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Modeling Climate Change:
Sensitivities of The Social Cost of Carbon Under Parametric Uncertainty

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ABSTRACT

The economics of climate change combines research from a wide range of physical sciences and economic theory into complex mathematical models called integrated assessment models. This study analyzes the impact of parametric uncertainty in these models as they calculate the social cost of carbon, a vital tool for policymaking. Uncertainty in total factor productivity growth, population growth, and equilibrium climate sensitivity are addressed for three prominent integrated assessment models, DICE, FUND, and PAGE. Through regression analysis, uncertainty in the equilibrium climate sensitivity parameter is shown to influence the social cost of carbon more than other inputs. The results of this study also support the use of a recently developed method of analyzing uncertainty in integrated assessment modeling of climate change.

Keywords: economics, climate change, integrated assessment modeling, uncertainty, social cost of carbon

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Chapter 1

Introduction

The economics of climate change involves a vast array of research and theory from both the physical sciences as well as economics. Studying such a large-scale phenomenon as climate change requires bringing together this broad range of knowledge into mathematical models called integrated assessment models (IAMs). The function of these models is to estimate future climate impacts, including outcomes such as emissions, temperature, sea level rise, damages, and the social cost of carbon, a measure of the marginal external cost of an additional ton of greenhouse gas emissions. The social cost of carbon (SCC) is an extremely useful policymaking tool, as it can be used to set prices or evaluate the costs and benefits of competing policy proposals. A major issue with calculating outcomes within integrated assessment models is the uncertainty involved. Economic forecasts of future growth, emissions, and population all have a degree of uncertainty based on how well economists understand the determinants of each outcome. Climate models are also a simplification of reality and rely on an incomplete knowledge of how these systems will react to extreme levels of greenhouse gas concentrations. The Intergovernmental Panel on Climate Change (IPCC) defined the uncertainty associated with IAMs to be a key research priority in the most recent assessment report (Edenhofer et al., 2014).

A recent paper by Gillingham et al. (2018) has begun the study of parametric uncertainty in major integrated assessment models. This paper analyzes the impacts of uncertainty in three key input parameters on outcomes for six IAMs by creating a three-dimensional grid of calibration runs, fitting response functions, and defining distributions for each input parameter. The present study is inspired by the Gillingham et al. methods and seeks to build upon its work by completing a more focused study on the calculation of the social cost of carbon. This paper will study the same three uncertain parameters, utilizing the same distribution functions and following a similar methodology. These uncertain parameters are total factor productivity growth, population growth, and equilibrium climate sensitivity. The set of IAMs analyzed were chosen to be three of the most cited models in the literature on climate change economics. These prominent models, DICE, FUND, and PAGE, are the primary IAMs used by the US Interagency Working Group on the Social Cost of Carbon (IWG, 2013).

This study will produce a grid of values based on estimated probability distributions for each uncertain input and use this to complete a set of calibration runs on the baseline scenarios for each integrated assessment model. The resulting dataset will be analyzed using regression to study the impact of parametric uncertainty on the social cost of carbon. While the social cost of carbon is extremely sensitive to the choice of discount rate, this analysis will take the default discount rate for each model as a given, instead comparing the relative impact of three chosen uncertainties. One major finding is that the equilibrium climate sensitivity parameter seems to have the largest impact on the SCC across all three models. This important uncertainty has implications for further research in climate change modeling. A more general contribution of this paper is evidence of the replicability and modification of the Gillingham et al. approach. This approach can usher in a series of research opportunities that improve the overall understanding and evaluation of parametric uncertainty in integrated assessment modeling for climate change. Ultimately, this approach can be used to emphasize the value of certain uncertainties to researchers and show where reducing uncertainty would have the highest payoff.

This paper will be organized as follows. An important background to studying the economics of climate change is understanding the underlying physical processes that cause climate change. The next chapter begins with a description of the greenhouse effect and how human emissions affect the climate and can cause significant impacts in the future. It also describes how economists study climate change, defining the issue of greenhouse gas emissions as a negative externality and describing the social cost of carbon. The following section explains the need and purpose for integrated assessment models, as well as their shortcomings. Chapter 4 will discuss in detail the three IAMs used in this paper, highlighting major studies as well as critiques of each model. The fifth chapter characterizes the methodology used for this analysis and Chapter 6 will present results and a summary of major findings, which will be followed by final remarks. Appendices include a set of useful definitions found in this paper as well as a complete record of the regression results.

Chapter 2

Carbon and Climate Change

It is important to begin this study with a common understanding of the various factors involved in order to build up to the necessity of uncertainty analysis in integrated assessment modeling. A primary purpose of these models is to analyze policies for mitigating the effects of climate change, a phenomenon that itself sparked debate when researchers first described the adverse effects of humankind on the planet. As scientists of many disciplines collected data, peer-reviewed research, and developed a better understanding of humanity's environmental impact, it has been helpful to aggregate this research to establish a scientific consensus. Broad research synthesis is necessary for educating the public on important issues that could affect their lives as well as government and international policymaking institutions that need to be informed to create the best policies.

One such group is the Intergovernmental Panel on Climate Change, or the IPCC. This premier international organization was created in 1988 "to provide policymakers with regular assessments of the scientific basis of climate change, its impacts and future risks, and options for adaptation and mitigation" (IPCC, n.d.). The IPCC releases reports created by hundreds of leading scientists and contributing authors that convey the scientific consensus at the time of its publication. The most recent report, the fifth assessment report, was released in 2013 (IPCC, 2013a). Selections from this work will be referenced several times throughout this chapter to convey the scientific consensus as accurately as possible. This chapter will be separated into two sections. The first focuses on the background scientific knowledge required to discuss climate change. It will include descriptions of the greenhouse effect and evidence of anthropogenic climate change as well as the expected future impacts on humans and the environment. The chapter will then pivot to the economics surrounding this scientific issue, describing how the field can uniquely address climate change.

