove important in choosing an GHG regulatory infrastructure.

These attributes, while beneficial in some respects, can also make evolutionary, agent-based models difficult to employ credibly in policy analyses. For instance, our model will focus attention on some types of expectations, such as what the government knows and does not know about future climate impacts and firms' judgments about the credibility of the government's declarations about future carbon tax trajectories, while treating other expectations much more simply. If the model were used for predictions of the future, it might be reasonable to wonder if the unmodeled expectations might significantly affect any forecast. Here, however, we ask a different question: What conditions distinguish futures favoring one policy architecture over another? This decision analytic framework makes it easier to determine when specific model simplifications may or may not be important. For example, RDM's iterative testing of the robustness of proposed policies will examine whether a richer treatment of expectations might change our policy conclusions. In Section 5's initial example, we conclude that such a richer treatment would not change the results.

Measures

The simulation reports a variety of outputs used to evaluate the relative success or failure of alternative policy architectures in each of the cases in the database of runs. As shown in the box on page 8, these measures include environmental outcomes, such as cumulative emissions and the impacts of climate change. These measures also include economic outcomes, such as total consumption and the carbon intensity of the economy. Using these measures, a transformation in the modeled system would constitute a significant decrease in carbon intensity, along with attendant political changes in the constellation of lobbying forces needed to maintain carbon taxes at a level consistent with the low carbon intensity. We can measure the desirability of any transformation in the system (or the lack of such a transformation) by comparing outputs, such as the total consumption and environmental outcomes, against those for an otherwise similar case in which the government was able to set the carbon price at a socially optimal level with perfect information and no constraints on its choice.

Here, as in many RDM analyses, we chose to use regret to compare the performance of alternative policies (Lempert and Light, 2009; Lempert, Popper and Bankes, 2003). Regret for a proposed strategy is defined as the difference between its performance and the performance of the best strategy in each state of the world. To calculate regret for each case in our database, we calculated the outcomes that would result from the best possible strategy in that case and then calculated how far the performance of a proposed strategy deviates from those optimal outcomes in each case. As described in "Damages from Climate Change and the Social Cost of Carbon" in Section 3, we used the social cost of carbon to define the best possible strategy. Clearly, the social cost of carbon varied over the cases (otherwise there would be a single carbon price clearly robust over all the uncertainties). The scenario discovery cluster analysis then helped identify the range of conditions over which a proposed strategy has low and high regret.

Using such a regret measure is useful because we expect that specific near-term actions make little difference in some futures, while the choice of near-term policy may prove more consequential in others. For instance, in cases with severe climate change but little potential for low-carbon technology, no policy architecture will produce desirable outcomes. In cases with sufficiently abundant potential for low-carbon technology, all policy architectures may lead to desirable results. But in some cases, the ability to catalyze a timely technology transformation may depend strongly on near-term policy choices. The regret measure proves useful because it focuses attention on cases in which the choice of policy architecture makes a significant difference in policymakers' ability to achieve their long-term goals (Lempert, 2009).

Experimental Design

The results of this simulation for any given policy architecture depend on a wide range of uncertainties. As shown in the box on page 8, these uncertainties include those related to the sensitivity of the climate system and any impacts of GHG emissions, the ability of the government to estimate the socially optimum carbon price accurately and its willingness to deviate from the estimated price, firms' expectations and the parameters governing their allocation of resources, the intrinsic potential for emission-reducing technologies, and how demand and market share respond to price.

Following the RDM approach, we used this simulation to compare the ability of alternative policy architectures to bring about long-term transformations in the carbon intensity of the economy. For each of several alternative combinations of the policy levers, we ran the model for each of many cases representing plausible future states of the world. Each such case is described by a particular combination of parameter values for the uncertainties listed in the box on page 8. We then ran scenario discovery cluster algorithms over the resulting database of cases, seeking to characterize the futures in which certain initial policy architectures result in beneficial transformations more consistently than do other initial policy choices.

An ideal policy architecture would catalyze transformational change in every case in which such change would produce desirable outcomes, as defined above, and would deter transformational change in every case in which it would not prove desirable. The results of our analysis will provide a deeper understanding of the policy architectures that approach this ideal and of the key combinations of uncertainties that suggest policymakers should choose one type of architecture over another. The analysis described in this report will clearly not address the full range of potential policy options and market processes. However, it will provide a framework for a set of policy analytic tools that can be used in the future to address this broader array of policy architectures and system processes.

3. Model Design

This section describes in more detail the components of the model shown in Figure 2.2. The appendixes provide further details regarding some components. As will rapidly become apparent, the model contains many uncertain parameters that can potentially prove important to comparisons among alternative policies. The RDM process described above and the calibration procedure described in Section 4 are designed to use this model to make useful policy arguments by identifying the combinations of conditions for which one type of policy leads to more favorable results than others.

The model proceeds by iterating through the steps schematically illustrated in Figure 2.2. Each iteration through the model represents one year. Many firm variables in the model depend on the year t. If a variable x may depend on its previous value, we explicitly denote this dependence using the notation x(t) when expressing how it changes over time, otherwise we omit the time dependence. In general, we follow Dosi et. al.'s work, except when our focus on building a tool to compare the long-term trajectories of alternative near-term carbon reduction policies requires elaboration of specific elements or allows simplification of others.

We chose Dosi et. al.'s model as the starting point for this work because it already incorporated many of the features we desired to model. Firms must make decisions in the face of uncertainty regarding R&D spending, capital acquisition, and scrapping existing capital. Additionally, the Dosi model explicitly focuses on the macro implications of the actions of heterogeneous firms.

We explored other models in depth, including Silverberg and Verspagen, 1994, and Ciarli et al., 2010, but they either lacked desired details of firm behavior (the former) or included overly many for our purposes (the latter). An excellent overview of the main types of evolutionary economic models can be found in Kwasnicki, 2001; Fagerberg, 2003; and Witt, 2008. For an overview of the various methods used in such models, see Safarzyńska and van den Bergh, 2010.

The Time Line of Events

We will begin with a brief overview of the sequence of events that occur in any given period, highlighting the differences between this model and the underlying Dosi model:

1. In the first step, firms decide how much to produce and invest. These algorithms largely follow Dosi's model for consumption good firms. One of the largest changes we made to the Dosi model was to collapse Dosi's machine goods and final goods sector into one. Rather than have a sector devoted to R&D (as in Dosi), firms in our model internalize their R&D efforts and produce their own new capital, rather than purchase it from a machine goods sector. While this seems like a large change structurally, it is not functionally. Technology can still spread throughout the economy via imitation, and

innovative activities still generate new types of capital. The questions we hope to answer do no rely on a vertically segregated industry, so we simplified by aggregating R&D and production in the same firm.

2. Firms engage in R&D activities that potentially discover new technologies or allow them to imitate one of their competitors. These algorithms follow the Dosi methodology but with substantial modification to accommodate R&D activities across both labor and carbon factors of production (the Dosi model uses labor only as a factor of production).
3. The imperfectly competitive final goods market opens. The market shares of firms evolve according to their price competitiveness in a manner similar to Dosi. However, we use an exogenous demand curve to specify the total demand, while Dosi bases demand on total worker wages and an exogenously defined public sector expenditure.
4. As in Dosi, firms sell their goods according to their market share and update their inventory and net liquid assets.
5. Climate damages are calculated based on the economy's cumulative emissions, and the next period's overall demand is reduced accordingly.
6. Firms enter and exit the market place in line with the Dosi model. Firms with near-zero market share or net negative liquid assets are removed and replaced with new firms. Entry differs from the Dosi model in that new firms copy the best technology of a success-weighted, randomly selected firm.
7. Machines ordered at the beginning of the period arrive and are made available for production in the next time step.
8. The government updates its estimate of the optimal carbon price. Firms use this to update their lobby membership and the negotiated price of carbon is determined for the next period.

Modeling Firm Finances, Their Competitiveness, and the Economy

Each firm has a vintage capital structure that includes a set of machine types, each embodying a specific technology. Production occurs in fixed proportions between labor and carbon, where the technology determines the respective coefficients. To match general usage, we refer to *labor productivity* (a larger value is better) and *carbon intensity* (a smaller value is better)—although in this case, intensity is simply the inverse of productivity and vice versa. Capital is normalized such that one unit of capital produces one unit of final good; thus, there is no capital intensity factor. The composition of a firm's vintage capital (i.e., its inventory of machines available for production) determines its production cost. The j^{th} firm's i^{th} type of capital is characterized by its labor productivity $b_{i,j}$ and carbon intensity $a_{i,j}$, with resulting unit cost of

$$u_{i,j}(p_c, w) = a_{i,j}p_c + w/b_{i,j}, \tag{1}$$

where w is the wage rate and p_c the price per ton of carbon emissions. The production cost to firm j depends on its demand D_j and on its vintage capital.[5] We assume that each firm calculates

[5] In reality, the firm would meet its demand by employing its machines, starting with its most cost-effective one and possibly idling its least cost-effective machines. Depending on the values of w and p_c, a firm's cost-effective

its average carbon intensity a_j and average labor productivity b_j over its entire capital. Denoting the number of units of production capital i that firm j has by $K_{i,j}$, these averages are expressed as

$$a_j = \frac{\sum_i K_{i,j} a_{i,j}}{K_j}, \tag{2}$$

and

$$b_j = \frac{K_j}{\sum_i K_{ij}/b_{i,j}}, \tag{3}$$

where $K_j = \sum_i K_{i,j}$ and is firms j's total number of units of capital (which is also its maximum possible annual production).

Capital is subject to a constant depreciation rate of δ,

$$K_{i,j}(t) = K_{i,j}(t-1)[1-\delta]. \tag{4}$$

Figure 3.1 illustrates a firm's vintage capital structure. This representation shows one circle for each unique technology a firm possesses. The size of the circle indicates how much capital (productive capacity) that technology embodies, and the position illustrates the labor and carbon productivities. Black dots represent technologies available to the firm that have not yet been embodied. This two-dimensional representation can be collapsed to a one-dimensional scale by considering the costs of labor and carbon and plotting techniques by unit cost.

A firm's average production cost is then given by

$$u_j = a_j p_c + w/b_j. \tag{5}$$

In this case, firm j's production cost, u_j, varies continuously with w and p_c. Firm j's total production cost is given by $u_j Q_j$, where Q_j represents number of produced units of the final good. The price at which firm j sells each unit of final good is given by

$$p_j = a_j p_c + (1+\mu_j) w/b_j, \tag{6}$$

where μ_j is the markup over the labor cost. We assume that there is no markup over the carbon cost and that firms simply pass this cost on to consumers. The firm's costs are covered by selling the final good at a markup. For simplicity, we assume that all firms use the same markup factor, $\mu_j = \mu$. The average sector price of the final good is given by

$$\hat{p}(t) = \sum_j f_j(t-1)\{a_j p_c + (1+\mu) w/b_j\} = \hat{a} p_c + w/\hat{b}, \tag{7}$$

where the weights $f_j(t-1)$ represent firm j's market share of the previous year and where we define

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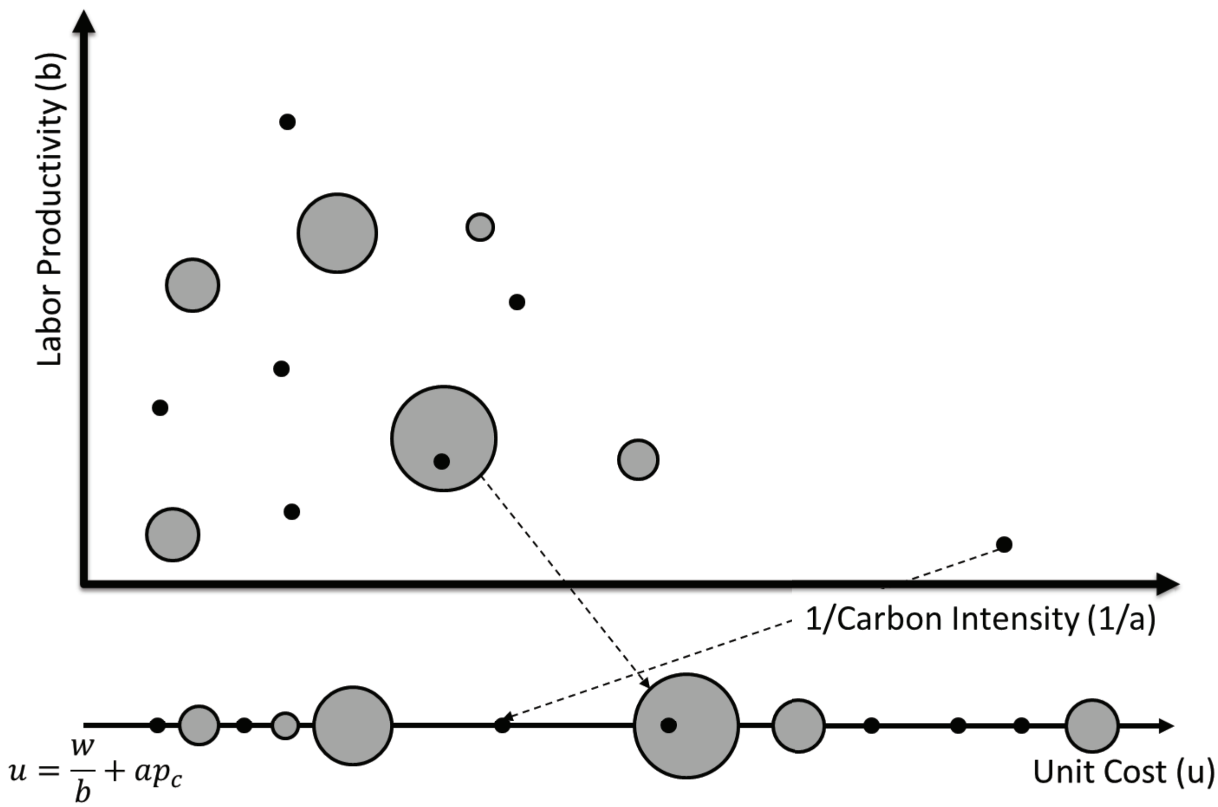
average production cost can be computed for a given demand. As either or both w and p_c change, a firm would rearrange the order of its most cost-effective machines; for a given fixed demand, this changes its average production cost by discrete, noncontinuous jumps. To avoid this complication, we follow the Dosi model in using the average production cost.

Figure 3.1. Illustration of a Firm's Capital Structure



$$\hat{a} = \sum_j f_j(t-1)a_j \tag{8}$$

as the market share weighted sector average carbon intensity and

$$1/\hat{b} = \sum_j f_j(t-1)/b_j \tag{9}$$

as the average of the inverse of labor productivity. For simplicity, we will refer to $f_j = f_j(t)$ as firm j's market share in the current year and$\tilde{f}_j = f_j(t-1)$ as that of the previous year.

While we assume that the wage is the same across all firms, it does vary over time in proportion to changes in average labor productivity:

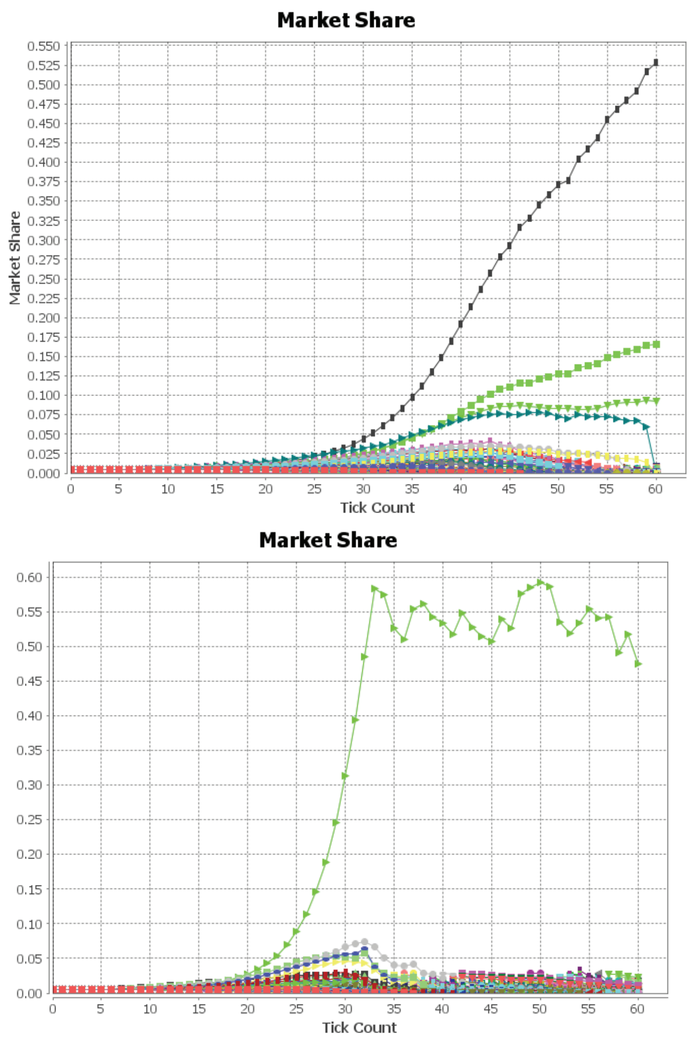
$$w(t+1) = w\left(1 + \beta * \frac{\hat{b}(t+1) - \hat{b}}{\hat{b}}\right). \tag{10}$$

Each firm's carbon intensity and labor productivity influence its market share. Thus, the distribution of carbon intensity and labor productivity across firms and how these factors evolve over time play important roles in shaping the modeled industry structure. As in Dosi's model, firm j's market share, f_j, changes according to a replicator equation given by

$$f_j = \tilde{f}_j \left(1 - \chi \frac{p_j - \hat{p}}{\hat{p}}\right), \qquad (11)$$

where χ measures the yearly response rate of market share adjustment in relation to changes in the fitness or competitiveness of the firm, which is characterized by the retail price of the final good, p_j.[6] Figure 3.2 provides two examples of the dynamics of a firm's market share. The replicator dynamics for market share given by Eq (11), together with the structure of the model, tends to produce one or a few dominant firms. This is because, once a firm gets a price advantage, it can invest in more efficient capital, lower its prices further, and set up a positive

Figure 3.2. Two Examples of the Dynamics of Firm Market Share



[6] Replicator dynamics is the most common market share mechanism in evolutionary economics models. See Samuelson, 1998.

feedback loop. Both graphs start with the same market structure but have different economic parameters. These differences, combined with stochastic fluctuations, produce very different outcomes. The first (above) produces an oligopoly of firms and the second (below) produces a monopoly with a market share that oscillates as new entrants come into the market.

Many evolutionary economics models tend toward monopolies,[7] but in our model, the stability of that monopoly critically depends on the entry and exit procedures. If new firms enter the market with better-than-average technology and a large initial market share, the tendency is for monopolies to fail eventually, when confronted with new challengers and a new monopoly to evolve. However, if firms enter with average technology and a small market share, the monopoly may temporarily lose market share before reasserting itself.

A firm's market share determines its demand D_j, which is given by

$$D_j = D f_j, \tag{12}$$

where D is the total demand. Firms make production decisions before their true demand is revealed; therefore, in general, firm inventory will fluctuate from year to year. We assume that the total demand is exogenously determined and given by

$$D = \kappa \hat{p}^{\varepsilon}, \tag{13}$$

where ε is an exogenous demand elasticity and κ is the consumption budget. The consumption budget is the overall yearly amount of wealth that consumers are willing to spend to buy goods when the elasticity ε is 1. We assume that the consumption budget grows at an exogenously determined constant rate γ and is reduced at a damage rate d, which provides a measure of the economic effects of climate change on consumers. The computation of the damage rate is endogenous to the model and is described in the subsection on "Damages from Climate Change and the Social Cost of Carbon." Many evolutionary economics models regard demand as endogenous. Our choice to focus on an exogenous demand influenced by carbon prices and climate change effects reflects our interest in the factors most directly related to the long-term trajectories of alternative carbon reduction strategies.

The consumption budget in our model changes according to

$$\kappa(t) = \kappa(t-1)[1 + \gamma - d]. \tag{14}$$

Figure 3.3 presents two examples of the dynamics of total market consumption, desired consumption, capital, production, and inventory with corresponding market share dynamics given by Figure 3.2. Total consumption in the model is given by the sum of S_j over all firms and this is compared to the desired consumption given by the demand D.

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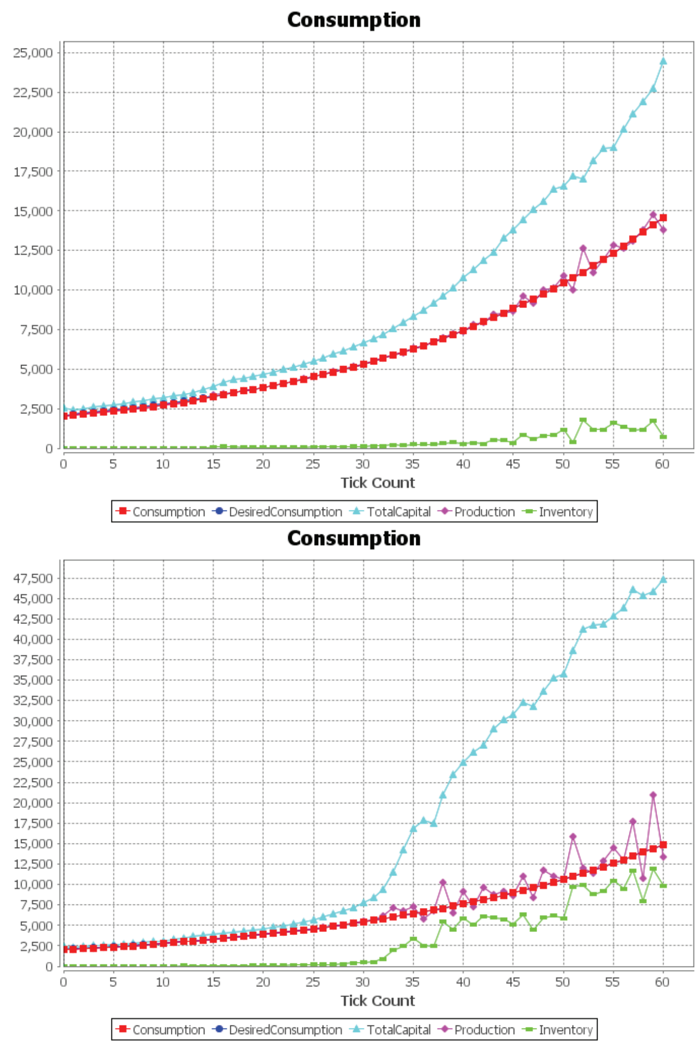
[7] For example, see the original Nelson Winter model, 1982, and some situations in Valente, 2003.

Figure 3.3. Two Examples of the Dynamics of Total Market Consumption



The number of units sold by firm j is given by

$$S_j(t) = \min[D_j(t), Q_j(t) + N_j(t-1)], \tag{15}$$

where $N_j(t-1)$ is the inventory of unsold goods produced in previous years. Its revenues are thus given by $p_j S_j$. The firm's unfilled demand is given by $max[0, D_j(t) - Q_j(t) + N_j(t-1)]$, and the inventory is updated as follows:

$$N_j(t) = N_j(t-1) + Q_j(t) - S_j(t). \tag{16}$$

Each firm uses its available funds to finance its running costs over the course of the year. The amount of funds available to a firm has two components: its liquid assets, which can be positive or negative, and a possible bank loan based on the firm's previous year revenues, i.e., $p_j(t-1)S_j(t-1)$. A firm's liquid assets are simply the aggregated profits the firm has accrued over the years.[8] If the liquid assets are negative, it represents an overall accrued debt. Banks set a maximum debt to sales ratio value of Ω, allowing firm j to have access to a maximum loan of $\Omega[p_j(t-1)S_j(t-1)]$. Denoting firm j's available funds as A_j and its liquid assets as L_j we have that

$$A_j(t) = L_j(t-1) + \Omega[p_j(t-1)S_j(t-1)]. \tag{17}$$

At the end of each year, the model computes the profit and potential debt for each firm. The debt is given by

$$\Xi_j(t) = \max[0, u_j(t)Q_j(t) + I_j(t) + R_j(t) + \Lambda_j(t) - L_j(t-1)], \tag{18}$$

where u_jQ_j is the production cost; I_j is the costs associated with capital expansion and replacement; and $\Lambda_j(t)$ is lobbying costs and R_j is R&D costs. These costs will be described in detail in the subsections on "Firm R&D" and "Carbon Price Lobbying." In formulating Eqn. (18), we made the assumption that all sales of the final good occur at the end of the year. Therefore, the total yearly operational cost is given by $u_j(t)Q_j(t) + I_j(t) + R_j(t) + \Lambda_j(t)$. If the liquid assets, $L_j(t-1)$, are positive and sufficient to cover all these costs, the firm required no loan during the year. If the liquid assets are negative or insufficient to cover these costs, the firm will have had to take a loan during the year. At the end of the year, the firm makes its sales and receives revenue, p_jS_j. The firm's end-of-year profits are then given by

$$\pi_j = p_jS_j - u_jQ_j - r\Xi_j - I_j - R_j - \Lambda_j, \tag{19}$$

and the liquid assets is updated by

$$L_j(t) = L_j(t-1) + \pi_j(t). \tag{20}$$

Firms must be able to service their debt and pay their lobbying dues at the beginning of the year, an amount of $rL_j(t-1) + \Lambda_j(t)$. These expenses may be paid via a new loan, but if the maximum loan amount has been reached, the firm declares bankruptcy and exits the market.

Firm Production and Investment Spending

After paying lobbying dues and servicing debt, firms allocate the remainder of their available funds to the production of the final goods, purchasing expansion and replacement capital, and conducting R&D. If available funds are insufficient to cover all the desired expenses, the firms prioritize as shown in Figure 3.4 and use all the funds available to them. This prioritization approach to spending decisions is based on the Dosi et al. model. Firms' choices regarding investments in R&D, capital expansion, and capital replacement can play an important role in the market structure over time and the comparative success of alternative carbon reduction strategies.

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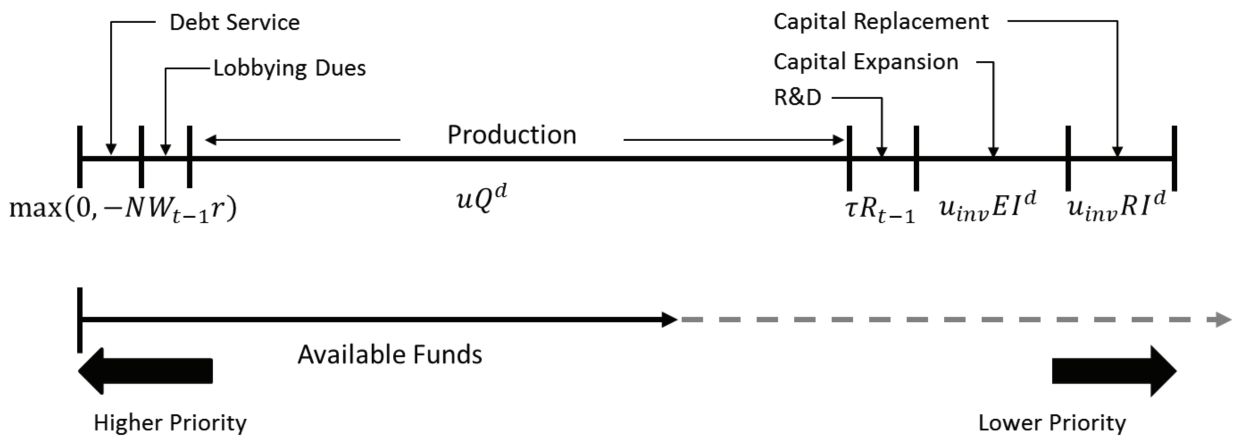
[8] Firms start life with an enough funds to produce at full capacity for an exogenously specified number of years, given by L^{ini}.

Figure 3.4. Spending Priorities



The first of these allocation priorities (after lobbying dues and debt service) is production. If a firm has more demand than productive capacity, it will attempt to expand its capital stock to match its demand in future years. Since firms make production decisions before they know their true demand, they must estimate demand each period. Firms use a simple rule when estimating their demand for the following year. They expect no changes in demand in the next year: the expected demand, D_j^e, is given by the current year's demand, D_j. In Dosi, Fagiolo, and Roventini, 2006, more exotic rules did not produce significantly different results. A firm's desired production is therefore given by

$$Q_j = \min[K_j, \max[0, D_j^e - N_j(t-1)]]. \tag{21}$$

However, depending on the available funds, the firm may not be able to satisfy its desired production. Without sufficient funds for production, the firm closes down and exits the market.

A firm's next priority in spending is investing in R&D. A fixed proportion, τ, of labor production costs, known as the R&D turnover, is allocated to R&D spending. Firm j's desired R&D spending is thus given by

$$R_j = \tau S_j w / b_j. \tag{22}$$

The actual amount spent on R&D will depend on how much of the original available funds remain.

Next, firms prioritize expansion capital. When purchasing capital, firms always invest in their lowest unit cost technology. A firm will want to satisfy all its demand by operating at a certain fraction, υ,of its productive capacity. Thus, a firm's desired production capital is given by D^e/υ, and therefore, its desired expansion capital is given by

$$K_j^e = \max[0, D^e/\upsilon - K_j]. \tag{23}$$

The unit cost of new capital is constant across firms and technologies and is represented by

$$u^{inv} = p^{inv} w / \hat{b}, \tag{24}$$

where p^{inv} is an exogenous parameter that represents the “real price,” in that it is a multiple of the average per-unit labor cost of the final good. This ensures that the cost of new capital grows as labor becomes more expensive but falls as labor becomes more productive. Although $\hat{b}$, as given by Eq. (9), provides the sector weighted averaged labor productivity of inventory in producing final goods, it is used in Eq. (24) as a proxy for labor productivity in producing new inventory. We assume that the production of new capital is carbon free and thus the cost is independent of the price of carbon, p_c.

The firm then uses its remaining available funds for capital replacement. Firms use a simple payback period routine, as in Dosi et al. The production cost of capital, $u_{i,j}$, of each machine type i belonging to the firm’s vintage capital is compared to the best (i.e., lowest) production cost of capital, $u_{b,j}$. The difference between these two costs is compared to the capital unit cost u_j^{inv}. If a machine type i that the firm owns has a ratio $u_j^{inv}/(u_i - u_b)$ below a threshold quantity, y, known as the payback parameter, the firm will want to replace it with a more productive capital. Labeling the set of production capital identifiers (i.e., the values of i) that satisfy this condition as R, the total number of units of production capital that firm j wishes to replace is given by the following:[9]

$$K_j^r = \sum_{i \in R} K_{ij}. \tag{25}$$

and

$$I_j = u_j^{inv}(K_j^e + K_j^r). \tag{26}$$

Firm Welfare

Ignoring capital investments, inventory fluctuations, and R&D, a firm’s welfare is best approximated by its profit. Due to our cost markup pricing rule, this simplifies to

$$W_j = p_j D_j - u_j Q_j = \frac{\mu_j w D_j}{b_j}. \tag{27}$$

From Eqs. (11) through (13), the welfare can be represented as a function of carbon price, p_c, as

$$W_j(p_c) = (\mu_j w/b_j)\tilde{f}_j K_D \hat{p}^{\varepsilon}\left\{1 - \chi\left[\frac{p_j - \hat{p}}{\hat{p}}\right]\right\}. \tag{28}$$

The model uses a firm’s welfare to determine which lobby group, a low carbon price (LCP) or a high carbon price (HCP) lobby, it will join for the coming period. Firms’ lobbying is

[9] Note that the deprecation rate of capital, δ, does not enter Eq. (26) in determining the replacement capital. This is because we model depreciation as a reduction in capital rather than a reduction in productivity, as given by Eq. (4).

explained in the subsection on "Carbon Price Lobbying" and in Appendix B. The derivative of the welfare with respect to carbon price, p_c, is given by[10]

$$\frac{\partial W_j(p_c)}{\partial p_c} = (\mu_j w/b_j)\tilde{f}_j K_D \hat{p}^{\varepsilon-2}\{\chi(1+\mu)w(\hat{a}/b_j - a_j/\hat{b}) + \varepsilon\hat{a}[\hat{p} - \chi(p_j - \hat{p})]\}. \tag{29}$$

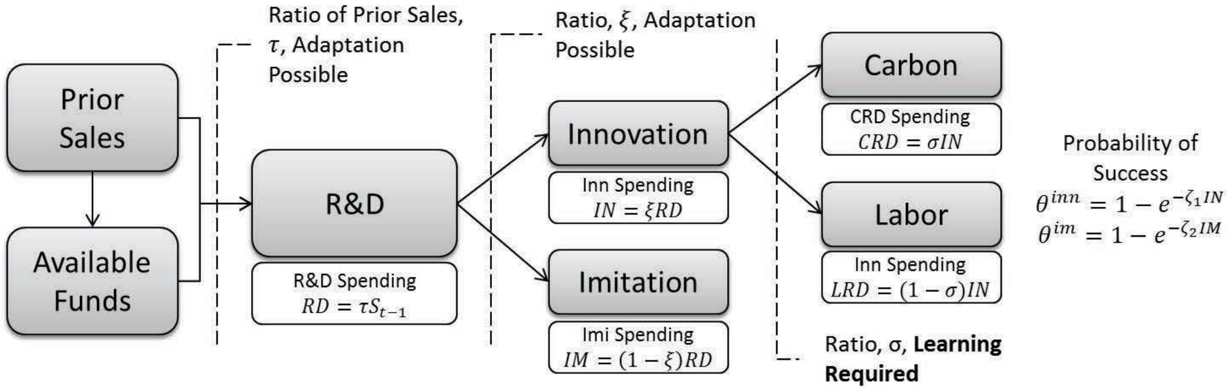
(Recall that a carrot over a value represents a market share weighted average). The welfare derivative is in this form to showcase the two main effects of a change in carbon price. The first term within the main braces results from how market share is expected to change due to a firm's competitiveness. Notice that this term can be positive or negative and depends on more than just a firm's relative carbon intensity. A firm can have a better-than-average carbon intensity, yet still lose market share if the price of carbon increases if the firm also had especially good labor productivity. In this case, the firm's competitive advantage from its labor productivity erodes as the relative fiscal effect of carbon increases. The second term in the braces relates to the change in overall market demand due to the change in carbon price. This term is always negative because an increase in the carbon price will always lead to less overall demand. Thus, increasing the price of carbon decreases the total size of the demand pie, but some firms can still be better off if their slices of the new pie are sufficiently large. In general, any given firm may shift over time from one lobby to the other as conditions change.

Firm R&D

A firm that manages to fulfill its desired production will allocate funds for the purpose of R&D. As in Dosi, these funds are split between efforts for innovation into new capital and efforts for imitation of competing firms' existing capital. As shown in Figure 3.5, a proportion ξ of R_j (firm j's allocated R&D funds) is spent on innovation and the remaining amount is spent on imitation. The first two choice parameters in Figure 3.5 (τ and ξ) are parameters that firms could conceivably update over time, but are constant for our purposes. There is evidence that the fraction of revenue invested in R&D, τ, is largely determined by the innovative opportunities in a particular sector (Pavitt, 1984; Klevorick et al., 1995). The last parameter, σ, determines the split between carbon and labor R&D. This parameter is not found in Dosi et al. and proves particularly important to the behavior of our model. Appendix C will provide details on how firms choose σ. Note here, however, that this parameter largely determines the effectiveness of different carbon price mechanisms because influencing firms' R&D investments is the only way to modify our model's endogenous rate of technological progression toward lower carbon intensity.

[10] Deriving this requires substituting Eq. (7), expressing $\hat{p}$ as a function of p_c, into Eq. (28).

Figure 3.5. Steps in R&D Spending Model



As in Dosi's model, firms invest a fixed fraction of their prior-period sales in R&D and divide this amount between innovative and imitative activities. Imitation is handled in the same manner as in Dosi, but the addition of carbon as a factor of production led us to modify Dosi's method for modeling innovation substantially.

Indeed, no evolutionary economics model could be found that allowed for the concurrent R&D investment in two independent factors of production. This appears to be the case more broadly, as Acemoglu (2001) states: "Although there is relatively little current research on biased technical change, an earlier literature was devoted to studying related issues," and later, "This whole literature was also criticized for lack of micro-foundations. . . . These shortcomings reduced the interest in this literature, and there was little research for almost 30 years. . . ." Acemoglu concludes that factor prices, relative factor levels, and innovation possibilities are all important in determining a firm's optimal R&D investment. We have tried to capture these aspects in the firm's carbon versus labor R&D decision in a way that adheres to the heuristic nature of evolutionary economics. For details, see Appendix C.