2.1 Overview of the Physical Science

The Greenhouse Effect

The Earth is heated by radiation from the sun in the forms of visible light and other invisible energy waves, such as ultraviolet radiation. When this energy reaches Earth, around 30% of it is reflected back out into space. The energy is reflected by gases in the atmosphere, clouds, or the Earth's surface. The other 70% of the energy is absorbed by the planet or the atmosphere. To stay in equilibrium as an energy system, the planet releases the same amount of energy in the form of infrared waves (Denchak, 2019). The most complex gases in the atmosphere, called greenhouse gases (GHGs), can absorb this type of energy before releasing it again in a random direction. The energy may then get absorbed and rereleased by other greenhouse gas molecules as the pattern repeats. Essentially, some of the infrared heat released by the Earth escapes to space while some is trapped and sent back, heating the planet. This process of trapping energy within the planet's atmosphere is called the greenhouse effect (Shaftel et al., 2008b).

By itself, the greenhouse effect is good for the Earth. This effect is what holds heat in at night and helps distribute energy across all latitudes. Otherwise, the planet would be below freezing and even colder after the sun sets (UCAR, n.d.). The issue arises when the concentration of greenhouse gases in the atmosphere increases. To keep the Earth's temperature at equilibrium, the amount of energy entering the system must be the same as the amount escaping. As the sun's energy does not change rapidly, the majority of fluctuations in the planet's energy system come from changes in albedo, a measurement of reflectivity, or shifts in outgoing radiation. As humans emit more greenhouse gases into the atmosphere, infrared radiation passing through is more likely to be stopped and trapped within the atmosphere. This reduces the amount of energy leaving the planetary system and thus increases the temperature (Cubasch et al., 2013; UCAR, n.d.).

There are several different gases considered to be greenhouse gases. The most well-known is carbon dioxide (CO_2). This gas is one of the least potent of the greenhouse gases but accounts for the majority of the greenhouse effect because of its abundance compared to other GHGs. In many cases, the total effect of greenhouse gases in the atmosphere is converted to its CO_2-equivalent, which is the amount of carbon dioxide that would have the same impact as the given mixture of GHGs. Carbon dioxide is notably released through the burning of fossil fuels, in addition to deforestation and cement processing (Rodhe, 1990; Shaftel et al., 2008b). Other greenhouse gases include methane (CH_4), water vapor (H_2O), nitrous oxide (N_2O), ozone (O_3), and chlorofluorocarbons. Some of these are much more potent than carbon dioxide. One molecule of methane contributes 25 times more to atmospheric warming than carbon dioxide and nitrous oxide contributes 200 times as much. Nitrous oxide also decays more slowly than carbon dioxide, meaning that its effect last even longer (Rodhe, 1990). Methane is released into the atmosphere by landfills, agriculture, and livestock digestion. Nitrous oxide is most commonly found in fertilizers (Shaftel et al., 2008b).

Rising Emissions and Temperature

Since the beginning of the industrial revolution, human activities that release greenhouse gases into the atmosphere have expanded rapidly. Much of this occurs in tandem with the burning of fossil fuels that are used to run engines, power machinery, and generate electricity. Atmospheric CO_2 concentrations are currently at 415ppm, 47% higher than the year 1850 (Shaftel et al., 2008a). Carbon dioxide is the most common driver of the greenhouse effect, making up 76% of human-caused emissions globally. Coal power plants are one of the largest culprits of producing the gas, but it is also produced by transportation, industry, agriculture, and land use changes like deforestation. Countless facets of modern human civilization currently rely on processes that emit carbon dioxide. The largest and most developed countries contribute the most to global emissions, with China, the United States, the European Union, and India combining for nearly 60% of all carbon dioxide emissions. Individually, China produces 27% of CO_2 emissions while the United States is responsible for 15% (Denchak, 2019).

Concentrations of carbon dioxide are much higher than they have ever been according to scientific assessments of historical levels. Figure 1 displays historical CO_2 concentrations across the past 800 thousand years through indirect measurement. This data is reconstructed by the NOAA by studying ice cores, which can contain bubbles of gas and preserve matter from freezing seasons long ago. There is clearly a sharp and sudden spike in atmospheric carbon dioxide concentrations which surpasses any historical precedent. This is indicative of human impacts, not simply coincidental natural processes (Shaftel et al., 2008a). Similarly, Figure 2 shows the direct measurements of atmospheric CO_2 for about 50 years since 1960. This graph depicts the steady upward trend of emissions due to human production. The red line shows measurements from Mauna Loa, while the black line is measured from the South Pole, where the seasonal variation due to vegetation growth is less extensive (IPCC, 2013b). The direct measurements of atmospheric carbon dioxide validate and support the data taken indirectly through ice cores. Both point to a significant upswing in the concentration of greenhouse gases in the atmosphere as a result of human emissions.

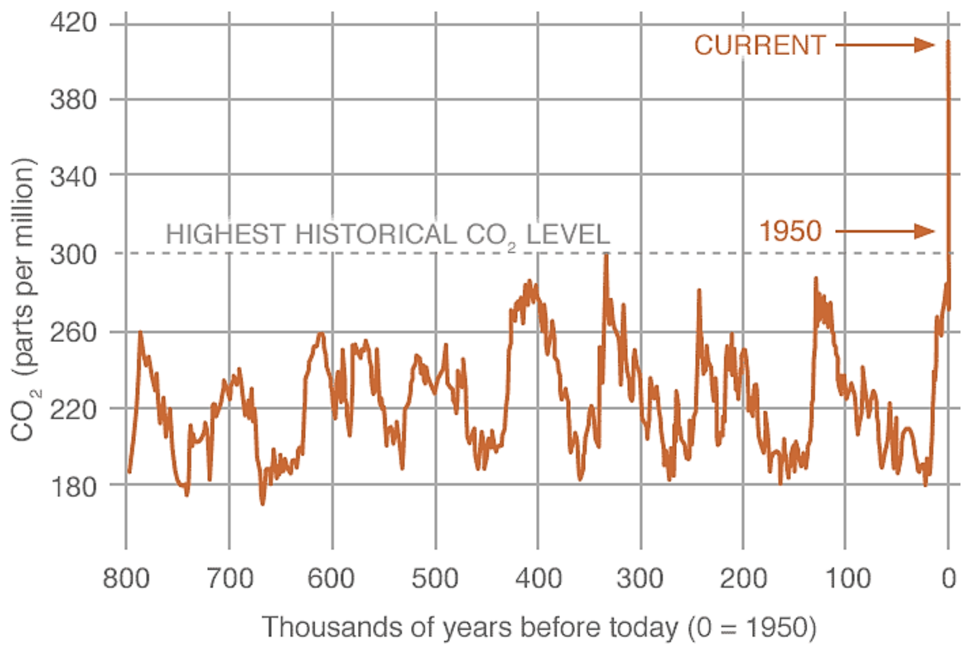

Figure 1: Historical CO2 concentrations, constructed from ice cores

Source: Shaftel et al. (2008a)