As in Dosi et al., innovation is a two-step process: (1) A firm either does or does not successfully innovate, and (2) successful firms receive a new technology based on draws from related beta distributions. In the first step, the probability that a firm successfully innovates is given by

$$\theta_{inn} = 1 - \exp[\zeta_{inn} \xi R_j], \tag{30}$$

where ζ_{inn} is referred to as the "firm search capability parameter" in Dosi et al. While this is an exogenous parameter in Dosi, we chose to reparameterize ζ_{inn} to make the meaning more intuitive. We exogenously specify the expected fraction of firms that should successfully innovate in the first period and then calculate ζ_{inn} as

$$\zeta_{inn} = -N \text{ Ln}(-\theta^{r}_{inn})/(\text{D}\xi\tau w/b^{*}), \tag{31}$$

where θ^{r}_{inn} is the aforementioned share of initial successful innovations, and N is the total number of firms. This parameter is calculated once at the beginning of the simulation and remains constant thereafter and assumes that all firms are homogenous to begin with.[11] The firm that successfully innovates will have the possibility in the next iteration to invest in its new technology via its capital expansion routine.[12]

If a firm successfully innovates, it proceeds to step two. The carbon intensity and labor productivity of the new technology are a_{inn} and b_{inn}, respectively. These are given by

$$a_{inn} = a_b(1 + x_C)^{-1} \tag{32}$$

and

$$b_{inn} = b_b(1 + x_L), \tag{33}$$

where a_b and b_b are the carbon intensity and the labor productivity of the firm's most cost effective machine, and x_C and x_L are random variables taken from two different but related beta distributions.[13] The upper bound of these beta distributions is a function of the firm-specific parameter, $\sigma_j(t)$, which changes with time. This parameter provides the proportion of the firm's R&D funds allocated to innovation that are spent on lowering its carbon intensity and varies between 0 and 1. The upper limit of the beta distributions is a linear function of $\sigma_j(t)$ such that, if no funds are used for carbon (or labor), the upper bound collapses to the lower bound:

$$\tilde{\omega}_{C,u} = \omega_{\mathrm{C,l}}(1 - \sigma) + \omega_{\mathrm{C,u}}\sigma \tag{34}$$

and

$$\tilde{\omega}_{L,u} = \omega_{\mathrm{L,l}}\sigma + \omega_{\mathrm{L,u}}(1 - \sigma), \tag{35}$$

where $\omega_{\mathrm{C,l}}$ and $\omega_{\mathrm{C,u}}$ are the exogenous lower and upper limits for the carbon R&D beta distribution, and $\tilde{\omega}_{C,u}$ is the upper limit adjusted for actual carbon R&D expenditures. The lower bounds can be negative, indicating a situation in which firms are increasingly likely to see reductions in productivity if they fail to invest in that particular R&D dimension. See Figure 3.6 for a graphical representation. The upper left quadrant has equal spending on carbon and labor, the upper right less on carbon, lower left more on carbon, and lower right has all funds devoted to carbon. The star represents the firm's current lowest unit cost technology.

The proportion $\sigma_j(t)$ changes from year to year based on (1) which lobby the firm belongs to, (2) on the reputation of the government in following its carbon price policy, (3) the firm's current average expenditure on carbon and labor, and (4) information about the shape of the

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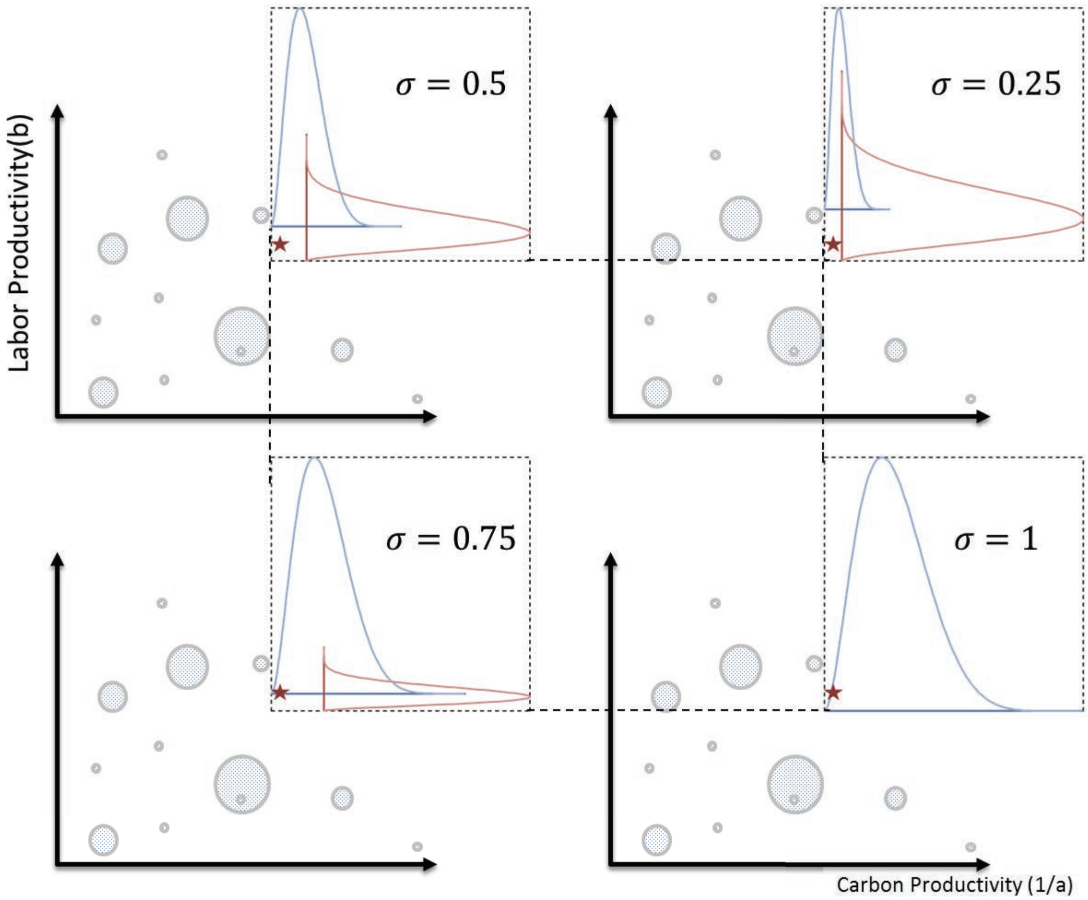
[11] Note that this reparameterization has not changed the model in any way. We simply provide a more intuitive parameter for the user to input and then convert that to Dosi et al.'s "firm search capability parameter" using a few simplifying assumptions.

[12] It is important to notice that, in the model, the probability of innovation depends only on the current innovation investment, ξR_j, made in the current year, not on cumulative R&D investments since the last time innovation was successful. This follows the Dosi model and, indeed, many other evolutionary economic models.

[13] After deriving this setup, it came to our attention that Nelson and Winter had proposed a similar method back in 1975 (Nelson and Winter, 1975). Our version differs in that the support of the distributions from which innovations are drawn changes with a firm's relative investment in the different factors.

Figure 3.6. Beta Distributions for Carbon and Labor Innovation for Four Different Values of σ



carbon and labor R&D distributions. The investment strategy firms follow changes via an adaptation and learning process based on past experience with government carbon pricing policies. A detailed description of this process is described in Appendix C.

The probability that the firm successfully imitates is given by

$$\theta_{imi} = 1 - \exp[-\zeta_{imi}(1-\xi)R_j], \tag{36}$$

where ζ_{imi} is Dosi et al.'s firm search capability parameter for imitation R&D. Just as for innovation, we specify an exogenous initial imitation rate, θ^{r}_{imi}, and then derive ζ_{imi}.

Imitation is a two-step process: (1) a firm either does or does not successfully imitate, and (2) successful firms are assigned a firm to imitate. For the first step, the firm successfully imitates with probability θ_{imi}. If successful, the inverse difference between average unit costs for all other firms is computed and used as a weight to randomly select a firm to imitate. This results in firms with similar unit costs being imitated more frequently. This procedure is consistent with the Dosi model but modified to accommodate the presence of carbon R&D in addition to labor R&D. The capital stock with the lowest production cost from the competing firm is made available to the imitating firm. In the next iteration, the firm will be able to invest in this new capital stock via its production capital expansion.

Market Entry and Exit Conditions

Firms exit the market for two reasons: lack of funds or insufficient market share. Firms with a market share below some exogenous small fraction are deemed insolvent and forced to exit. Firms that cannot pay their lobby contribution or service their accumulated debt go bankrupt and are removed from the market. The lobby contribution exit condition provides a simple means of imposing a penalty that prevents free-riding behavior. Experiments with the model rarely found cases of a firm being forced to exit because it could not pay lobbying dues that would not have left the market a period or two later.

Firms enter the market by imitating a demand share growth rate weighted, randomly selected firm. The new firm receives the best technology of the imitated firm and an amount of capital, K^*, drawn from a uniform distribution based on the market share weighted average amount of capital. Exogenous parameters are used to construct the lower and upper bounds of this distribution:

$$K^* \sim Uniform[\rho_l \widehat{K}, \rho_u \widehat{K}]. \tag{37}$$

This capital allocation mechanism is taken from Dosi et al. The entrant firm's initial market share is made proportional to its supply of capital relative to the market's total capital stock. This can create an aggressive entry mechanism as new firms potentially start with large amounts of capital and very competitive technology. We chose such an entry mechanism because it may be representative of the conditions necessary (but not sufficient) for a potential transition to a future low-carbon world. Since our model only treats a single sector, it cannot follow the fate of capital a firm exiting the market previously owned. The lack of a secondary market for capital leads to its disappearance when a firm exits. However, capital also spontaneously appears when a firm enters, and this simplifying assumption is not expected to have a substantive effect on the policy results the model generates.[14]

Damages from Climate Change and the Social Cost of Carbon

We employ two important simplifications in representing the interactions between the economy and climate system. First, we assume that the damages due to climate change depend only on cumulative emissions. Second, we use the social cost of carbon (SCC) as the framework for representing the government's knowledge about and response to climate change.

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[14] Other methods exist for dealing with capital issues with regard to market entry and exit. Some models simply prohibit entry and exit (see Saint-Jean, 2006, and the original Nelson-Winter model, Nelson and Winter, 1982), while others ensure that the capital from exiting firms has already depreciated to negligible amounts (Silverberg and Verspagen, 1994). The model does provide outputs for the total capital gained and lost during market entry and exit.

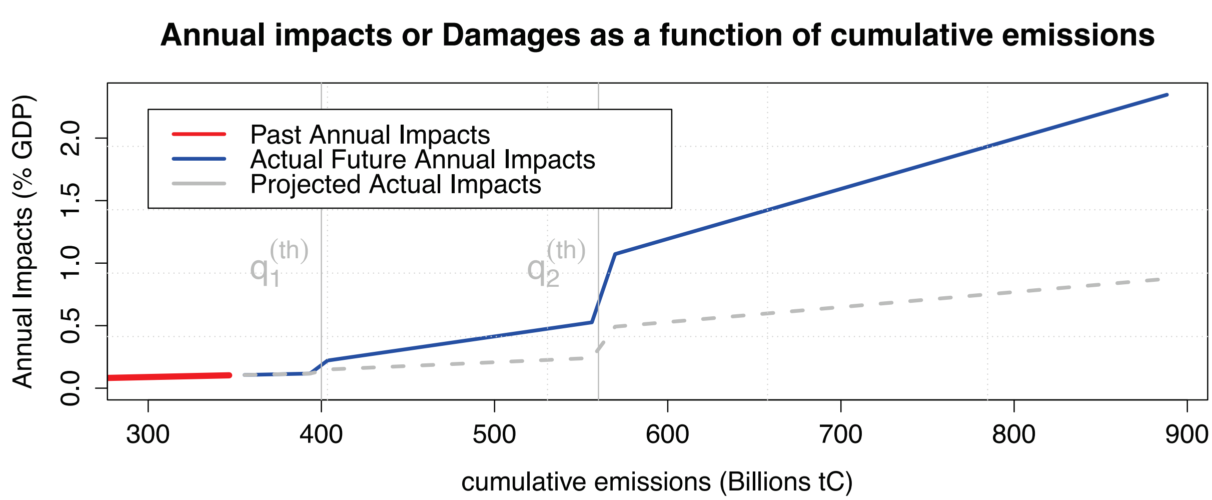
Assuming that damages depend only on cumulative emissions allows simple consideration of the potential for, and imperfect information about, abrupt changes in the climate system. We expect that the potential for such abrupt changes may have important interactions with policies that can induce inexpensive and/or rapid technology transformations. The assumption does neglect any dependence of how climate affects the rate of emission growth or reduction but is consistent with recent literature emphasizing that the adverse impacts of emissions in any given year can last for centuries (Solomon, 2009) and offers proposals for using cumulative emissions as a metric for emission-reduction policies (Allen, 2009, and Broecker, 2007).

In our model, the economic damages due to the present level of cumulative emissions are given by

$$d(t) = D\left[\sum_{l=0}^{t} \epsilon(l)\right] = D[q(t)], \tag{38}$$

where $\epsilon(l)$ is the combined total of anthropogenic emissions from all firms in year l and $q(t)$ is the cumulative emissions at time *t*. The function $d(t)$ is the reduction in annual GDP (i.e., annual impacts) as a function of cumulative emissions. For simplicity, we assume this function is piecewise linear. As shown in Figure 3.7, this assumption allows a straightforward representation of any potential discontinuities caused by various threshold responses in the interacting climate, biophysical, and/or socioeconomic systems. Discontinuities can occur when the cumulative emissions reach user-supplied threshold values, labeled $q_i^{(th)}$. Dark lines in the figure show the actual impacts function and gray dotted lines show the government's estimated effects function for a value of $\lambda = 0.3$. The annual damages d(t) slow the growth of the economy as described in the time line of events presented earlier.

Figure 3.7. Annual Impacts or Damages as a Function of Cumulative Emissions



The model uses the SCC to represent the government's expectations about the future damages from climate change. The SCC is useful for this purpose because the governments of the United States and United Kingdom are already using it as a basis for evaluating climate policies, which increases the relevance of our analysis and also provides a source of estimates that can be used to calibrate the model.

The SCC provides an estimate of the monetized damages associated with an incremental change in GHG emissions in a given year. The SCC is defined as the change in the discounted value of the utility of consumption denominated in terms of current consumption per unit of additional emissions. To calculate the SCC, analysts generally use integrated assessment models that generate an optimal emission reduction path contingent on assumptions about both the costs of emission reductions and the benefits of the avoided climate change. The SCC is then given by the per-unit cost of any deviation of emissions from that optimal path in any given year.

Our model considers two related, but distinct, SCC values. The first is the "actual" SCC, which is the best estimate of the cost the government would calculate if it had complete information about the damage function. The second is the government's estimated SCC, which is based on imperfect information, as described below.

We write the actual SSC in year t as

$$p_g^a = GDP\left\{\frac{1}{r}\sum_{i=1}^{M} m_i\left(e^{-rt_{i-1}} - e^{-rt_i}\right) + \sum_{i=1}^{M-1}\frac{d_{h,i}e^{-rt_i}}{\sqrt{\epsilon_0^2 + 2\rho(q_{h,i} - q_0)}}\right\}, \qquad (39)$$

where

GDP = the current period's GDP

r = represents the discount rate

M = the number of segments in the damage function

t_i = the estimated time of the i$^{\text{th}}$ jump in the damage function

m_i = the slope of the i$^{\text{th}}$ segment of the damage function

$d_{h,i}$ and $q_{h,i}$ = the magnitude and location of the i$^{\text{th}}$ jump in the damage function

ϵ_0 and q_0 = the current period's annual and cumulative emissions, respectively

ρ = the estimated emission slope found by linearly extrapolating the last *N* years of emissions.

Appendix A provides the mathematical derivation to obtain the above expression.

We use this estimate of the actual social cost of carbon to define the optimum policy the government could pursue. This optimum policy is used in the calculation of regret described in the "Measures" subsection of Section 2.[15]

[15] It is possible that other policies could perform better than this "optimal" one. Technological change is stochastically determined in this model so certainty about abatement costs is not possible. More generally, the government does not anticipate the impact of a price of carbon on firm's R&D and capital investment decisions and the resulting changes in future carbon emissions. Rather, it uses a slowly updating emissions estimate based upon

In general, the government will have only imperfect information on the SCC. To model the resulting imperfect estimates of the SCC, we assume that the government can observe only the segments of the impact function within a "distance" Δ of the current cumulative emissions. That is, the government will have perfect information about the segment of the impact function currently (or previously) causing damage and about any segment that is sufficiently close in terms of cumulative emissions. The government will have imperfect information about any segment further away than Δ from the current level of cumulative emissions. In Figure 3.7, the dotted gray line shows the imperfect information about any segment that the government relies on. This imperfect information is represented by scaling each future unknown segment by a factor λ. When $\lambda = 1$, the government estimates future damages correctly; when $\lambda = 0$, the government projects current impacts indefinitely into the future, $\lambda < 1$ represents underestimation of future impacts, and $\lambda > 1$ represents overestimation. Figure 3.7, for example, shows the government's estimated impacts function for $\lambda = 0.3$.

A plot from a sample model run illustrates some of these dynamics (Figure 3.8).

Figure 3.8 shows time series for several different carbon prices from a sample model run. Each point represents the cost of carbon calculated at the specified tick count (i.e., time step) in the model run. Four different costs of carbon are calculated at each tick count. The black line, AScc, is the actual social cost of carbon, while the gray line, Pg, is the government's best estimate of the social cost of carbon.[16] These are calculated in the absence of lobby influence. At time step 40, the gray joins with the black line. At that time, the final segment in the damage function is within Δ time steps in the future. Consequently, the government finally sees the correct magnitude of the last large jump in the damage function and begins to estimate the cost of carbon correctly. The sudden drop at time step 50 occurs after the threshold is reached. After this, the social cost of carbon no longer includes any large jumps and is instead based solely on the marginal damage of each additional ton of emissions. This behavior reflects the assumption of irreversible impacts built into a cumulative emission damage model. Once a threshold has been crossed, there is no remaining social benefit to emission reductions aimed at avoiding that threshold.

The red (PcH), cyan (Pc), and blue (PcL) lines correspond to the various lobbying-derived carbon prices. The red line would be the price of carbon if the government only negotiated with only the HCP lobby, likewise for the blue line and the LCP lobby. The cyan line is the negotiated price of carbon between the government and both lobbies and is what firms actually pay for

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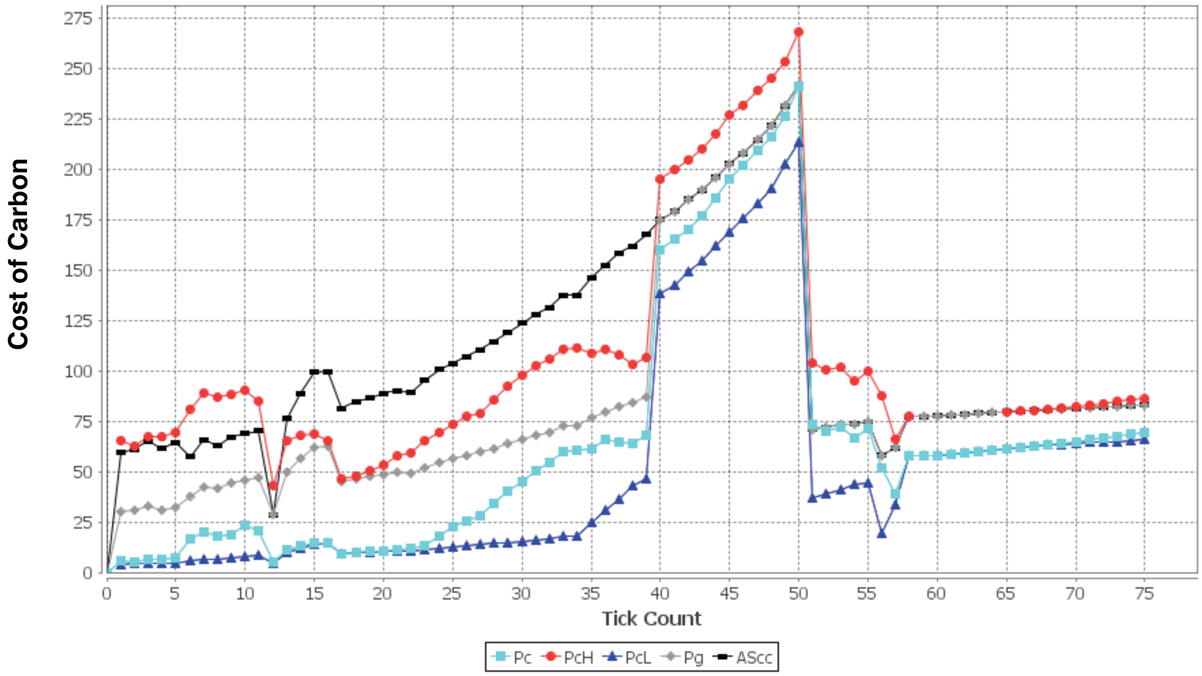
prior trends. But the calculation does approximate the best the government could do given perfect information about the damage function, and so provides a reasonable basis for policy comparisons in this study.

[16] Note that none of the lines represent the government's expectations of future carbon prices. Each point on the gray curve represents the government's final estimation of the socially optimal cost of carbon for that period. Thus, the price "announced" to the two lobbies is the one the government will choose, given no lobbying efforts. The black line is the same, except that it assumes perfect knowledge of the damage function.

Figure 3.8. Example Plot of Various Carbon Prices



emissions in that period. Notice that the single-lobby carbon prices (red and blue) always bracket the government's estimated social cost of carbon (gray) and the negotiated carbon price (cyan).

One can also see that the LCP lobby is usually more successful in its lobbying efforts (the negotiated price is less than the government's desired price) than the HCP lobby. This is to be expected because LCP firms generally have more to lose from high carbon prices than HCP firms have to gain (see the "Firm Welfare" subsection).

The Government's Welfare

Our model attempts to capture the interaction between the government and firms as the former attempts to pursue socially beneficial policies and the latter attempt to influence the government's choices consistent with their own interests. Following Grossman and Helpman's (1994) work in the trade economics literature, we assume that the government makes decisions to maximize a welfare function with two components: one related to the policy that generates the largest social welfare and one related to the policy that will produce the largest benefit for the government. In our model, the government addresses the first component when it chooses a carbon tax based on its estimate of the social cost of carbon. The latter, self-interested component can be thought of in multiple ways. A cynical interpretation might assume that the government weighs campaign contributions against societal welfare in making decisions. A less cynical interpretation might assume that the government balances the formal estimate of the SCC against other social needs and that the government's information about and perception of these other needs is influenced by lobbying (or informational) activities that incur some costs from the firms.

To capture this dynamic, we assumed the government seeks to set the carbon price to maximize its own welfare function, $W_G(p_c)$. In the absence of any lobbying or political pressure, we assumed that setting the carbon price at its estimate of the SCC maximizes the government's welfare. However, in the presence of lobbying, the government may increase its welfare by choosing a carbon price different from p_G. We assumed that a lobby that successfully convinces the government (through a process described in the next section) to set a carbon price different from p_G will compensate the government by an amount related to the size of the deviation from p_G. Quantifying this compensation thus provides an important input to how our model treats the competition for influence on the government between firms that seek higher or lower carbon prices.

We define a government contribution function, $G(p_c)$, that represents the compensation a lobby would have to pay the government to set the carbon price at p_c. We assume that this contribution function has several properties. First, the compensation required for a socially optimal carbon price is zero (i.e., $\mathrm{G}(p_G) = 0$). Second, we assume the government is only willing to vary the carbon price within a certain range, so that the contribution becomes infinite outside this range. Third, we assume that, close to the social optimum $p_G(t)$, the contribution varies quadratically with the carbon price. We thus note that

1. The domain of the function $\mathrm{G}(p_c)$ is defined for p_c values within a range of $p_c^{min} \leq p_c \leq p_c^{max}$.
2. The contribution is such that $\mathrm{G}(p_c^{min}) \to \infty$ and $\mathrm{G}(p_c^{max}) \to \infty$.
3. The function $\mathrm{G}(p_c)$ is quadratic within a subdomain of p_c values given in the range of $p_c^{(b)} \leq p_c \leq p_c^{(t)}$.
4. The form of $\mathrm{G}(p_c)$ implicitly depends on time t via its dependence on $p_G(t)$.

In the quadratic region we have

$$\mathrm{G}(p_c) = s(p_c - p_G)^2, \tag{40}$$

where s is the steepness of the curve and has units of one over dollars. This parameter will be referred to as the "government stringency" because it characterizes how willing (or unwilling) the government is to deviate from its estimate of the optimal carbon price. To ensure smooth derivatives,[17] we assume that outside the quadratic region, $C_G(p_c)$ tends toward ∞, according to

$$\mathrm{G}(p_c) \coloneqq p_c^{-1}, \tag{41}$$

such that we get two asymptotes at p_c^{min} and p_c^{max}. We use the methodology of splines to make sure the derivatives over the transition from the quadratic to the inverse sections are smooth. Therefore, at $p_c^{(b)}$ and $p_c^{(t)}$, the two functional forms are required to yield the same value and derivative. By imposing these constraints, we can define four sets of parameters given by

[17] Smooth derivatives help ensure that the numerical solver we use finds a solution.

$$a_L = 2s(p_G - p_c^{(b)})(p_c^{(b)} - p_c^{min})^2, \tag{42}$$

$$a_H = 2s(p_G - p_c^{(t)})(p_c^{(t)} - p_c^{max})^2, \tag{43}$$

$$c_L = s(p_c^{(b)} - p_G)^2 + 2s(p_c^{(b)} - p_G)(p_c^{(b)} - p_c^{(min)}), \tag{44}$$

and

$$c_H = s(p_c^{(t)} - p_G)^2 + 2s(p_c^{(t)} - p_G)(p_c^{(t)} - p_c^{(max)}) \tag{45}$$

that we use to define the government contribution function over the entire domain:

$$\mathrm{G}(p_c) = \begin{cases} \frac{a_L}{(p_c - p_c^{(min)}) + c_L}, \mathrm{p_c} < p_c^{(b)} \\ s(p_c - p_G)^2, p_c^{(b)} \leq \mathrm{p}_c \leq p_c^{(t)} \\ \frac{a_H}{(p_c - p_c^{(max)}) + c_H}, \mathrm{p_c} > p_c^{(t)} \end{cases}. \tag{46}$$

Figure 3.9 shows the contribution function for different values of the optimal cost of carbon p_G. Note that the contribution function (blue) and the quadratic function extend beyond the domain of influence (green).

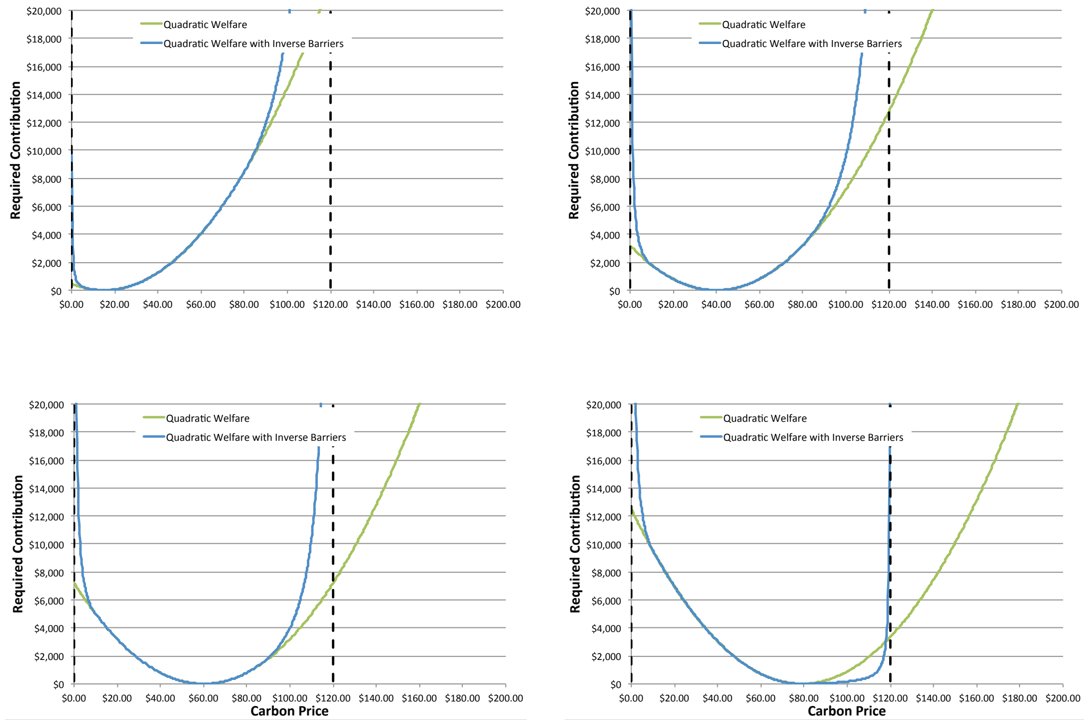
Few data exist to inform the choice of the steepness of the contribution function. However, we expect this parameter to prove important in determining the relative success of alternative carbon reduction policies. Initially, this value will be such that the negotiated price of carbon is some exogenous fraction of the government's preferred carbon price. An exogenous multiplier scales this steepness value to allow exploration over worlds in which the strength of the government varies. In any given run, the steepness value grows at the same rate as actual consumption to ensure that, as time progresses, the relative strength of the government does not diminish relative to the strength of the firms.

Carbon Price Lobbying

As described above, firms have to pay a carbon tax, p_G, set by the government for every unit of carbon emitted. Firms thus have an incentive to organize themselves into lobbies that seek to influence the government's choice of the carbon tax and, if successful, will incur costs in doing so. In our model, firms must join either the LCP or HCP lobby, depending on whether they prefer a smaller or a larger carbon tax than the government's estimate of the social optimally tax. A firm joins the LCP lobby if the derivative of its welfare with respect to the carbon price, p_c, computed in Eq. (29), is negative when evaluated at p_G. If, instead, this derivative is positive, the firm joins the HCP lobby.

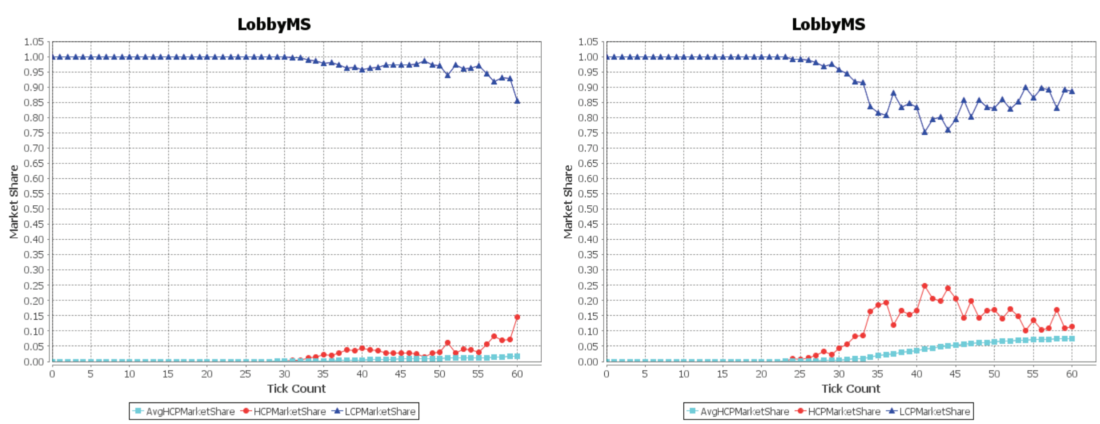
Figure 3.10 shows the dynamics of lobby membership in terms of market share. It is possible that all firms have a negative derivative evaluated at p_G and that they therefore all join the LCP. Therefore, two distinct situations can occur in any iteration in our model, the first when only one lobby (the LCP lobby) exists and the second when both lobbies form and battle in a bidding war

Figure 3.9. Contribution Function and Quadratic Function for Different Optimal Costs of Carbon



NOTE: The four plots all have the same limits, but different p_G values of \$15, \$30, \$60 and \$80.

Figure 3.10. Two Examples of the Dynamics of the Aggregated Firm's Belonging to the LCP or HCP Lobby



NOTE: The lowest line is a moving average of the HCP market share over the course of the simulation. These examples respectively relate to those shown in Figure 3.2.

with each other. Appendix B provides a complete description of how we model the way that lobbies negotiate with the government in changing the carbon price. In this section, we list only the important equations the model uses in computing the carbon price fixed by the government when influenced by lobbies and the monetary compensation the government receives from the lobbies in return.

W_L and W_H are the sums of all the welfares of firms belonging to the LCP and HCP lobbies, respectively, where firm welfares are given by Eq. (28). We first consider the case in which only one of the two lobbies has formed. Therefore, p_L and p_H are the carbon prices that would result if only the LCP or HCP lobby, respectively, negotiated with the government. These prices, p_L and p_H are found by solving

$$\partial \mathrm{G}(p_c)/\,\partial p_c = \partial W_i(p_c)/\,\partial p_c \tag{47}$$

for p_c for $i \in \{L, H\}$. Therefore, in absence of the other lobby, our model fixes the carbon price at $p_c = p_i$. The government receives compensation from lobby i in the amount of $\mathrm{G}(p_i)$. Firm j's contribution is based on its market share:

$$\Lambda_j = \hat{f}_j \mathrm{G}(p_i). \tag{48}$$

It is important to note that, when only one lobby is present, the compensation that it would offer the government for setting the carbon price to the social optimal p_G is zero. We define a generalized government compensation function, $\mathrm{G}(p_c, K)$, where K represents the government compensation for setting the carbon price to p_G. As stated, when only one lobby is present, $K = 0$. However, as shown in Appendix B, this is not the case when both lobbies are formed. When two lobbies are present, the bidding war between them results in a progressive increase in the value of K. This shifts the government contribution curve upward. Eventually, equilibrium is reached, and no further unilateral lobby contribution changes the carbon price. The equilibrium carbon price that results from this bidding war, p_{LH}, is found by solving

$$\partial \mathrm{G}(p_c)/\,\partial p_c = \partial W_L(p_c)/\,\partial p_c + \partial W_H(p_c)/\,\partial p_c \tag{49}$$

for p_c. Further, K° is the equilibrium value of K, and $\mathrm{G}^0(p_{LH}) = \mathrm{G}(p_{LH}) + K^\circ$ is the total compensation that the government obtains from the two lobbies, where

$$K^\circ = W_H(p_H) + W_L(p_L) - W_H(p_{LH}) - W_L(p_{LH}) + \mathrm{G}(p_{LH}) - \mathrm{G}(p_L) - \mathrm{G}(p_H). \tag{50}$$

The total compensation is split between the two lobbies according to the lobbying game such that $\mathrm{G}^0(p_{LH}) = C_L^\circ(p_{LH}) + C_H^\circ(p_{LH})$, where $C_L^\circ(p_{LH})$ and $C_H^\circ(p_{LH})$ represent the compensations to the government provided by the LCP and the HCP lobbies, respectively, and are given by

$$C_L^\circ(p_{LH}) = [W_H(p_H) - W_H(p_{LH})] + [\mathrm{G}(p_{LH}) - \mathrm{G}(p_H)] \tag{51}$$

and

$$C_H^\circ(p_{LH}) = [W_L(p_L) - W_L(p_{LH})] + [\mathrm{G}(p_{LH}) - \mathrm{G}(p_L)]. \tag{52}$$

As before, firms make their contributions based on their market shares. Therefore, a firm makes a contribution

$$\Lambda_j = \hat{f}_j C_i^{\circ}(p_{LH}), \tag{53}$$

where $i \in \{L, H\}$, according to whether the firm belongs to the LCP or HCP lobby.

4. Calibration

We developed this model to conduct an RDM analysis that compares the ability of alternative near-term carbon reduction policies to result in a long-term transformation to a low-carbon economy. We thus required a suitable experimental design over the model input parameters that enables testing policy performance over a wide range of plausible futures, as represented by the model. Two types of information can help guide the choice of cases. First, estimates exist for the upper and lower bounds for individual model input parameters. Second, the model should reproduce the historical record reasonably well. We sought a set of cases consistent with these two constraints.

To choose the cases in our experimental design, we used an approach similar to those in some previous RDM analyses (Dixon et al., 2007; Robalino and Lempert, 2000). We ran a large Latin hypercube experimental design over a subset of the model's input parameters: those related to the model's representation of the economy but unrelated to future climate change, future innovation, and future government choices on carbon reduction policies. We then filtered these cases, retaining only those that successfully reproduced relevant historical trends over the last 50 years. To scale the experimental design to our available computational limitations, we choose a diverse subset of ten of these plausible model cases. We could then use these ten cases as a foundation for many thousands of cases that additionally explore many different assumptions about future climate change, the potential for low-carbon innovations, and government response to lobbying.

Table 4.1 summarizes the model's uncertain economic parameters explored in the first phase of this process. Note that the table does not list parameters relating to the government's response to lobbying and climate damage parameters because we disabled these components for this historical analysis.

The values of these model parameters were estimated to lie within the given uncertainty range. We created a 15,000-case Latin hypercube experimental design. Each combination provides a model scenario, which is characterized by a unique set of parameter values sampled within their uncertainty range. For each scenario, we ran 100 independent stochastic realizations, providing a total set of 1.5 million runs. Each model realization was run for 60 iteration years, representing the market evolution between the years 1950 and 2010. To represent greenhouse policies and conditions between these years, the realizations ran using no carbon taxation and no firm lobbying. The model was initiated with 200 firms, each with equal market share. We chose to run the model for 60 years because this provides sufficient time for the model to evolve past its transient dynamics. Although these runs do not include a carbon tax, they still compute the SCC and split firms into those that would belong to a LCP lobby and those that would belong to a HCP lobby.