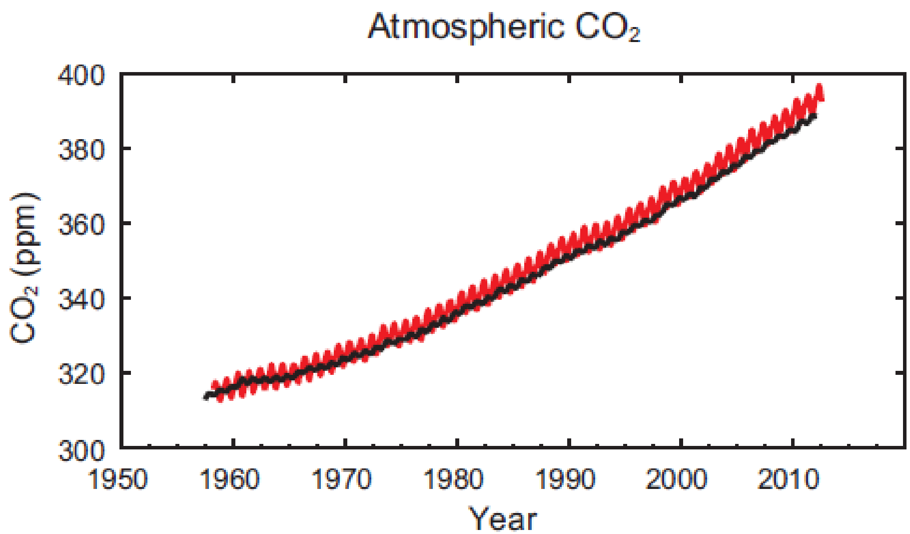

Figure 2: Atmospheric CO2 concentrations, direct measurements

Source: IPCC (2013b)

There is already evidence that greenhouse gas emissions have caused global temperature increases in the past 100 years. The most recent report by the IPCC documents the average global land and ocean temperature since 1850, which shows a sharp increase in recent decades (IPCC, 2013b). This data is presented in Figure 3. Close to 1850, near the start of the industrial revolution and before human GHG emissions were growing at high rates, the average temperature anomaly was relatively low and steady. As time passes and industrial production booms, emissions translate to increases in average surface temperature across the planet (IPCC, 2013b). Such anthropogenic effects have been documented by scientists at least since the influential "hockey stick" graph was published by climatologist Michael Mann (Mann et al., 1998). The IPCC reports that the average temperature anomaly between 1880 and 2012 is 0.85°C. More specifically, the scientists and contributing authors write, "Warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia. The atmosphere and ocean have warmed … and the concentrations of greenhouse gases have increased" (IPCC, 2013b).

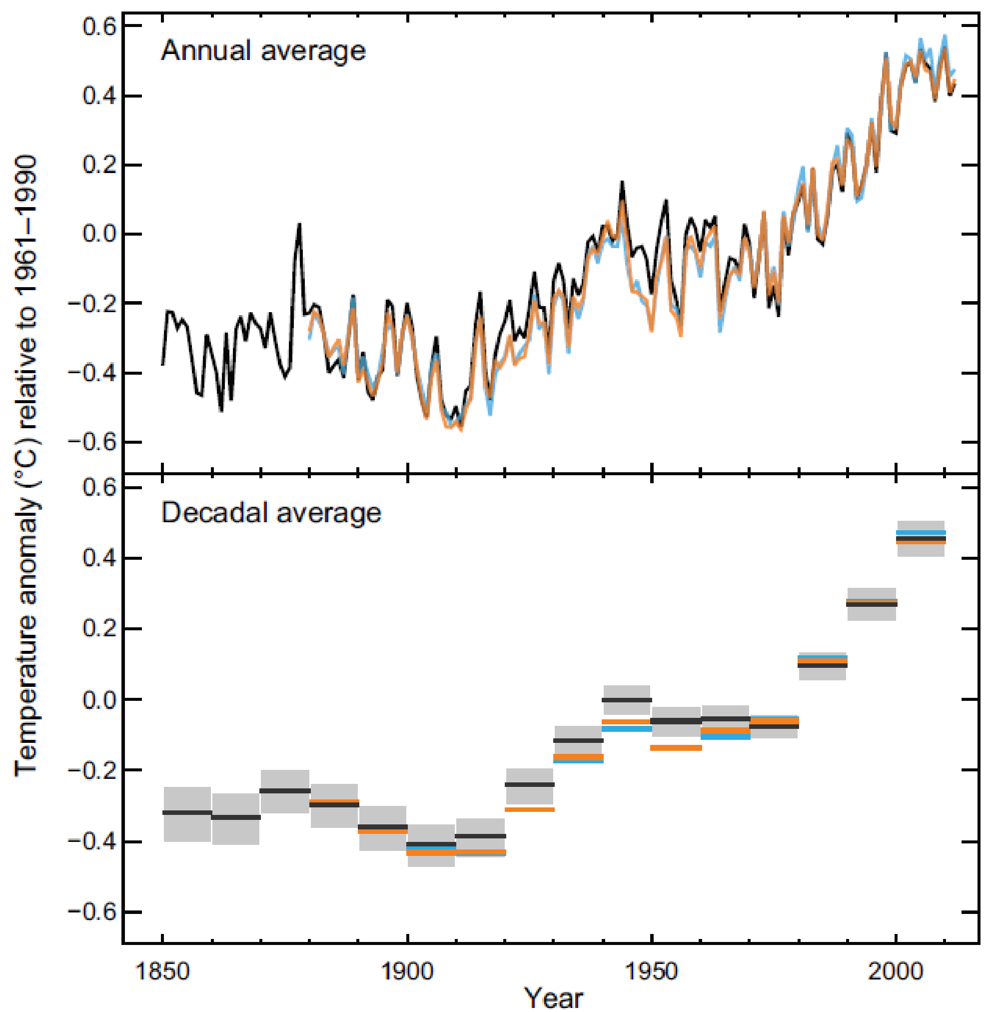

Figure 3: Average surface temperature anomaly (1850-2012)

Source: IPCC (2013b)

Future Impacts

On a global scale, temperatures have already begun to rise because of climate change. The IPCC estimates that there is more than a 90% chance that the number of warm days and nights has increased globally since 1950 (IPCC, 2013b). However, temperature is not the only way in which the climate is expected to change. Glaciers and sea ice will melt, changing habitats and adding water to the oceans. With more water in general, and due to thermal expansion as the temperature increases, the sea level will rise, which can cause major problems in coastal cities and communities. In addition to this, extreme weather is expected to become more intense and more frequent. This means there could be more and/or larger hurricanes, longer droughts and heatwaves, and more flooding. Weather patterns will also change, forcing ecosystems to adapt quickly or migrate. Many of these impacts have already begun to take hold today (Denchak, 2019). For example, the IPCC states it is "virtually certain" that the upper ocean warmed from 1971 to 2010. Looking forward, the estimated probability of heavy precipitation events increasing in either frequency or intensity is over 90%. The estimated likelihood of increased incidence and magnitude of extreme high sea level in the 21st century is also over 90% (IPCC, 2013b). Another global impact of climate change is ocean acidification. This occurs when the ocean absorbs carbon dioxide from the atmosphere, upsetting the pH balance. Ocean acidification is accelerated when there are high concentrations of CO_2 in the atmosphere and can threaten vulnerable ecosystems like coral reefs (Rhein et al., 2013).

NASA has documented the most dramatic impacts in the United States by region. These are currently happening and are expected to continue. In the Northeast, heat waves, heavy downpours, and sea level rise are expected to have lasting effects on infrastructure, agriculture, and ecosystems. The Northwest is experiencing reduced access to water and increases in wildfires and insect outbreaks. The Southeast is most affected by sea level rise and extreme heat, much like the Southwest, which is additionally exposed to drought and reduced agricultural yields. The Midwest has experienced a significant increase in flooding that affects infrastructure and agriculture, among other things (Shaftel et al., 2008c).

While most impacts of anthropogenic climate change are continuous, increasing steadily with emissions, this is not always the case. There are some impacts called "tipping points," which are like thresholds after which dramatic changes might occur. A tipping point could be analogous to a roller coaster hill. When the car reaches the top, a critical point, it only takes a small push to release the potential energy and create a dramatic change as the car rushes down its coaster. In a similar way, climatic tipping points are self-reinforcing; once the system is past its critical point and the process has begun, taking away the initial push cannot stop the motion (Lenton, 2012; McSweeney, 2020). One of the most straightforward positive feedback loops in climate change is ice melting. As the atmosphere warms and the Greenland ice sheet experiences melting, the surface becomes darker in color. Water is not as bright or reflective as ice, and foliage is even more light absorbing. When the surface gets darker, it absorbs even more heat from sunlight and the ice melts faster (McSweeney, 2020).

In addition to being self-reinforcing to the point of often being irreversible, climatic tipping points are dangerous because it is difficult to know where the critical point occurs. Another illustrative analogy for tipping points is an avalanche. When the conditions are just right, only a small perturbation can cause a mountain of snow to collapse. Unfortunately, it is not obvious when these are conditions are right, or how close it might be to the point of no return. Some potential tipping points that could occur in the future include the collapse of the Greenland ice sheet, melting of arctic permafrost, and a breakdown of major ocean currents (Lenton, 2012). If the Greenland ice sheet were to collapse due to warming, returning the climate to preindustrial conditions would not be enough for the ice to come back. Barring a new ice age, losing the Greenland ice sheet would mean losing it permanently. This dramatic change would deposit large amounts of fresh water into the ocean, raising the sea level, changing water density patterns, and having the potential to disrupt global ocean currents that help keep northern regional climates warm. Losing a major Atlantic Ocean current could cause widespread cooling in northern regions of as much as 5°C (McSweeney, 2020). Another major climate feedback occurs through the melting of permafrost. The long-frozen ground traps vast amounts of carbon as well as methane, so a significant thaw would accelerate the rate of warming as these GHGs are released. This is only a sample of the potential nonlinear impacts of climate change. Others include a die-off of coral reefs, disintegration of the West Antarctic ice sheet, and a boreal forest shift (McSweeney, 2020). Anthropogenic climate change is capable of significant widespread, and at times unexpected, effects on the planet and its ecosystems. These impacts are already happening in some cases. The science is thorough and well defined, leaving only the question of how to react to this reality.

2.2 Application in Economics

Greenhouse Gas Emissions as a Negative Externality

In a typical economic decision, an individual makes their optimal choice based on the direct costs and benefits (or profits). Traditionally, they do not consider the effects that this decision may have on others because this does not apply a direct cost or benefit in their utility optimization. A cost or benefit to an individual decision-maker is called a private cost/benefit, while the total effect including others is called the social cost or benefit. While individuals only weigh the private costs and benefits, the welfare maximizing choice from society's standpoint must weigh the total social costs and social benefits. This outside effect is called an externality. Positive externalities occur when someone's decision has a larger social benefit than private benefit. Negative externalities are the opposite; the societal cost is larger than the private cost (Helbling, 2020). These situations are called market failures because private decision makers, though acting rationally, do not make optimal decisions for society. Such a market failure does not correct on its own and so a third party, usually a government, must step in to help individuals internalize their external costs (Helbling, 2020).

As human society produces greenhouse gas emissions through the burning of fossil fuels, deforestation, and other means, no one is paying for the future harm it will cause. Climate change will have negative net effects throughout society that are not taken into account by producers today, which is why GHG emissions are considered to be a negative externality. The standard economic theory shows that positive externalities lead to underproduction and negative externalities lead to overproduction. This would suggest that from a total welfare perspective, the current level of greenhouse gas emissions is much higher than optimal (Rezai et al., 2012; Helbling, 2020). Rezai et al. (2012) find that there is a large potential for Pareto improvements through investment in climate change mitigation. Based on standard economic models by Keynes and Ramsey, the authors show that society would benefit from reduced emissions to prevent climate damages. This includes benefits to current as well as future generations (Rezai, et al., 2012).