Table 4.1. Key Economic Parameters Varied During the Calibration Analysis

Parameter	Parameter Description	Lower Bound	Upper Bound
$\boldsymbol{\Omega}$	Debt to sales ratio	2	10
$\boldsymbol{\kappa}$	Demand growth	0.030	0.032
$\boldsymbol{\delta}$	Depreciation rate	0.03	0.06
$\boldsymbol{\varepsilon}$	Elasticity of demand	–0.5	–0.1
$\boldsymbol{\rho_u}$	Entrant capital upper bound	0.02	0.2
$\boldsymbol{\zeta_{imi}}$	Imitation rate	0.01	0.5
$\boldsymbol{\zeta_{inn}}$	Innovation rate	0.05	0.2
$\boldsymbol{L^{ini}}$	Initial years of self-financing available	1	5
$\boldsymbol{\mu}$	Markup	0.2	0.4
$\mathbf{y}$	Payback Parameter	4	20
$\boldsymbol{\omega_{C,l}}$	Lower bound of carbon R&D beta distribution[a]	0.02	0.04
$\boldsymbol{\alpha_L}$	Alpha shape parameter of labor R&D beta distribution	2	10
$\boldsymbol{\beta_L}$	Beta shape parameter of labor R&D beta distribution	2	10
$\boldsymbol{\omega_{L,l}}$	Lower bound of labor R&D beta distribution	0.01	0.03
$\boldsymbol{\omega_{L,u}}$	Upper bound of labor R&D beta distribution	0.03	0.08
$\boldsymbol{\xi}$	Ratio between innovative and imitative R&D expenditures	0.25	0.75
$\boldsymbol{p^{inv}}$	Real capital price	2	6
$\boldsymbol{\chi}$	Replicator coefficient	0.25	1.5
$\boldsymbol{\upsilon}$	Utilization rate	0.75	0.9

[a] Since the price of carbon was zero in all these runs, firms never invested in carbon R&D, and thus, every new innovation received the lower limit of the carbon R&D beta distribution. The upper limit and shape parameters are not applicable in this situation.

At the end of the 60 iterations, the model produces final outputs. We focused on four specific model outputs for which data exist over the last 50 years and that seem particularly relevant to the model's ability to project the comparative future performance of alternative carbon reduction policies: growth rate, decarbonization rate, labor productivity growth rate, and market share of the LCP. We filtered the 1.5 million runs by selecting runs that produced outputs within the historical ranges given in Table 4.2. Our aim was to obtain a set of ten runs with different parameter value combinations that satisfy all four of our filtering constraints.

Out of the total of 1.5×10^6 runs, about 3.8×10^5 runs passed the growth-rate filter, 2.1×10^4 runs additionally passed the decarbonization rate filter, 1.2×10^3 runs additionally passed the labor productivity rate filter and only 183 runs additionally passed the LCP market share filter. Only 20 unique parameter combinations passed all four filters.[18] Of these 20 runs, we

[18] The 183 runs represent different random seed values for the 20 unique cases. Although 20 out of 1.5×10^6 represents a small percentage of runs that pass the filter, this number is not that small when considering the

Table 4.2. Historic Filtering Criteria

Output Metric	Historical Value	Acceptable Range
Growth Rate (%)	3.20	3.00–3.40
Decarbonization (%)	2.24	2.15–2.35
Labor Productivity Rate (%)	3.00	2.80–3.20
LCP Market Share (%):	83.00	80.0–90.0

selected the ten that provided the most diverse set of parameter value combinations. This filtering of one and one-half million model runs down to 20 is similar to how an optimizer might examine many millions of parameter combinations before identifying the one combination that best fits the data. Here, however, we used a satisficing criterion, sifting through many model runs to find those few that fit the data well enough.

To select this most diverse set, we first rescaled each parameter value and its boundaries so that it would lie within a range bounded by [–1,1]. We then randomly generated 10^4 unique sets of ten runs out of the 20 that passed the filter. For each of these combinations, we calculated the sum of the Euclidean distances between each of the ten runs. The combination with the highest summed Euclidean distance was deemed most diverse, and its members were our ten starting cases.

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parameter value variability in our 19-dimensional space (Table 4.1). The chances of random selection of our parameter values taken within their uncertainty ranges that fall within 10 percent of the true parameter value for each of our 19 dimensions is just 10^{-19}.

5. Representative Analysis

To help verify the model and explore some interesting aspects of the political feedback mechanism, we conducted an exploratory analysis of approximately 20,000 cases. The range of inputs differed from the calibration analysis in important ways. First, the representative analysis included many new inputs that were not applicable in the calibration analysis, such as the parameters relating to the government's response to lobbying and the shape parameters for the carbon R&D beta distribution. Second, a new input parameter, called the *starting case*, was added. This parameter takes values 1 through 10 and corresponds to the ten starting cases generated during the calibration analysis. For details on this and other parameters fixed for this experiment, see Appendices D and E. Table 5.1 summarizes the parameters varied for this experiment.

The range on the carbon R&D beta distribution is larger than the one for labor to reflect the possible presence of rapid technological progress once a carbon tax is in effect (whereas labor has always been an expense).

One possible analysis that serves as a useful verification of the model is to scale all the inputs to have mean zero and unit variance and then to do a simple linear fit between outcomes of interests and the inputs. Figures 5.1 and 5.2 plot the resulting coefficients for two important outputs.

One may observe from Figures 5.1 and 5.2 that the primary drivers of the decarbonization rate and the labor productivity growth rate are the lower bounds of the carbon and labor R&D beta distributions respectively.[19] The lower bound is more important than the upper bound because the upper bound is modified by actual R&D expenditures; so, if a firm invested equally in carbon and labor, the upper bounds for each distribution would be cut in half. The β shape parameters have a negative coefficient because an increase in β shifts the mean left, reducing technological progress. The government lobbying parameters have very little effect, except for the stringency parameter, s. This implies that exact specification of the inverse barrier functions that lie outside the quadratic negotiating zone is relatively unimportant. However, the lower bound multiplier ($\boldsymbol{g^{LBM}}$) is somewhat significant for the decarbonization rate that follows from the fact that the HCP lobby is often ineffective; thus, the price of carbon locates near this point.

[19] Comparing the sizes of the labor and carbon R&D parameter coefficients requires care because these depend on the ranges chosen for the experiment, which differed substantially.

Table 5.1. Parameter Ranges for the Representative Analysis

Parameter	Parameter Description	Min	Max
$\boldsymbol{\kappa}$	Demand growth rate	0.01	0.03
$\boldsymbol{\eta}$	Firm optimism	0	0.5
$\boldsymbol{g^{LBM}}$	The lower bound multiplier. This determines the lower extent of the government's quadratic negotiating region.	0.25	0.5
$\boldsymbol{g^{UBM}}$	The upper bound multiplier. This determines the upper extent of the government's quadratic negotiating region.	2	5
$\boldsymbol{g^{ULM}}$	The upper limit multiplier. This determines the maximum carbon price the government would consider.	1.5	2
$\boldsymbol{\theta^{r}_{inn}}$	Expected proportion of firms that successfully innovate in the first period.	0.05	0.2
$\boldsymbol{\theta^{r}_{imi}}$	Expected proportion of firms that successfully imitate in the first period.	0.05	0.2
$\boldsymbol{\alpha_c}$	Alpha shape parameter of the carbon R&D beta distribution	1.5	5
$\boldsymbol{\beta_c}$	Beta shape parameter of the carbon R&D beta distribution	5	10
$\boldsymbol{\omega_{C,l}}$	Lower bound of the carbon R&D beta distribution	–0.01	0.05
$\boldsymbol{\omega_{C,u}}$	Lower upper of the carbon R&D beta distribution	0.05	0.2
$\boldsymbol{\alpha_L}$	Alpha shape parameter of the labor R&D beta distribution	1.5	5
$\boldsymbol{\beta_L}$	Beta shape parameter of the labor R&D beta distribution	5	10
$\boldsymbol{\omega_{L,l}}$	Lower bound of the labor R&D beta distribution	–0.01	0.01
$\boldsymbol{\omega_{L,u}}$	Upper bound of the labor R&D beta distribution	0.02	0.05
e	Weight given to prior carbon prices when projecting future prices.	0.5	0.8
s	Stringency of the government	1	20

Figure 5.3 shows the results for the HCP lobby average market share. One can readily see that good carbon R&D opportunities relative to labor R&D lead to a more successful HCP lobby. The negative coefficients on the initial innovation and imitation rates are also interesting. As noted earlier, the HCP lobby is driven by variation. High levels of innovation and imitation reduce the technological variability in the market and act to inhibit the formation of a strong HCP lobby.

These results are, of course, true only on average, and there are important situations in which the relationships can reverse in sign. One example concerns the situations that produce a strong HCP lobby. The analysis above suggests this is most likely when the carbon R&D opportunities are high relative to the labor opportunities. Analyzing the data further reveals a second set of cases with a strong HCP: those with poor carbon R&D opportunities relative to labor. This results in a strong HCP lobby with a different motivation. Rather than desiring a high carbon price to pull ahead of the competition, the high price represents an attempt by the majority of the market to slow down the firms that are rapidly acquiring improved labor technology but still

Figure 5.1. The Decarbonization Rate Scaled Input Coefficients

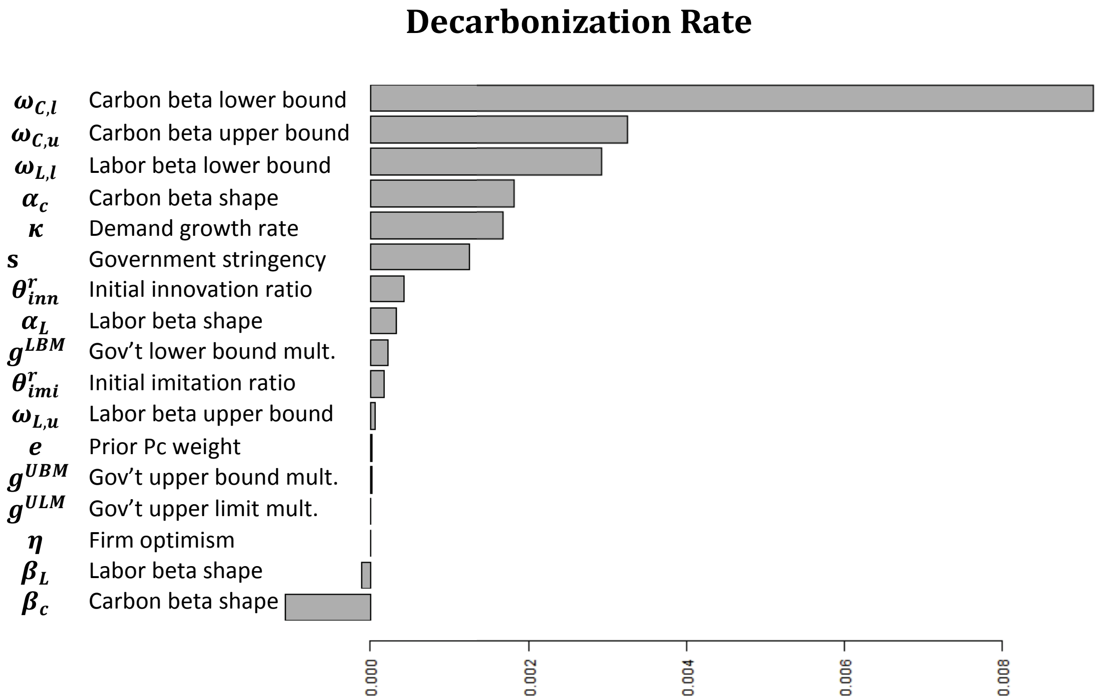


Figure 5.2. The Labor Productivity Growth Rate Scaled Input Coefficients

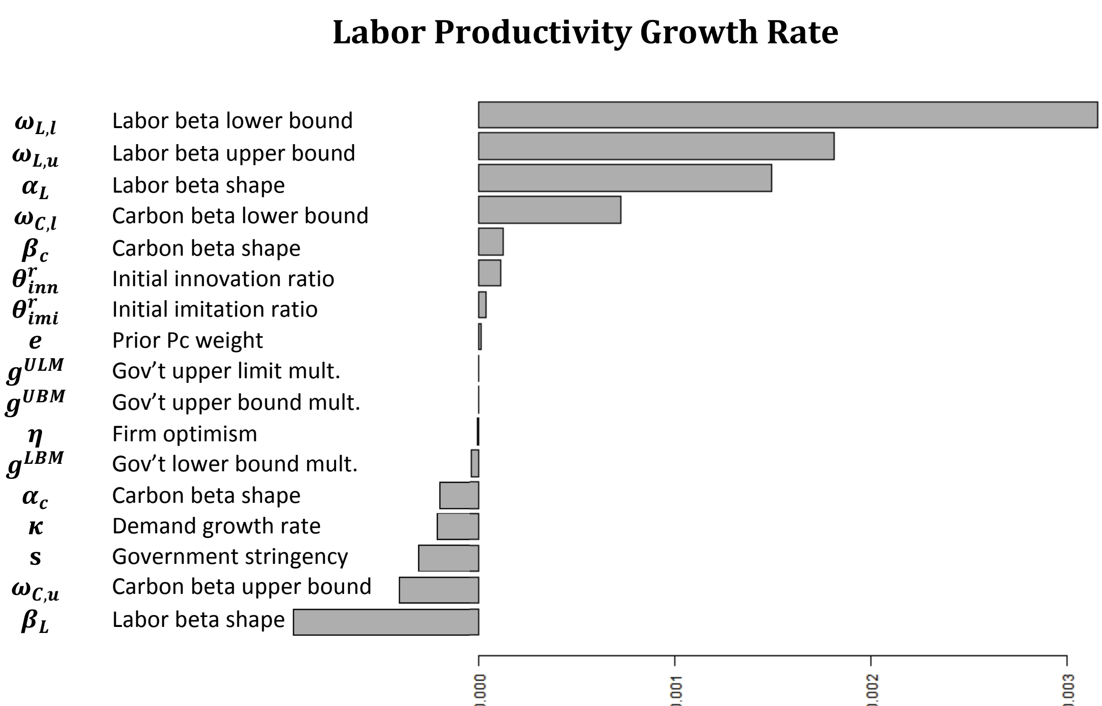
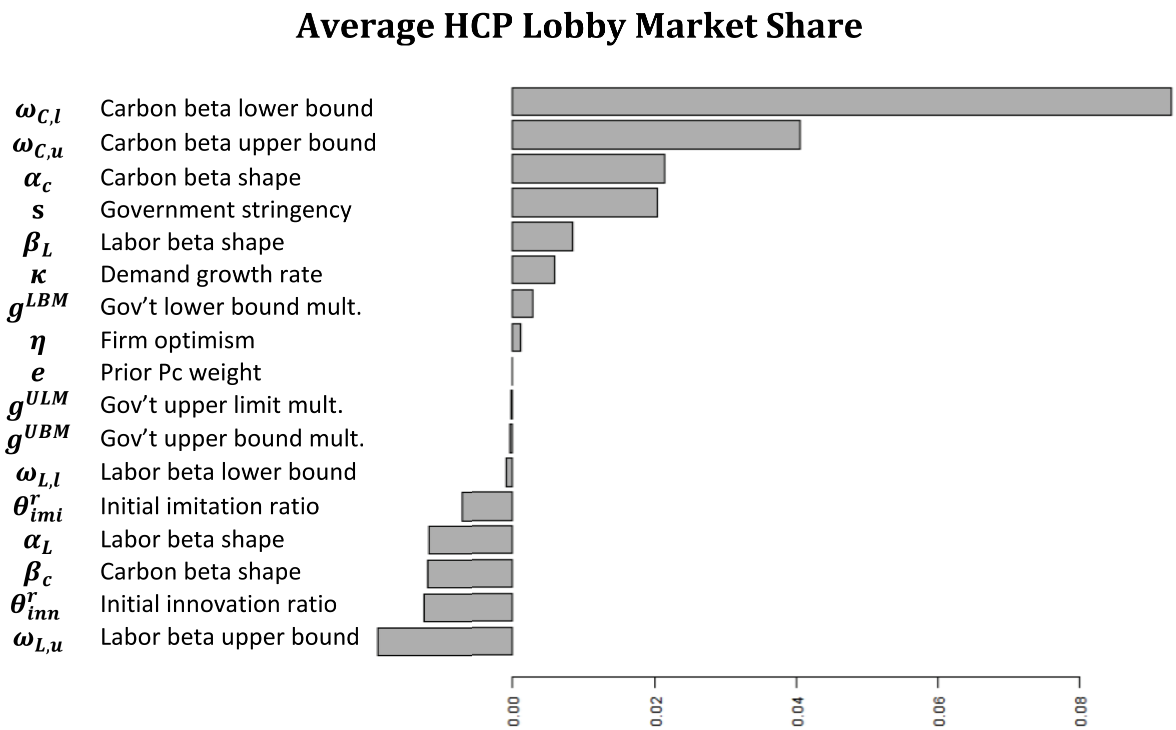


Figure 5.3. Average HCP Market Share Scaled Input Coefficients



have relatively weak carbon technology. The increased carbon price results in a shift toward the relative importance of carbon technologies, thus reducing the competitive advantage of the firms with the best labor technology.

The second experiment conducted concerned the policy option of grandfathering capital. Capital that existed at the start of the simulation was exempted from the usual carbon tax for a user-defined length of time. This was modeled by calculating each firms' effective carbon intensity, which reflected the fact that their initial capital paid less in carbon tax:

$$a_{j,eff} = \frac{\sum_i K_{i,j} g_{i,j} a_{i,j}}{K_j}, \tag{54}$$

where $g_{i,j}$ is the grandfathering ratio applied to capital *i* of firm *j*. This value is typically zero, corresponding to full grandfathering. A value of 0.5 would mean eligible capital would pay one-half the tax normally due. This effective carbon intensity is then used in the lobbying algorithms instead of the usual carbon intensity. This setup ensures that capital firms acquire after the start of the simulation, and all entrant firms' capital, pays the normal carbon tax. As legacy firms acquire new capital, their effective carbon intensity rises, reflecting their higher tax liability.