The next step is to determine how to prevent this sort of negative externality. One perspective is that intervention by governments or international organizations is the best way to prevent market failure. Economist Arthur Pigou is famous for his suggestion that governments should apply taxes equal to the difference between the social and private cost. This type of tax on a negative externality would raise the good's price to the level it would be if all costs were considered, thus forcing private individuals to internalize the externality. The overproduction would be corrected, generating welfare gains across society (Helbling, 2020). Another potential solution to a negative externality would be to allow all affected parties to negotiate, so that an agreed upon payment is made to correct the market failure. This view was promoted by Ronald Coase, but it is reliant upon the costs of bargaining being low. In a situation like global climate change, people from across continents and across generations cannot all meet to negotiate collectively (Helbling, 2020).

The Social Cost of Carbon

In order for policies to be created to solve the negative externality of global greenhouse gas emissions, the value of climate change's impact needs to be known. The amount of action needed to correct the externality depends on the difference between the social and private costs. Economists use a term called the social cost of carbon to describe the total impact of climate change. Like other economic valuations, the social cost of carbon (SCC) is usually calculated as a net present value with discounting for each year in the future. This immediately introduces the problem of how to discount future costs. Sometimes, discount rates are determined by the interest rate on alternative investments. Other times, this level of discounting is considered too harsh of a tradeoff from a perspective of intergenerational equity. An individual might be able to invest at a high rate, but that rate might not accurately reflect the value put on future generations. Regardless, the choice of discount rate makes a large impact on estimates of the SCC (Watkiss, 2005).

The job of calculating the social cost of carbon comes from an estimate of the marginal costs associated with emitting one additional ton of carbon dioxide. As time passes and more emissions are already in the atmosphere, the marginal cost increases because damages become more dramatic. Though this cost measure has carbon in its name, it explains the costs of either carbon dioxide or an equivalent amount of other greenhouse gas emissions (Nordhaus, 2017b). There are many complex factors that affect the social cost of carbon. Emissions change the climate through the greenhouse effect, but exact rates and processes are difficult to measure directly. Even if these calculations are not precise to a high degree, it is extremely useful to have a close estimate of what the social cost of carbon should be. Calculations of the SCC can be used for cost-benefit analyses within projects and government regulations, setting specific levels for economic taxes and similar instruments, and for broader sustainability targets. For these purposes, the SCC is sometimes reported as a range of likely values, more accurately communicating knowledge about the true value (Nordhaus, 2017b; Watkiss, 2005). The present study analyzes the climate economy models that are intricately designed to calculate, among other results, the social cost of carbon.

Chapter 3

Modeling Climate Change

Estimating outcomes for the future climate requires the efforts of numerous scientific models. The global climate has many moving parts which are often intricate and interconnected. Years of scientific research and models run using supercomputers have combined to form our current understanding of how the planet responds to changes in emissions. Emissions, on the other hand, are primarily created by humans. Understanding potential future emissions relies on economic models, using ideas such as growth and productivity. Also, the real effect of future climate change is calculated by economists, who can take outcomes and convert them into cost values in units that can be compared. In order to do these types of calculations that involve both scientific and economic models, modelers use Integrated Assessment Models (Auffhammer, 2018).

3.1 Integrated Assessment Models

Integrated Assessment Models (IAMs) are the complex mathematical models that scientists and economists use to study the future effects of climate change. They are named in this way because they combine models from multiple disciplines. IAMs integrate equations that model energy systems, economic systems, and climate science. Though integrated assessment models are a broad category that include many types of models unrelated to climate change, this paper addresses those IAMs of climate change (Hare et al., 2018). A typical IAM has several compartmentalized modules which are used to calculate its output. For example, a growing population might increase demand for energy, but this increases prices and feeds back into the economy by decreasing the amount of energy demanded and improving demand for alternative sources. All of this helps determine the amount of emissions, which in turn determines the temperature increase across the globe. While a complete IAM has many more equations than just these, the same process of interactions and feedback apply. Each module feeds into others to reflect the many aspects of the real world that are interconnected (Evans & Hausfather, 2018).

Models may be structured very differently from one another. Some are built as extensions to existing climate models and have smaller supplemental economic components. Others are designed specifically to cover the economics in detail, with these modules being the most detailed ones. An economic model could study specific sectors apart from the rest to isolate specific factors that may be relevant to climate change, such as in the energy production sector. All IAMs start with a number of assumptions, such as the ways in which the population will grow in different regions of the world, how weather patterns will react to initial warming, or sometimes specific values of GDP and productivity growth (Edenhofer et al., 2014; Evans & Hausfather, 2018). These are like the inputs to a model. The IAM then computes values by time – often by year or even longer periods – for its several outputs. Rates and concentrations of greenhouse gas emissions, population, global (or regional) income, industrial production, land-use changes, energy use, and climate damages are all useful outcomes that modelers study. Integrated assessment models are also vital for calculating the social cost of carbon. The models must calculate all of the future damages given its initial conditions, and then discount these impacts to find a single cost value for the desired reference year. The result, with major policy implications, is the external cost of a marginal ton of greenhouse gas emissions (Evans & Hausfather, 2018; Auffhammer, 2018).

3.2 Uncertainties and Shortcomings

Like other scientific and economic models, IAMs at their core are simplifications of reality. They are limited by the understanding of researchers and the power of computers to solve complex equations. When a modeler creates an IAM, they make their own decisions about which components to emphasize and which to allocate less computing power to. For these reasons, integrated assessment models cannot capture every nuance of the climate-economy that it attempts to represent. For example, coupling a more accurate model of temperature changes in the ocean could change IAM results by more than double (Marten, 2011). There are also major impacts of the choice of damage function, despite this choice sometimes being arbitrarily up to the researcher (Bretschger & Pattakou, 2019). At other times, integrated assessment models lag behind the most recent scientific or economic research. This is an area where improvements in accuracy could be made without significant increases in computational cost (Dietz et al., 2020).

A modeler must make their own decisions about how to model each segment of the climate-economy and which parametric values to use. This can be quite impactful on the output of the IAM. One example is the choice of discount rate, useful for determining the social cost of carbon in the same way that it is used in a simple net present value calculation. It is often standard to use a discount rate based on the return from an alternative investment, such as financial assets. However, a standard rate depends greatly on the time frame being studied. There are no substitutable assets that cover the next century or more. For a short-term investment, substituting yields from financial markets is reasonable, but when assessing intergenerational costs, this argument becomes shaky. Discounting a future that contains different generations can be equated to valuing those generations less, bringing up moral arguments for a much lower discount rate. Due to the long time span of integrated assessment models, the choice of a high or low discount rate has a large impact on the social cost of carbon (Stern, 2015).

The significance of a researcher's seemingly arbitrary choice of input parameters and model specifications can be disheartening. In his article "Climate Change Policy: What Do the Models Tell Us?," Robert Pindyck (2013) simply answers, "Very little." Pindyck points out the issues with the way IAMs appear to present precise results when they are sensitive to many unknowns. He believes instead that more accurate method to assess the social cost of carbon would be through surveying experts about potential values and ranges of the SCC (Pindyck, 2019). This does not entirely remove the role of the IAM; the climate change experts are the ones using integrated assessment models to better understand values like the SCC. Many critiques of IAMs in general acknowledge their inherent importance, advocating for improvements in certain components or details rather than against the models altogether (Marten, 2011; Espagne et al., 2018).

Many of the inputs to integrated assessment models come with notable uncertainty. Equilibrium climate sensitivity, a parameter that represents the increase in global temperature due to a doubling of CO_2 in the atmosphere, is clearly a relevant input for climate-economy models. It has a direct impact on the amount of warming that comes in response to increases in emissions. At the same time, its true value is very difficult to forecast, introducing uncertainty into the model's results. Many other forward-looking inputs are estimates, nearly guesses, such as GDP and population growth rates. Further uncertainty comes from the choice of integrated assessment model. Some models tend to produce low damages and call for minimal mitigation. Others value future damages highly and calculate a much larger SCC (Marten, 2011; Gillingham et al., 2018). Several works have called for extensive sensitivity analyses for within-model and cross-model comparison. This type of analysis could elucidate model uncertainty and quantify where parametric uncertainty is most impactful, directing researchers towards the most productive avenues for improvement (Anderson et al., 2014; Rose et al., 2017; Gillingham et al., 2018).

3.3 Modeling Applications

Integrated assessment models are increasingly relied upon by policymaking organizations. IAMs can be used to run policy simulations to answer a variety of questions, showing how much change would need to happen to reach certain climate targets, quantifying the impact of delaying action, and more. IAMs can be used to construct feasible pathways into the future of emissions and mitigation with a particular goal of keeping warming below a certain level or sticking to a carbon budget, a predetermined emissions limit that is undesirable to exceed. Data from these pathways can also act as milestones for short-term mitigation goals (Evans & Hausfather, 2018). When presenting a policy in a political setting, important analysis can be done with the help of IAMs. The models are often used to compare the costs and benefits of multiple proposed policies. The Intergovernmental Panel on Climate Change relies on IAMs to generate long-term pathways for policy assessment (Edenhofer et al., 2014). The Working Group III of the IPCC specifically uses IAM scenarios in analyses of climate change mitigation, socioeconomic impacts, risk and uncertainty, land use changes, and several other topics. Because of the importance of the IPCC and its reports, many integrated assessment models use their published scenarios, called Representative Concentration Pathways, for baseline calibration runs of the model. This allows the IAMs to be easily peer-reviewed and vetted by outside experts.

Baseline scenarios are more stable and consistent across models because of these forces (Edenhofer et al., 2014; Evans & Hausfather, 2018).

Chapter 4

Widely Used Integrated Assessment Models of Climate Change

This chapter will discuss several prominent IAMs that are used to study the climate economy at global and regional levels. The three models included are DICE, FUND, and PAGE. Each model includes similar basic structures, including representations of the economy, emissions, climate systems, and their interactions. All contain ways to connect climate costs back to the economy, being able to compute an estimate of climate damages and the SCC. There are significant variations in other parts of these models, such as regional disaggregation, macroeconomic modules, and damage functions. The following sections of this chapter will discuss each of the three models separately and in detail, describing works by the model creators as well as significant studies by others using these models. It will also discuss critiques of each model individually and some studies critiquing all three integrated assessment models together.

4.1 DICE Model

General Information

The Dynamic Integrated model of Climate and the Economy (DICE) is a global general equilibrium model created by William Nordhaus without any disaggregation, or only one region. With original versions documented in 1992, there have been several updates to the model as additional research has been done throughout the past quarter century. The most recent version is the 2016 update. DICE is primarily based on a neoclassical economic growth model, similar to work by Frank Ramsey and Robert Solow. In a simple multi-period version of neoclassical growth, a firm or a social planner might choose to take some portion of the labor force away from production and assign them to do research and development. Research would lead to the discovery or invention of new technologies which increases the efficiency of production. Investing in research and development reduces consumption today but increases consumption in future periods. If the society is forward-looking, it will be beneficial to sacrifice some happiness today for additional prosperity in the future.

Nordhaus addresses the climate system like a "natural capital" where reducing GHG concentrations reduce damages and lead to higher levels of consumption in the future. Like research and development generally, it is therefore beneficial to invest in climate change mitigation in order to improve the future wellbeing of society (Nordhaus & Sztorc, 2013). The economic variables are standard to neoclassical economics with adjustments made to account for climate feedback. For example, production has additional components that account for damages and abatement costs, reducing the amount of output that can be apportioned to consumption or traditional economic investment (Nordhaus & Sztorc, 2013).

The climate system depicted by DICE focuses only on CO_2, taking other greenhouse gases to be exogenous (or possibly, controlled through outside means such as the Montreal Protocol for CFCs). It is based on a three-reservoir model which tracks carbon accumulation in the atmosphere, upper oceans, and in the deep ocean. This model uses an equilibrium climate sensitivity measure of 3.1 °C per equilibrium CO_2 doubling (Nordhaus, 2017a). DICE also has a regional model variation called RICE (Regional Integrated model of Climate and the Economy), which divides the global equilibrium into 12 subregions, each having their own values for each variable. This can be very helpful for other applications, such as policy analysis, but this study will focus on the better known and documented DICE model (Nordhaus & Sztorc, 2013).