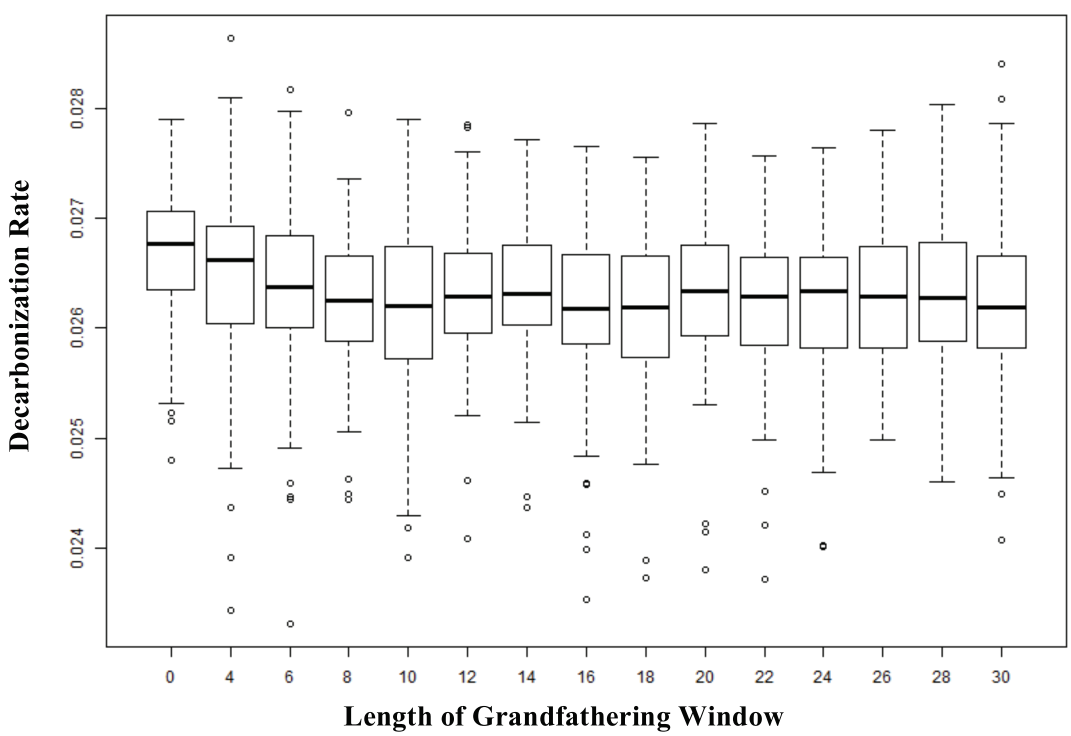
This implementation assumes very myopic firms. Legacy firms do not consider their future welfare change due to the expiration of the grandfathering window. However, as will be discussed, this does not change the results.

We conducted multiple experiments across a broad range of parameters. However, grandfathering did not prove to be an effective policy option. It had little or no effect on the decarbonization rate or the consumption growth rate. Figure 5.4 is a representative result from the set of experiments conducted.

One can see that the length of the window during with grandfathering was in effect had very little effect on the overall decarbonization rate.

Further examination showed that, while grandfathering did increase the share of legacy firms joining the HCP lobby, it also had the unexpected effect of causing new firms (and any legacy firm that acquired new capital) to lobby more strongly against a higher carbon price than they otherwise would have. This can best be understood by examining how firms' welfare changes with the carbon price, shown in Eq. (29). When all firms have an effective carbon intensity of zero (all their capital is grandfathered), their welfare is independent of the carbon price (since no firm has to pay it). However, when an entrant joins the market, the situation changes. The legacy firms are still relatively disinterested in the carbon price because the entrant firm typically starts with a small market share and thus has very little effect on the market average price. So they cannot gain market share with a higher carbon price, and the entrant does not change the average price enough to reduce overall demand appreciably. However, the situation is very different for the entrant firm. Its welfare is highly dependent on the price of carbon because all the legacy

Figure 5.4. Representative Plot for the Decarbonization Rate for Various Grandfathering Time Frames



firms have an effective carbon intensity of zero. This causes the entrants to lobby aggressively for lower carbon taxes. The same process occurs even without entrants, just at a slower rate. As a legacy firm's capital depreciates or its demand increases, it purchases new capital, which quickly causes it to lobby against carbon taxes, just like a new entrant.

This explanation was verified by looking at the difference between lobbying contributions for the HCP and LCP firms. The LCP lobby increased its contributions by a factor of ten, which then disappeared after the grandfathering window closed. This counteracting force largely negated any benefits of a larger HCP lobby, leading to the poor performance of the grandfathering policy option. More forward-looking firms would have resulted in even poorer performance for the grandfathering policy option because they would recognize that their advantage would eventually disappear and be less inclined to support higher carbon prices.

6. Next Steps

The evolutionary simulation model we have set forth in this report, and the RDM framework for exercising it, are intended to serve as a laboratory for examining how the choice of the initial design of GHG emission reduction policies may affect how such policies evolve over time and the extent to which they achieve their intended goals. In particular, we were interested in the situation in which policymakers have an opportunity to put in place a GHG regulatory system, which will then evolve over time outside their control. This evolutionary agent-based formalism aims to examine how policymakers might use their window of opportunity to choose a set of initial actions and means that increases the chances of achieving their long-term goals. The simulation combines (1) an evolutionary economics module that focuses on how the structure of an economic sector evolves as firms make investment decisions in production and in new emission-reducing technologies and (2) a game-theoretic element in which firms organize themselves into lobbies that either favor or oppose an increase in carbon taxes and attempt to influence government policy accordingly. The climate change community uses a wide range of integrated assessment models. In contrast to these others, the model we have described here is unique in its ability to examine how alternative near-term regulatory decisions may evolve over long periods in response to the resulting investment decisions of firms, patterns of technology change, shifts in market share, and the attempts of firms that may benefit and lose through changes in the carbon price to influence government policy.

Our initial experiments have generated both expected and surprising results. We explored the model's behavoir using over 20,000 different sets of assumptions about future states of the world. We found, as expected, that assumptions about the potential for significant advances in carbon emission reducing technology are key drivers of both the economy's overall decarbonization rate and the strength of the HCP lobby. In general, decarbonization is fast and the HCP lobby strong when opporunities for carbon reducing R&D are strong relative to opportunities for labor reducing R&D. As an example of the richness of the model's behavior, we also found some situations in which a strong HCP lobby pursued a high carbon tax, despite a dearth of low-carbon R&D opportunities, to remain competitive with firms with much higher labor productivity.

Initial experiments with grandfathering suggest that, contrary to our initial expectations, such a policy may have little effect on the decarbonization rate. We had expected that grandfathering would reduce the initial strength of the LCP lobby by reducing the incentive for existing firms to advocate for a low carbon price. But on average, this effect is countered by new entrants' increased need for a low carbon price in order to remain competitive with the incumbents.

In the next steps of our work, we will continue to explore the effects of alternative policies and the specific types of circumstances under which policies, such as grandfathering, may prove more or less effective. Overall, it is our intention to apply this model to an examination of how the interaction of between firms and the government may affect government choices about how to design market-based regulatory policies to improve their prospects of catalyzing potential carbon-reducing transformations of the economy. The current model is clearly a first step, but its combination of elements, combined with the means for exercising it, provide a unique platform for addressing such issues.

Appendix A. Computation of the Social Cost of Carbon

Conceptually, the SCC is calculated by determining the change in the net present damage (NPD) due to a unit of extra carbon emitted in the base year, and then dividing by the amount of extra emissions. The limit as the amount of extra emissions approaches zero is proportional to the SCC.

The impacts of carbon emissions are encapsulated in the damage function described in the subsection on "Damages from Climate Change and the Social Cost of Carbon" in Section 3. Damage is given as a percentage of GDP and is piecewise linear with multiple abrupt jumps in the damage level. (Here, we consider a maximum of two jumps, which seems sufficient for our purposes.) These abrupt jumps are meant to represent catastrophic climate events, such as the melting of the Greenland ice sheet or the sudden collapse of a major ocean current.

An additional unit of carbon has two effects: It incrementally increases the economic damages from climate change, and it brings nearer the abrupt jumps in damages due to catastrophic events. Fortunately, to a very close approximation, these effects can be treated separately.

The top graph in Figure A.1 shows a notional damage curve (black) and the resulting curve after the addition of an incremental amount of emissions to the first period (gray). This has caused the emission curve to shift backward in time because the damage is now slightly higher every period. The NPD would be the integral of the discount factor weighted damage function.

The change in NPD can be decomposed into slope components (middle plot in Figure A.1) and jump components (bottom plot in Figure A.1). The middle graph shows the slope-related aspect of the original and shifted damage function, while the bottom graph depicts the jump component. This simplification facilitates the math to follow and introduces very little, if any error, for any reasonably defined damage function.

Recall that the main goal is to calculate the following:

$$P_G^a = \lim_{\delta\varepsilon \to 0} \frac{\Delta NPD}{\delta\varepsilon}, \tag{55}$$

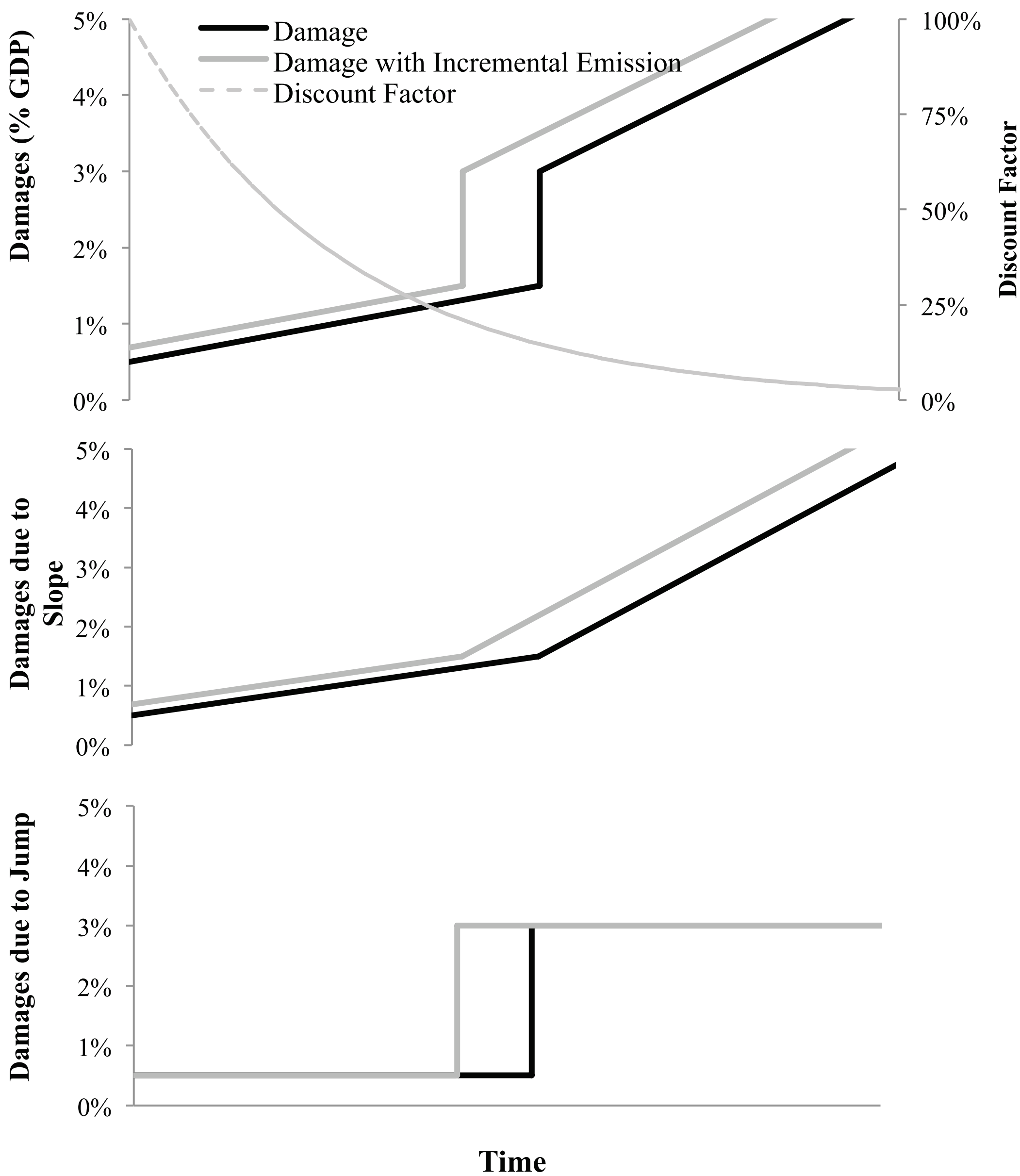
The change in net present damages for an arbitrary single segment is:

$$\Delta NPD_{slope} = \int_{t_1}^{t_2} e^{-rt} \{ D[q^{\delta}(t)] - D[q(t)] \} dt, \tag{56}$$

where D represents the damage function and q the cumulative emissions for any given time t; $q^{\delta}(t)$ is the same cumulative emission function but with a small $\delta\varepsilon$ of emissions added at time $t = 0$. The damage function for any given segment can be expressed as

$$D_i(q) = m_i q + c_i, \tag{57}$$

Figure A.1. The Decomposition of the Full Damage Function (top) into Slope Components (middle) and Jump Component (bottom)



where i represents the relevant segment of the piecewise function. The damage function generically has M segments (and thus M–1 possible jumps) though this model only uses a maximum of three segments. The cumulative emissions at any given time depend on the government's expectation of future emission rates. For this model, we chose a simple representation of the government's best guess of future emissions: a line is fitted to the last n years of simulated emissions data, and the resulting rate of change of emissions, ρ, is expected to remain constant indefinitely. This leads to the following estimates for per-period emissions and cumulative emissions:

$$\epsilon(t) = \epsilon_0 + \rho t \tag{58}$$

and

$$q(t) = \frac{\rho}{2}t^2 + \epsilon_0 t + q_0, \tag{59}$$

where the subscript *0* always denotes the simulation's current year value, and *t* is measured in years from that point. With these building blocks, we can compute the SCC due to the slopes of the damage function and the jumps in the damage function, starting with the analytically simpler one, the slopes.

Plugging Eqn. (59) into Eqn. (57), then into Eqn. (56) and canceling common terms yields

$$\int_{t_i}^{t_{i+1}} e^{-rt}(m_i \delta\varepsilon)dt, \tag{60}$$

Taking this expression and putting it into the original limit Eqn. (55) (after summing all M slope segments together) yields

$$\frac{1}{r}\sum_{i=1}^{M} m_i(e^{-rt_{i-1}} - e^{-rt_i}), \tag{61}$$

In this context, the t_is are the times at which the jumps in the damage function are reached, given the government's estimates of future emissions stated earlier. These can be solved for using Eqn. (59) via the quadratic formula. For completeness, t_0 is zero, and t_M is infinity (this means the last slope segment continues indefinitely). Notice the units are in percentage of GDP per unit of carbon per year. Thus, arriving at an actual value for the SCC requires multiplying by a value for GDP. In the model, this value is initially pegged to the real U.S. GDP in 2009, then grows in step with the model consumption path thereafter. This makes the assumption that the model's sectoral growth rate mimics that of the overall economy.

The second component of the SCC consists of discontinuities in the damage function. The derivation is more complex because the $\delta\varepsilon$ manifests in the limits of integration, rather than linearly in the integral as before (see the bottom graph in Figure A.1):

$$\Delta NPD_{jump} = \int_{t_h^\delta}^{t_h} e^{-rt} d_h dt, \tag{62}$$

where $\mathrm{t_h}$ is the estimated time that the relevant jump is reached, and $\mathrm{t_h^\delta}$ is the time the jump is reached after the addition of $\delta\varepsilon$ emissions at t=0. The height of the damage function jump is given by $\mathrm{d_h}$. Evaluating the integral and plugging the results into the foundational Eqn. (55) yields:

$$\lim_{\delta\varepsilon\to 0}\frac{\Delta NPD_{jump}}{\delta\varepsilon} = \lim_{\delta\varepsilon\to 0}\frac{d_{th}}{r}\frac{e^{-rt_h^\delta} - e^{-rt_h}}{\delta\varepsilon} \tag{63}$$

This limit evaluates to 0/0 and thus can be tackled with l'Hôpital's rule. After summing all jumps, the result is

$$\sum_{i=1}^{M-1} \frac{d_{h,i} e^{-rt_i}}{\sqrt{\epsilon_0^2 + 2\rho(q_{h,i} - q_0)}}, \tag{64}$$

where the denominator comes from taking the derivative to a solution of a quadratic equation, and $q_{h,i}$ is the user-input location of the i^{th} jump in the damage function. The units work out as before, and the two terms can be summed and scaled to find the government's estimated social cost of carbon:

$$p_g^a = GDP \left\{ \frac{1}{r} \sum_{i=1}^{M} m_i \left(e^{-rt_{i-1}} - e^{-rt_i}\right) + \sum_{i=1}^{M-1} \frac{d_{h,i} e^{-rt_i}}{\sqrt{\epsilon_0^2 + 2\rho(q_{h,i} - q_0)}} \right\}. \tag{65}$$

The situation in which the government imperfectly estimates the shape of the damage function is treated analogously simply by modifying the relevant slopes (m_is) and jump heights ($d_{h,i}$s).

Appendix B. The Lobbying Game

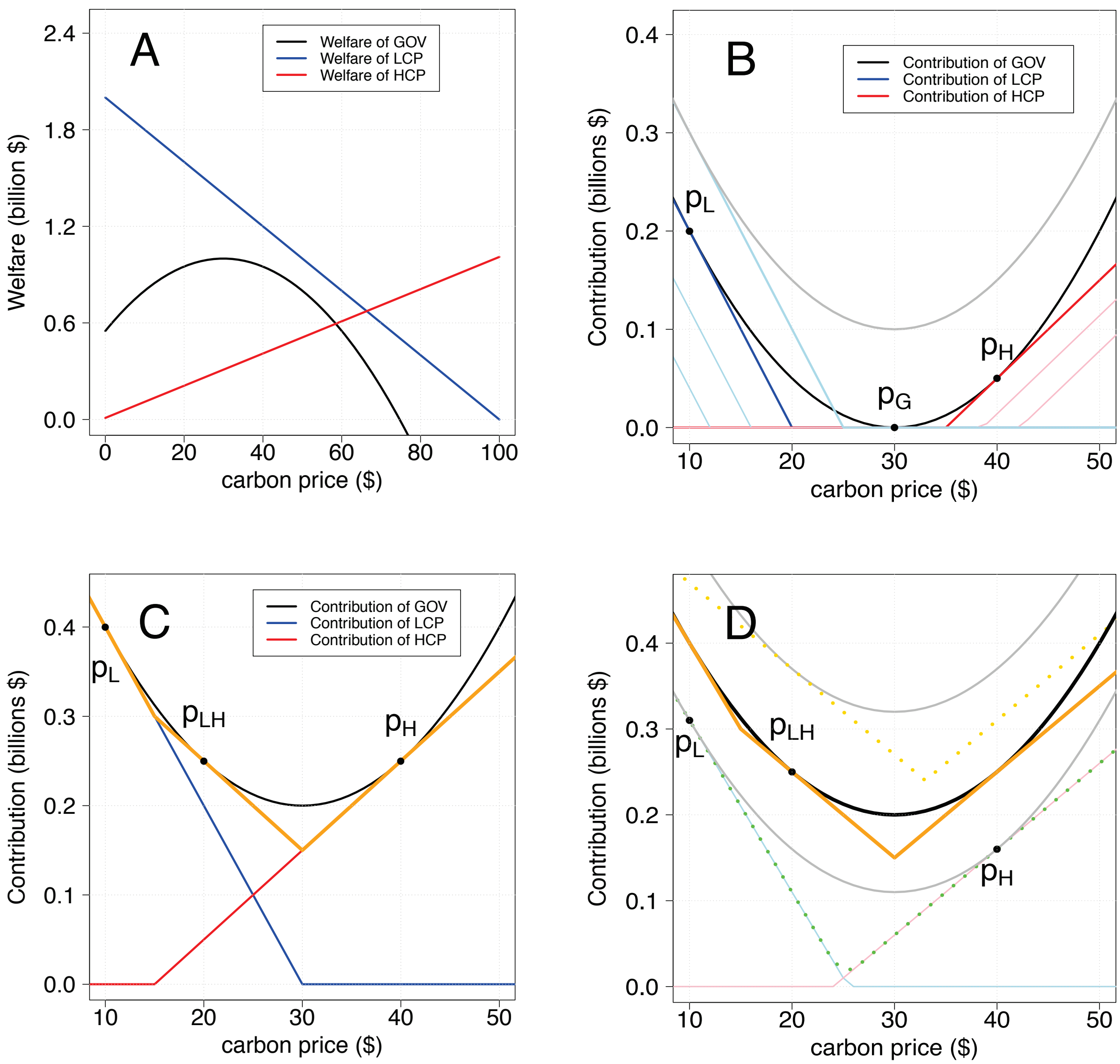
This appendix describes the lobby game and derives the equations for "The Government's Welfare" subsection in Section 3. Our approach is based on Grossman and Helpman, 1994. Grossman and Helpman developed a model in which special-interest groups make political contributions to influence an incumbent government's choice of trade policy. The government's choice is defined by preferences between campaign contributions and voter well-being. We adopted terminology and notation similar to those Grossman and Helpman used. In our view and for our purposes, this approach provides advantages in terms of simplicity and implementation. We will first providing a visual representation of how the lobby game works, then derive the mathematical equations. For this illustration, we consider the government welfare ($W_G(p_c)$) to vary as a quadratic function of carbon price with maximum value at the social optimal p_G and the welfare functions of the LCP lobby ($W_L(p_c)$) and the HCP lobby ($W_H(p_c)$) to be linear in the carbon price p_c, as illustrated in Figure B.1. For this appendix, p_c defines the variable carbon price and not the actual carbon price computed within a simulation time step, as used in the main text. Other variables may also not take the same meaning as provided in the main text. These will be formally defined and apply only within this appendix.