With a model that has had so many different iterations, it is worthwhile to note that different versions of the same model may produce a wide variety of results. Between the 2013 and 2016 revisions to the DICE model, updates were made to the estimation of damages, projected future population, equilibrium climate sensitivity, and major updates to the representations of economic activity and the carbon cycle. These updates caused many output variables to change drastically, such as the SCC which increased by 80% (Nordhaus, 2017a). While an 80% change may be surprising, the five named modifications account for the vast majority of output changes. These adjustments are all reasonable updates that have been made to increase the accuracy of the DICE model as new research is completed in the many areas spanned by the IAM.

Nordhaus (2017b) published an analysis of the changes in DICE from 1992 to the most recent model from 2016, and the differences are even more significant. Estimates of the global output in 2100 have increased to 3½ times the 1992 prediction. The estimate of the social cost of carbon in 2015 increased from $5 in DICE1992 to $31 per ton of CO_2 in the most recent iteration. The most major revisions throughout this period were to the economic components of the IAM, such as the damage function, utility function, and measurements of output. Most environmental variables, such as emissions, temperature change, or CO_2 concentrations, have not seen major changes in their predictions. In the conclusion to this paper, Nordhaus discusses the importance of studying the uncertainty of IAM predictions alongside the results themselves (Nordhaus, 2017b).

Major Studies and Critiques

DICE is a prominent integrated assessment model that has been useful both in the literature on the economics of climate change as well as in reference for government and policy makers. Unsurprisingly, the model has been referenced countless times in the literature and is central to many studies that seek to create extensions, provide adjustments, or check the robustness of the model. Often, modifications to DICE are used to critique the model by illustrating its sensitivity to some change that the authors wish to advocate for. One example of this is Ackerman and Finlayson (2006). This article modifies DICE with an adjusted lower discount rate, reduced assumptions of the benefits of moderate warming, and more considerations for the most recent (at the time) climate science, resulting in a much higher social cost of carbon. Many critique articles of this type have been written and have likely been heard throughout the numerous revisions to the DICE model.

A few studies have examined the role of uncertainty in the outputs of the DICE model. One of these studies is by Hu et al. (2012), which uses normal distributions to model each of the eight main uncertain parameters in DICE. By assessing policy proposals in relation to this method, Hu et al. conclude very similar results to Nordhaus' (2013, for example) direct work with DICE. Crost and Traeger (2011) use a modified recursive version of DICE to examine the impacts of risk and uncertainty within the model. Cai et al. (2013) investigate a more formal stochastic extension of DICE called DSICE to determine how much uncertainty effects the outcomes described in the original model. Both studies conclude that DICE2007 may understate the potential costs of climate change due to uncertainty, or put differently, understate the benefits of mitigation as a result of input uncertainty. It is possible that some of this was made up for by the upward revisions of the SCC for DICE2016, but the overall conclusion is still important. There is room for additional research on how uncertainty effects the relevant results in IAMs such as DICE.

4.2 FUND Model

General Information

The Climate Framework for Uncertainty, Negotiation and Distribution (FUND) is an integrated assessment model that focuses on specific areas of welfare impacts across 16 regions of the world. The model was originally created by Richard Tol and is now co-developed by David Anthoff as well as Tol. The current version, FUND 3.9, is operated using the programming language Julia and its code is available in an open-source format. Different from the DICE model, the economic components of FUND are based on exogenous scenarios. This means that rather than defining functions to model economic growth and related measures, FUND uses predetermined values that are fed into the rest of the model. There are five economic scenario sets with varying population growth rates and economic growth rates for each region by year (Anthoff & Tol, 2010). These exogenous scenarios are based on standard scenarios used by the IPCC, the Intergovernmental Panel on Climate Change, as described by Leggett et al. (1992). While data for these scenarios are thoroughly researched, they remain constant assumptions and may not be as dynamic as the endogenous economic modules in other IAMs. Specifically, FUND makes exogenous assumptions about population growth rates, economic growth, energy efficiency, and the rate of change of the carbon intensity of energy use. The central scenarios of FUND are not automatically updated as new research estimates are made (Waldhoff et al., 2014).

One of the most unique features of FUND is the level of detail regarding the welfare impacts of climate change. Among other topics, the model addresses changes in agriculture, effects of sea level rise, increases in extreme weather, and changes to morbidity rates due to specific prevalent diseases. For each of its regions, FUND tracks and predicts rates of dengue fever, malaria, and diarrhea, as well as cardiovascular and respiratory disorders caused by the changing climate. It uses these predictions to model the incidence of premature deaths and shocks due to climate migration (Anthoff & Tol, 2010). All of these welfare effects set FUND apart from similar models by having useful insights into the true impacts of future climate change on humanity.

The agricultural module within the FUND model is known for its treatment of carbon fertilization on crop yields and how this changes the resulting social cost of carbon. Because plants take in CO_2 from the air during photosynthesis, higher concentrations of the greenhouse gas in the atmosphere are beneficial for world crop production. Plants, such as those cultivated by humans for sustenance, grow more quickly and can ultimately produce more food (McGrath & Lobell, 2013; Reiny, 2016). Holding all other effects constant, more CO_2 in the atmosphere leads to greater food production and increased welfare across humanity, particularly for subsistence economies that rely heavily on seasonal yields. In the FUND model, climate change produces a strong net benefit in agricultural sectors for this very reason. Compared to other concurrent climate change impacts, it is unclear whether this effect would dominate. Waldhoff et al. (2014) find that the inclusion of this effect in the FUND model has a substantial impact on SCC results for the model as a whole.

Major Studies and Critiques

The authors have used their FUND model to test and research many topics related to the economics of climate change since the IAM's creation. These include dozens of papers written with contributions by Anthoff and/or Tol and cover important ideas such as changes to the discount rate, equity weighting, and uncertainty. Using an earlier version of the same model, FUND 2.8, Guo et al. (2006) study the effects of using a declining discount rate in addressing policy decisions. The literature posits that a constant discount rate may apply well for individuals but does not consider future generations. By "over-discounting" with a constant discount factor, models may greatly undervalue the welfare of future generations, a substantial problem for integrated assessment models due to their longer time horizons (Weitzman, 1998). The results of their study found that applying this type of discounting does in fact increase estimates of the SCC, in some cases by as much as 40 times (Guo et al., 2006).