In the following description, the subscript i takes categorical values $\{L, H\}$ to represent the LCP and the HCP, respectively. We start by considering the case in which only one lobby is present. If we were to set the retained welfare of the lobby to a constant value, B_i, then for a given value of p_c, the lobby would offer a contribution equal to $W_i(p_c) - B_i$. However, if the value of B_i is too large, it may be that no possible carbon price value p_c would produce a contribution that the government would agree to. For this value of retained welfare, the lobby does not produce a truthful contribution schedule. A truthful contribution schedule takes the form of

$$C_i(p_c, B_i) = \max[0, W_i(p_c) - B_i], \tag{66}$$

where, for the purpose of this appendix, C_i denotes a contribution, and B_i represents the retained welfare that each lobby maximizes, subject to the condition that $C_i\ (p_c, B_i)$ offers a contribution for a given p_c value that the government would consider accepting. For example, in Figure B.1-B, the black line shows an indifference contribution schedule: The government will find any contribution at or above this boundary curve acceptable and will be indifferent to contributions that lie at different points on this boundary curve. We define a viable option to the government to be any contribution that lies on the government's indifference contribution schedule. The blue line shows a set of indifferent contribution schedules that the LCP lobby may offer. Different points lying on a particular line provide the same utility value (i.e., retain the same welfare value, B_i) to the lobby. The first indifference line that represents a viable option to the government is

Figure B.1. Welfare Functions



NOTE: Here the social optimal for the government is to set $p_G = \$30$.

shown in dark blue. This line intersects the government's contribution function at the carbon price, p_L. However, should the LCP lobby provide a better contribution schedule (as shown by the contribution schedule just above the dark blue one in Figure B.1-B), the government would change its indifference contribution schedule function by shifting the parabola upward, as shown by the gray curve, and the carbon price would still be set at p_L. Therefore, as long as there is no competing HCP lobby, there is no incentive for the LCP lobby to provide a better contribution schedule than the one shown by the dark blue line. Mathematically, by maximizing the lobby's retained welfare, the truthful contribution schedule is shown by the dark blue line.

When the HCP lobby appears, a similar process occurs with the HCP contribution schedule. Each pink line shown in Figure B.1-B represents a line of constant utility to the HCP, and thus each remains indifferent to contributions along it. The red line shows the first contribution that presents a viable option to the government. This provides the government with the equally attractive alternative of setting the carbon price at the new intersection point, with carbon price p_H. Thus, the government would have three viable options for setting p_c: the social optimal p_G and the intersection points with the parabola, p_L and p_H. These are respectively shown by the blue and red lines. If the LCP lobby decreases its retained welfare, B_L, by a marginal amount, δ, thus increasing its contribution; as long as the HCP does not modify its own contribution schedule, this will be sufficient to convince the government to choose the low carbon solution, p_L. Likewise, the HCP can reason in a similar way by decreasing its retained welfare, representing the government with the equally attractive alternative of setting the carbon price at the carbon price p_H.

Thus, a bidding war between the LCP and the HCP lobbies begins. Once it does so, setting the carbon price to the social optimal p_G is no longer a viable choice for the government. This is because the lobby contributions shift the government's indifference contribution schedule function upward, such that it no longer intersects the carbon price axis at p_G. However, as the bidding war proceeds, with each lobby systematically reducing its retained welfares and consequently offering larger contributions, a region of carbon prices emerges in which both lobbies offer a nonzero contribution. Within this region, the government will consider accepting the sum of the contributions from both lobbies. Figure B.1-C shows such a region where the sum of the contributions of the lobbies is shown by the orange lines. In this case the sum provides a truthful contribution function as there exists a new value for the carbon price, denoted by p_{LH} where the sum of the contributions offers an equally attractive alternative to the contributions provided by each single lobby at the carbon price values of p_L and p_H.

Figure B.1-D shows the same situation as in Figure B.1-C, as well as two further cases. The first case shows an intermediate step in the bidding war, in which the sum of the two contributions (shown by a dotted green line) is insufficient to present an intermediate carbon price value with an equally attractive alternative to the contributions each single lobby offers at the carbon price values of p_L and p_H. The second case shows a hypothetical step in the bidding war game, in which each lobby reduces its retained welfare to the point that the sum of the two contributions (shown by a dotted yellow line) shifts the government's indifference contribution schedule function upward to the point that the contributions at the carbon price values of p_L and p_H are no longer viable alternatives. This situation is hypothetical, because the carbon price that the government would choose remains at the value of p_{LH}, offering no additional advantages to either lobby. Therefore, the bidding war ends as soon as the possibility for the government to set the carbon price at p_{LH} offers an equally attractive alternative to the contributions each single lobby offers at the carbon price values of p_L and p_H, as shown in Figure B.1-C.

The following two subsections develop the general mathematical framework for arbitrary functions $W_G(p)$, $W_L(p)$, and $W_H(p)$. We first consider the case for just one lobby present, then extend the analysis for two lobbies.

Mathematical Description of the Game for a Single Lobby

The contributions from lobby i (where $i \in \{L, H\}$ represents the LCP and HCP lobbies respectively) take the form

$$C_i(p_c, B_i) = \max[0, W_i(p_c) - B_i], \tag{67}$$

where W_i represents the welfare of the lobby, which is simply the aggregated welfares of all the member firms of the lobby, and B_i represents the retained welfare of the lobby. The aim of the lobby is to change the carbon tax, p_c, to a more favorable value while maximizing its retained welfare. For the government to consider the lobby contribution to be a fair compensation for changing the carbon tax, the lobby will have to compensate the government for its loss in welfare. We denote the government's welfare by $W_G(p_c)$ as a function of the carbon price, p_c. When the carbon price is at the social optimal p_G, the government welfare is at its maximum value. Thus, to change the carbon tax from the social optimal value of p_G to a different value p_c, the government will have to require a lobby contribution of at least $G(p_c, 0)$, where

$$G(p_c, K) = G(p_c, 0) + K = W_G(p_G) - W_G(p_c) + K, \tag{68}$$

and where, for the purpose of this appendix, K is a shifting constant that measures the contribution required to set the carbon tax at p_G. The function $G(p_c, 0)$ provides the first indifference contribution schedule, as illustrated by the black curve in Figure B.1. The parameter K shifts this indifference curve upward. For the case of just one lobby, there is no need to provide a contribution for setting the carbon tax at p_G because the government sets the tax to this value anyway in the absence of lobbying. Therefore, $K = 0$ in this case. Staring from offering zero contribution and assuming that the lobby has enough funds, it will systematically decrease its retained welfare and increase its contribution according to Eq. (67) until a new, more favorable carbon tax of p_i occurs that satisfies Eq. (68) with $K = 0$. The value of p_i when this occurs is found by solving

$$-\partial_p W_G(p_i) = \partial_p W_i(p_i), \tag{69}$$

and the corresponding contribution needed to set p_c to p_i is

$$C_i^*(p_i) = G(p_i, 0). \tag{70}$$

Since by requirement $C_i^* > 0$ it follows that the corresponding retained profits of the lobby are

$$B_i^*(p_i) = W_i(p_i) - C_i^*(p_i). \tag{71}$$

Mathematical Description of the Game with Both Lobbies

When both lobbies are present, each lobby will systematically increase its contribution schedule, as given by Eq. (67). This process will continue until a new solution, p_{LH}, occurs, in which the sum of the contributions of the two lobbies together is $G(p_{LH}, K)$ for a given value of $K > 0$, which we shall call K°. The new viable solution for the carbon price p_{LH} is found by solving

$$-\,\partial W_G(p_c)/\,\partial p_c = \partial[W_L(p_c) + W_H(p_c)\,\partial p_c] \qquad (72)$$

for p_c. However, due to our nonzero value of K, the lobbies' contributions will have increased, as given by Eq. (68). The value of K° necessary for p_{LH} to be a viable option to the government is given by

$$K^{\circ} = W_H(p_H) + W_L(p_L) - W_H(p_{LH}) - W_L(p_{LH}) + G(p_{LH}, 0) - G(p_L, 0) - G(p_H, 0). \qquad (73)$$

$-$

Using this expression for K°, the contributions of the LCP and HCP lobbies are respectively given by

$$C_L^{\circ}(p_{LH}) = [W_H(p_H) - W_H(p_{LH})] + [G(p_{LH}, 0) - G(p_H, 0)], \qquad (74)$$

and

$$C_H^{\circ}(p_{LH}) = [W_L(p_L) - W_L(p_{LH})] + [G(p_{LH}, 0) - G(p_L, 0)]. \qquad (75)$$

Appendix C. Adaptive Learning Model for R&D Decisions

In our model, firms need to decide how to split the funds allocated to R&D between labor productivity (increasing their b) and carbon intensity (decreasing their a). This appendix describes our approach to determining how firms make this decision.

It is useful to consider what a rational and perfectly informed firm would do. By assumption, the amount spent on R&D is fixed, so such a firm would seek to allocate its R&D to carbon and labor to acquire technology with the lowest possible expected unit cost. The unit cost of a newly acquired technology is[20]

$$u = \frac{w}{b^0}(1 - x_L) + p_c a^0 (1 - x_C) \tag{76}$$

where x_L and x_C are draws from the labor and carbon R&D beta distributions (discussed in the "Firm R&D" subsection of Section 3. Taking the derivative with respect to σ of the expected value of u yields

$$\frac{dE[u]}{d\sigma} = wb_b\tilde{\mu}_L \Delta x_L - p_c a_b \tilde{\mu}_C \Delta x_C, \tag{77}$$

where $\tilde{\mu}$ is the mean of the unscaled beta distribution (the beta distribution rescaled to have bounds of 0 and 1), Δx is the support of the scaled beta distribution, and b_b and a_b are the labor productivity and carbon intensity, respectively, of the firm's current lowest unit cost technology. Note that this derivative is a constant; thus, the optimal σ is at one of the boundaries, 0 or 1. This implies that a rational, fully informed firm would bounce between investing completely in carbon or labor, depending on the sign of Eqn. (77). Solving for when the derivative is negative (and thus $\sigma = 1$, or all carbon R&D, is optimal) yields

$$\frac{p_c a_b}{w/b_b} \cdot \frac{\tilde{\mu}_C}{\tilde{\mu}_L} \cdot \frac{\Delta x_C}{\Delta x_L} \geq 1, \tag{78}$$

Seeing as how actual firms do not bounce between putting all funds toward a single dimension of R&D, we have chosen to take the left side of Eqn. (78) as our estimate of ϕ, which is the ratio of R&D spending on carbon to R&D spending on labor. The conversion to σ is straightforward:

$$\sigma = \frac{\phi}{1 + \phi}, \tag{79}$$

Note that, if ϕ is 1, a rational firm would be indifferent between carbon and labor R&D, and our modeled firms would invest equally in carbon and labor R&D. However, if ϕ is slightly

[20] Actually, to match the Dosi et al. model, our model represents technological improvements as increases in factor productivity. The equation shown represents it as decreases in intensity. The results are nearly identical for small incremental improvements, and the math is considerably simpler for the case shown.

more than 1, the rational firm would invest everything in carbon R&D, while our modelled firm would only invest incrementally more in carbon R&D.

In this highly stylized model of technological change, this approximation has the benefit of incorporating all the important aspects that would go into a fully rational decision. Each term in equation (78) has a very intuitive meaning:

1. The first term is the ratio of carbon to labor costs. Increasing the relative cost of carbon increases the amount a firm will invest in carbon R&D technologies.
2. The second term is the ratio of the untransformed means of the carbon and labor beta distributions. This makes sense, in that a relatively higher mean from the carbon R&D beta should lead toward more carbon R&D.
3. The last term is the ratio of the ranges of the underlying beta distributions. For instance, if the range of the labor R&D beta is zero, meaning that a firm gets the same outcome regardless of how much R&D it performs, it should invest everything in carbon. So it is not only the mean of the distribution but the width (or support) that matters.

Items 2 and 3 assume a level of knowledge about the R&D distributions that firms may not possess. However, over time, firms may develop a sense for the likely magnitudes of technological innovations. The model has the ability to run with or without firms having access to the extra information.

Another important consideration is how firms expect carbon prices to change. Since technological advances occur in the future, firms should use estimates of the future price of carbon. We use an adaptive learning approach to describe how firms make this decision based on how much they learn to trust the government's carbon price schedule – $p_G(t)$. The general mathematical framework for this adaptation process has been used in other game theoretical models and, in particular, in the field of inductive reasoning games; see Ho, Lim and Camerer, 2006; Vardavas, Breban and Blower, 2007; and Challet, Marsili and Zhang, 2004. In our model, when the government keeps setting its carbon price far from its desired social optimal ($p_G(t)$) because of the effects of lobbying, firms will learn that the government is not that stringent on its carbon tax policy and will act accordingly. In this case, firms will base their R&D investments on their expectation of the carbon tax, which may be quite different from $p_G(t)$. We describe this mathematically as follows. A firm's expected carbon price in year t from its start up is given by[21]

$$\tilde{p}_c^e = \frac{\theta_L p_L + \theta_G p_G + \theta_H p_H}{\sum_{i\in\{L,G,H\}} \theta_i}, \tag{80}$$

where p_G, p_L and p_H are, respectively, the carbon prices for the government social optimal, the price with only the LCP lobby, and the price with only the HCP lobby. The term $\theta_i / \sum_i \theta_i$ (where $i \in \{L, G, H\}$) in this appendix represents a normalized weight such that

[21] For the purposes of this appendix, certain variables may not take the same meaning as in the main text. These will be formally defined and apply only within this appendix.

$$\theta_i(t) = e\theta_i(t-1) + \Delta_i, \tag{81}$$

where e represents an experience discounting factor and Δ_i represents the trustworthiness of the government in setting the carbon price close to p_i based only on the most recent outcome and in absence of any past experiences or observations to rely on. Eqn. (81) describes the learning process and is best described by example. If we assume for simplicity that the carbon price can be set at only the values of p_G, p_L, and p_H and also that $e = 1$ (i.e., no discounting), θ_L would represent the tally (i.e., a virtual point) of the number of times that the government sets the carbon price at p_L. Relaxing the latter simplifying assumption and allowing $0 < e < 1$, θ_L would represent a time-weighted tally of the number times that the government set its carbon price at p_L by placing more weight on the most recent event. Relaxing the former simplifying assumption, when the carbon price is between p_L and $p_{G,}$ the tally is to be split linearly according to which carbon price is the closest. Thus, for the case in which the realized carbon price p_c in year n could range from 0 to above p_H, we set the values of the Δs as follows:

$$\Delta_L = \begin{cases} 1 & \text{for } 0 \le p_c < p_L \\ \dfrac{p_c - p_G}{p_L - p_G} & \text{for } p_L \le p_c < p_G, \\ 0 & otherwise; \end{cases} \tag{82}$$

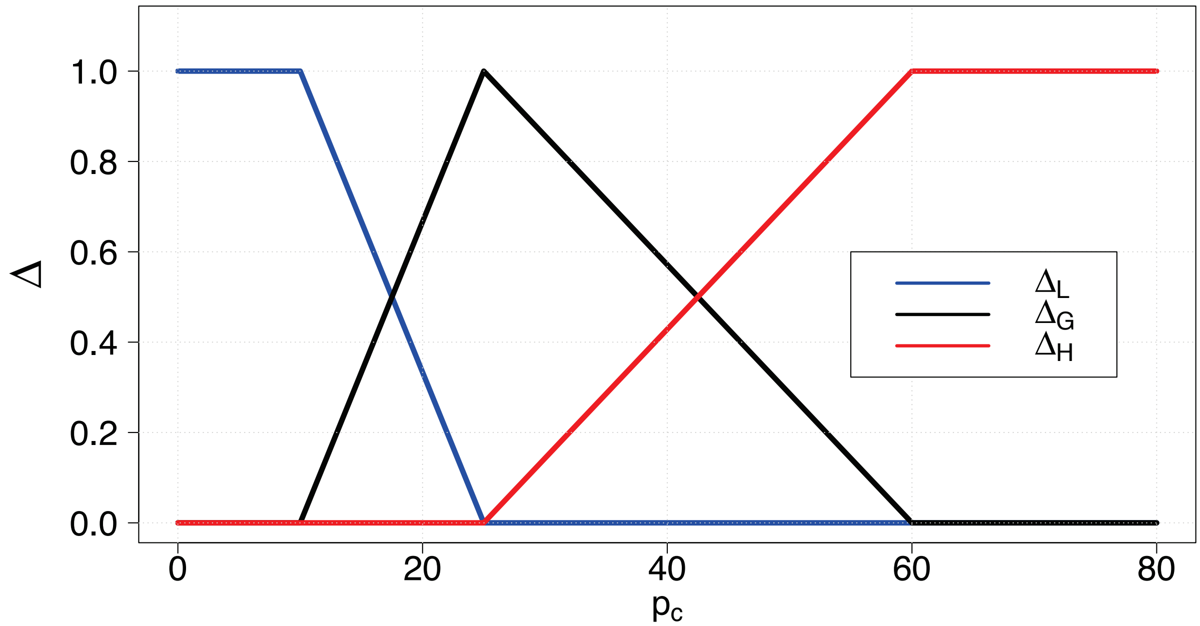
$$\Delta_G = \begin{cases} \dfrac{p_c - p_L}{p_G - p_L} & \text{for } p_L \le p_c < p_G \\ \dfrac{p_c - p_H}{p_G - p_H} & \text{for } p_G \le p_c < p_H' \\ 0 & otherwise; \end{cases} \tag{83}$$

$$\Delta_H = \begin{cases} 1 & \text{for } \mathrm{p_H} \le \mathrm{p_c} < \infty \\ \dfrac{p_c - p_G}{p_H - p_G} & \text{for } \mathrm{p_G} \le \mathrm{p_c} < \mathrm{p_H}. \\ 0 & \text{otherwise.} \end{cases} \tag{84}$$

Figure C.1 provides an example of how these Δs look.

Eqn. (80) provides the expected value of the carbon price, $\tilde{p}_c^e$, based uniquely on an adaptive learning process. Thus, if two firms start up in the same year and have the same experience discounting parameter, e, they would end up with the same expected carbon price every year, regardless of which lobby they joined. However, firms that join different lobbies may be more or less optimistic that their lobby will be successful. We thus introduce a firm's optimism parameter, η, such that its expected value for the carbon price, p_c^e, is a weighted average of (1) how optimistic the firm feels that its lobby will change the carbon price in the desired direction

Figure C.1. Lobby Game Example



NOTE: p_G = 25; p_L = 10, and p_H = 60.

and (2) the carbon price given by the firm's adaptive learning process. Therefore, for a firm in the LCP lobby,

$$p_c^e = (1 - \eta)\tilde{p}_c^e + \eta p_L, \tag{85}$$

while for a firm in the HCP lobby,

$$p_c^e = (1 - \eta)\tilde{p}_c^e + \eta p_H. \tag{86}$$

Appendix D. Starting Cases

The parameter values for the ten starting cases derived in Section 4, "Calibration," are presented in Tables D.1 through D.3. Table D.1 lists the parameters that remained constant for all starting cases.

Table D.1. Parameters That Remain Constant Across Starting Cases

Parameter	Parameter Description	Value
ρ_l	Entrant capital lower bound	0.01
r	Interest Rate	0.02
τ	R&D turnover rate	0.04
β	Wage adjustor	0.35
F	Initial number of Firms	200

Table D.2. Details for Starting Cases 1 Through 5

		Starting Case				
Symbol	**Parameter**	**1**	**2**	**3**	**4**	**5**
$\omega_{C,l}$	Lower bound of carbon R&D beta distribution	3.6%	3.9%	3.4%	3.7%	3.7%
$\omega_{L,l}$	Lower bound of labor R&D beta distribution	2.5%	1.6%	2.6%	1.4%	2.3%
$\omega_{L,u}$	Upper bound of labor R&D beta distribution	8.0%	6.6%	5.3%	8.0%	6.4%
β_L	Beta shape parameter of labor R&D beta distribution	4.1	2.3	4.7	9.8	5.8
α_L	Alpha shape parameter of labor R&D beta distribution	2.1	6.1	4.5	9.3	6.3
ζ_{inn}	Innovation rate	8.7%	9.9%	17.4%	10.6%	17.6%
ζ_{imi}	Imitation rate	40%	41%	16%	41%	12%
ξ	Ratio between innovative and imitative R&D expenditures	51%	54%	74%	72%	68%
ρ_u	Entrant capital upper bound	3.2%	10.7%	8.8%	11.9%	16.9%
y	Payback Parameter	7.6	7.1	15.8	12.1	11.0
L^{ini}	Initial years of self-financing available	4.3	3.6	3.2	1.9	3.6
ε	Elasticity of demand	–0.12	–0.12	–0.11	–0.16	–0.15
Ω	Debt to sales ratio	8.1	7.2	7.3	2.0	9.0
χ	Replicator coefficient	1.43	0.76	0.95	0.86	1.12
κ	Demand growth	3.0%	3.2%	3.1%	3.0%	3.0%
υ	Utilization rate	76%	89%	86%	78%	82%
δ	Depreciation rate	5.8%	3.1%	3.2%	5.0%	3.6%
p^{inv}	Real capital price	4.0	4.9	2.2	2.5	5.8
μ	Markup	24%	23%	22%	34%	32%

Table D.3. Details for Starting Cases 6 Through 10

Symbol	Parameter	Starting Case				
		6	7	8	9	10
$\omega_{C,l}$	Lower bound of carbon R&D beta distribution	3.1%	3.5%	3.4%	3.7%	3.9%
$\omega_{L,l}$	Lower bound of labor R&D beta distribution	2.8%	3.0%	2.8%	1.6%	2.3%
$\omega_{L,u}$	Upper bound of labor R&D beta distribution	6.0%	6.4%	7.8%	7.9%	7.9%
β_{L}	Beta shape parameter of labor R&D beta distribution	5.4	6.7	6.3	7.2	4.5
α_{L}	Alpha shape parameter of labor R&D beta distribution	6.5	7.4	4.0	7.2	4.4
ζ_{inn}	Innovation rate	16.4%	12.3%	10.1%	14.3%	16.5%
ζ_{imi}	Imitation rate	13%	28%	19%	50%	6%
ξ	Ratio between innovative and imitative R&D expenditures	44%	33%	40%	35%	37%
ρ_{u}	Entrant capital upper bound	3.4%	13.5%	12.3%	8.6%	19.4%
y	Payback Parameter	18.6	14.3	15.3	11.6	13.2
L^{ini}	Initial years of self-financing available	2.4	4.1	2.2	1.9	1.5
ε	Elasticity of demand	–0.10	–0.11	–0.11	–0.12	–0.15
Ω	Debt to sales ratio	9.4	8.9	5.0	6.6	3.4
χ	Replicator coefficient	0.63	1.27	1.10	1.26	0.83
κ	Demand growth	3.1%	3.1%	3.1%	3.1%	3.0%
υ	Utilization rate	79%	87%	81%	84%	84%
δ	Depreciation rate	3.6%	4.4%	5.1%	4.5%	5.0%
p^{inv}	Real capital price	3.4	5.1	2.1	2.6	2.3
μ	Markup	38%	40%	40%	25%	35%

Appendix E. Representative Analysis Details

The starting case was used to determine the values for the following parameters (see Table E.1):

To limit the size of the experiment, climate-related parameters and the initial ratio between carbon and labor intensity were fixed (see Table E.2). During the calibration runs, the carbon intensity did not matter because firms paid no carbon tax and invested no funds in explicit carbon reduction R&D. Therefore, it is reasonable to rescale the carbon intensity independent of the labor productivity. Rescaling consists of adjusting each firm's intensity such that the mean value matches the desired starting condition while keeping the distribution equal to that generated by the calibration analysis.

The initial ratio between carbon and labor expenses is important when a carbon tax is present. This was determined by looking at the energy sector in the United States. Total energy production was obtained from the EPA's E-GRID dataset (EPA, 2012) along with total carbon emissions. This yielded a sector wide average carbon intensity of 0.15 tons of carbon per megawatt hour. The corresponding labor productivity was found using the aforementioned total energy production and the total hours of labor expended in the U.S. energy sector in 2009, as published by the Bureau of Labor Statistics (BLS, 2010) for the electric power generation, transmission and distribution industry. The average labor productivity was 4.45 MWh per hour of labor.

Table E.1. Parameters Set by the Starting Case for the Representative Analysis

Symbol	Parameter
ξ	Ratio between innovative and imitative R&D expenditures
ρ_l	Entrant capital lower bound
ρ_u	Entrant capital upper bound
y	Payback Parameter
L^{ini}	Initial years of self-financing available
ε	Elasticity of demand
Ω	Debt to sales ratio
χ	Replicator coefficient
υ	Utilization rate
δ	Depreciation rate
p^{inv}	Real capital price
μ	Markup
r	Interest Rate
τ	R&D turnover rate
β	Wage adjustor

Table E.2. Values That Were Kept Constant for the Exploratory Experiment Described in Section 5

Symbol	Parameter	Value
λ	Damage function uncertainty factor	0.75
δ	Climate damage sight factor (in GtC)	100
M	Number of segments in the damage function	3
$\mathrm{d}_{\mathrm{h},1}$	Magnitude of the first damage function jump (in %GDP)	0.1
$\mathrm{d}_{\mathrm{h},2}$	Magnitude of the second damage function jump (in %GDP)	0.5
m_1	Slope of the first segment of the damage function in %GDP/GtC	0.0003
m_2	Slope of the second segment of the damage function in %GDP/GtC	0.002
m_3	Slope of the third segment of the damage function in %GDP/GtC	0.004
$\mathrm{q}_{\mathrm{h},1}$	Location of the first abrupt change in climate damages (in GtC)	500
$\mathrm{q}_{\mathrm{h},2}$	Location of the second abrupt change in climate damages (in GtC)	800
g^{LLM}	Determines the lowest carbon price the government would consider	0
GDP	The initial GDP level (see Appendix A for details)	12703.1
a^{ini}	Initial market average carbon intensity	0.15
b^{ini}	initial market average labor productivity	4.45
w^{ini}	Initial wage rate	57
End tick	Number of simulated years to run	75
Information level	A switch indicating that the firms have knowledge of the shape of the R&D beta distributions	1

Appendix F. Parameter List

Tables F.1 through F.5 list the model parameters that describe the firm finances, competiveness, and the economy as introduced in the "Modeling Firm Finances, their Competitiveness and the Economy" subsection in Section 3. Here, parameter symbols use the following notation: Subscripts i and j, respectively, indicate that the parameter describes the quantity of a machine or capital stock of type i belonging to firm j. In our description and throughout this report, we use the terms a *machine* and *capital stock* interchangeably.

Table F.1. Model Parameters of the Economy Having Constant Value Throughout a Model Run

Parameter	Description
r	Interest rate.
χ	Yearly response of market share adjustment per changes in firm competitiveness.
δ	Yearly capital depreciation rate due to wear and tear.
μ	Markup on the final good.
κ	Consumption budget.
ε	Demand elasticity.
γ	Growth rate of the consumption budget.
Ω	Maximum debt to sales ratio for all firms.
p^{inv}	Real price per unit capital.
y	Payback parameter.
L^{ini}	Number of years of self-financing given to new firms.
β	Wage adjustor—controls how wage varies with average labor productivity.

Table F.2. Model Parameters of the Economy with Values That Vary Endogenously During a Model Run

Parameter	Description
p_c	Price per ton of carbon emission.
w	Wage rate.
D	Total demand.
d	Reduction rate of the consumption budget due to the economic impact of climate change damages.
$\hat{a}$	Market share weighted average carbon intensity over all firms
$\hat{b}$	Market share weighted average labor productivity over all firms.
$\hat{p}$	Average retail price of the final good.
u^{inv}	Price per unit of capital.
u_i	Unit production cost of the final good by machine of type *i*.

Table F.3. Firm-Specific Model Parameters That Vary Endogenously During a Model Run

Parameter	Description
$a_{i,j}$	Carbon intensity of a machine of type *i* in firm *j*.
$b_{i,j}$	Labor productivity of a machine of type *i* in firm *j*.
u_j	Average unit production cost of the final good.
a_j	Average carbon Intensity.
b_j	Average labor productivity.
K_{ij}	Number of machines of type *i* owned.
K_j	Total number of machines owned.
f_j	Current market share.
$\tilde{f}_j$	Previous year's market share.
p_j	Retail price of the final good sold.
Q_j	Number of produced units of the final good .
S_j	Number of units of the final good sold.
N_j	Total inventory of the final good.
Ξ_j	Debt.
A_j	Available funds.
L_j	Liquid assets.
I_j	Capital expansion costs .
Λ_j	Lobbying costs.
R_j	R&D costs.
π_j	Profits.
D_j^e	Expected demand.
K_j^e	Quantity of expansion capital.
K_j^r	Quantity of replacement capital.
W_j	Welfare.
$u_{b,j}$	Lowest unit production cost.
a_b	The carbon intensity of the firm's current lowest unit cost machine.
b_b	The labor productivity of the firm's current lowest unit cost machine.

Table F.4. Model Parameters Describing Firms' R&D Spending Behavior Having Constant Value for All Firms Throughout a Model Run

Parameter	Description
θ_{inn}^{r}	Expected proportion of firms that successfully innovate in the first period.
θ_{imi}^{r}	Expected proportion of firms that successfully imitate in the first period.
ζ_{inn}	Firm innovative search capability (Derived from θ_{inn}^{r})
ζ_{imi}	Firm imitation search capability (Derived from θ_{imi}^{r})
τ	Proportion of total labor production costs spent on R&D.
ξ	Proportion of allocated funds for R&D spent on innovation R&D. The remaining amount is spent on imitation R&D.
$\omega_{C,l}$	Lower bound on the carbon R&D beta distribution
$\omega_{C,u}$	Upper bound on the carbon R&D beta distribution
$\omega_{L,l}$	Lower bound on the labor R&D beta distribution
$\omega_{L,u}$	Upper bound on the labor R&D beta distribution
η	Firm optimism parameter used to weight a firm's carbon price expectation toward its lobby's best outcome (same value for all firms).
e	Firm memory factor. Values closer to 1 indicate less discounting of prior carbon prices when projecting future carbon prices.

Table F.5. R&D Firm-Specific Model Parameters That Vary Endogenously During a Model Run

Parameter	Description
θ_{inn}	Probability that a firm successfully innovates.
θ_{imi}	Probability that a firm successfully imitates.
σ_j	Proportion of innovation R&D funds allocated by firm j that are used for carbon intensity R&D. The remaining funds are used for labor productivity R&D.
x_C and x_L	Random variables taken from two different but related beta distributions.
$\widetilde{\omega}_{C,u}$	Upper bound on the carbon R&D beta distribution adjusted for firm specific carbon R&D efforts
$\widetilde{\omega}_{L,u}$	Upper bound on the labor R&D beta distribution adjusted for firm specific labor R&D efforts

Tables F.6 and F.7 list parameters that relate to how the model computes the economic damages due to climate change and how the government calculates the social cost of carbon.

Table F.6. Climate Change Model Parameters Associated with the Computation of the SCC That Remain Constant Throughout a Model Run

Parameter	Description
M	The total number of staggered linear segments assumed on the graph of annual impacts due to climate change versus cumulative emissions. The total number of discontinuous jumps (i.e., thresholds) in impacts is therefore $M-1$.
$q_{\mathrm{j}}^{(th)}$	The threshold value in cumulative emissions at the end of the $M_j^{(th)}$ segment. By definition, $q_0^{(th)}=0$ and $q_M^{(th)}=\infty$.
m_j	Gradient of the segment bounded by the $(j-1)^{th}$ and j^{th} cumulative emission thresholds.
Δ	Government's range of future cumulative emissions where it has a correct knowledge of impacts caused by cumulative emissions. For segments that fall beyond this range, the government incorrectly assumes lower impacts as modeled by the parameter λ.
λ	Multiplicative factor ranging from 0 to 1 that represents the factor by which impacts are assumed lower than they really are by the government.

Table F.7. Climate Change Model Parameters Associated with Computing SCC and That Vary Endogenously During a Model Run

Parameter	Description
ε	Total yearly anthropogenic emissions.
q	Total cumulative anthropogenic emissions.
$p_G^{(a)}$	The actual social cost of carbon, representing the price per unit of carbon emission that the government would need to charge to compensate for the economic damages caused by emissions, given that production and consumption stay unaltered and that the government has full information of future impacts of emissions on climate change.
p_G	The social cost of carbon, representing the price per unit of carbon emission that the government would need to charge to compensate for the economic damages caused by emissions, given that production and consumption stay unaltered and that the government has imperfect information of future impacts of emissions on climate change.

Table F.8. Model Parameters That Define the Government Contribution C_G (p_c) Function and Remain Constant Throughout a Model Run

Parameter	Description
g^{ULM}	The upper limit multiplier. This determines the maximum carbon price the government would consider. $p_c^{max}=g^{ULM}g^{UBM}p_G$
g^{UBM}	The upper bound multiplier. This determines the upper extent of the government's quadratic negotiating region. $p_c^{(t)}=g^{UBM}p_G$
g^{LBM}	The lower bound multiplier. This determines the lower extent of the government's quadratic negotiating region. $p_c^{(b)}=g^{LBM}p_G$
g^{LLM}	The lower limit multiplier. This determines the minimum carbon price the government would consider. $p_c^{(min)}=g^{LLM}g^{LBM}p_G$
a_L, a_H, c_L and c_H	Parameters that describe the government contribution function via the methodology of splines.
s	Government stringency factor. It is the coefficient determining the shape of the quadratic negotiating region.

Table F.9. Model Parameters That Define the Government Contribution $C_G(p_c)$ Function and Vary Throughout a Model Run

Parameter	Description
p_c^{min}	Lower bound of carbon price whereby the government contribution function is defined.
p_c^{max}	Upper bound of carbon price whereby the government contribution function is defined.
$p_c^{(b)}$	The bottom of the government's negotiating region.
$p_c^{(t)}$	The top of the government's negotiating region.
a_L, a_H, c_L and c_H	Parameters that describe the government contribution function via the methodology of splines.

Tables F.10 and F.11 list parameters used to describe how lobbies are modeled. We use the following notation: Subscripts L and H indicate parameters associated with the LCP and the HCP, respectively. The subscript LH indicates that the parameter is found when both lobbies are present and results from the lobbying bidding game. The superscript o indicates that the parameter is found at equilibrium conditions, in which both lobbies are present and neither has any interest in pursuing more favorable carbon prices.

Table F.10. Parameters That Are Used Here as Dummy Variables in Describing How the Lobbying Game Works and Are Therefore Not Computed in the Model

Parameter	Description
p_c	The carbon price.
K	The variable compensation the government expects to receive for setting the carbon price at the value of the social cost of carbon p_G.
$W_L(p_c)$ and $W_H(p_c)$	The welfare of the firms belonging to the LCP and HCP lobbies respectively when the carbon price is set to a value of p_c.
$G^o(p_c)$	The compensation the government expects to receive from the lobbies for setting the carbon price at p_c given that for p_c equal to p_G (i.e., the social cost of carbon) the compensation is equal to $K°$.

Table F.11. Model Parameters That Are Used to Calculate Lobby Contributions and Vary Endogenously During a Model Run

Parameter	Description
p_L and p_H	The carbon prices that would result if only the LCP or the HCP lobby negotiated with the government respectively.
p_{cLH}	The carbon price that results when both the LCP and the HCP lobbies negotiate with the government.
$K°$	The compensation the government expects to receive for setting the carbon price at the value of the social cost of carbon p_G. This is an equilibrium value found by increasing the parameter Kuntil the condition whereby both lobbies have no added interest in continuing their bidding war.

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