Equity weighting is a similar type of suggestion often applied to IAMs. When comparing the welfare across a large group of people the way the FUND model does, equity and income/wealth disparity are important topics to address. The properties of decreasing marginal utility mathematically model this by showing how the same absolute increase or decrease in income creates a much larger welfare change for a poor person than a rich person. Equity weighting is one way to account for the damage inequality not addressed by traditional methods of summing up welfare to compare climate change scenarios. This is especially significant because climate change is expected to have the worst effects in the poorest regions of the world. Anthoff et al. (2009) test the effects of equity weighting within the FUND model. This study shows that calculating the damages of climate change is significantly impacted by the use of equity weighting and its specifications, and thus it is an important topic to better model and understand (Anthoff et al., 2009).

Anthoff and Tol (2013) have also studied uncertainty in relation to their FUND model. Using FUND 3.7, the authors investigate the effects that parametric uncertainty have on the estimated social cost of carbon. They find that the most important uncertain parameters are energy demand due to climate change and the equilibrium climate sensitivity, the latter of which is addressed in the present study (Anthoff & Tol, 2013). The importance of equilibrium climate sensitivity is also notable because it can affect how the model reacts to changes in other parameters synergistically. For example, Dayaratna et al. (2020) cite studies with a very low climate sensitivity parameter. In combination with an increased rate of agricultural productivity gains, the authors find SCC estimates using FUND 3.8 to be low or even negative up to the year 2050 (Dayaratna et al., 2020).

The FUND model is known for estimating the SCC to be lower than most other prominent integrated assessment models. Ackerman and Munitz (2012; 2016) provide research and critiques on the FUND model, pointing out certain aspects that contribute to its low SCC estimates. As of FUND 3.5, many modules of the IAM were still relying on older research which may understate the costs of certain climate impacts. The authors show that FUND finds extreme weather events and sea level rise to be negligible to the calculation of the SCC. In addition, some mathematical damage corrections could raise the estimated SCC by nearly a factor of three (Ackerman & Munitz, 2012). Similar results were found using a more recent version of the model, FUND 3.8. In this study, 12 out of the 15 damage categories showed nearly insignificant costs. In addition, carbon fertilization plays a very large role in offsetting climate damages and reducing the SCC, primarily from the assumed productivity benefits in China. The authors also critique FUND's assessment of adaptation reducing vulnerability to climate impacts over time (Ackerman & Munitz, 2016).

4.3 PAGE Model

General Information

The Policy Analysis of the Greenhouse Effect (PAGE) model is another well-established integrated assessment model. It was originally developed in 1993 by Chris Hope and was updated several times before reaching its current version, PAGE09. This IAM disaggregates the world into 8 regions with a timespan from 2008 to 2200. It models the emissions and climatic effects of four greenhouse gases, CO2, CH4, N2O, and a grouping called Linear Gases (dubbed 'linear' because of their relationship between concentrations and radiative forcing). (Moore et al., 2018). Like the FUND model, PAGE uses exogenous inputs for some of the economic factors of its model, such as economic growth, emissions growth, and population growth. Damages are modelled across four categories, including market damages, nonmarket damages, sea level rise, and discontinuous impacts, which include tipping point scenarios (Hope, n.d.). The IAM is more policy focused than others by seeking to match and respond to data put out by international policy organizations. Specifically, the PAGE model is closely aligned with the science coming out of the Intergovernmental Panel on Climate Change. Most of its exogenous parameters and inputs come from IPCC reports and baseline scenarios (Hope, 2006; Hope & Alberth, 2007).

Compared to other major IAMs, PAGE estimates damages and the SCC to be relatively high. The most recent iteration of the model calculates the SCC in 2009 to be around $100. While this is much larger of an estimate than some other climate-economy models, some of the discrepancy is explained by a difference in discount rate. This model uses a discount rate near 1%, while the Nordhaus model uses 2%. If the PAGE model used the same discount rate as the DICE model, resulting SCC calculations would be quite similar (Hope, 2011).

Updates and changes to the PAGE model are well documented. Particularly because of the widespread use of the former PAGE2002, Hope (2013) describes the specific adjustments that were made to create the current PAGE09. One of the major changes was the adoption of a different exogenous scenario, the IPCC scenario A1B. This consists of different socioeconomic variables that are most favored by the policymaking institution. Instead of directly using a climate sensitivity parameter, PAGE09 uses a transient climate response value with a warming half-life variable to calculate climate sensitivity within the model. Though this does not change the baseline value for climate sensitivity, it allows for a larger right tail probability which more accurately reflects the current scientific understanding (Hope, 2013, 2011). This update also decreased the rate of adaptation in response to critiques that it was too optimistic. In total, the changes from 2002 to 2009 increased the social cost of carbon by around $25 (Hope, 2013).

Major Studies and Critiques

Hope has been involved in many studies using the PAGE model, especially after the IAM became well known in 2006. One significant paper investigates the sensitivities of the 2002 model, finding that the SCC calculation reacts the most to the climate sensitivity parameter and the choice of PTP (discount) rate. It is also sensitive to parameters for non-economic impacts and equity weighting, as well as the half-life of global warming (Hope & Newbery, 2008). This paper also shows how the social cost of carbon is less responsive to changes in emissions growth than purely economic or purely scientific models would suggest. Through the interactions of nonlinear warming, discounting over time, and other factors, the resulting SCC does not change very much in different emissions scenarios (Hope & Newbery, 2008). Still using the 2002 version of the PAGE model, Hope (2008) follows the study of SCC sensitivities by analyzing the effects of equity weighting. As discussed previously, equity weights are a way to address the inequality of climate damages based on wealth. Due to decreasing marginal utility, a dollar is much more valuable to a poor person than a rich person. It follows that climate costs will be more impactful in poor communities, especially because climate change is expected to have the worst effects in the poorest regions of the world. Surprisingly, analysis of the PAGE model finds that the social cost of carbon has a negative relationship with equity weights. Using equity weights in this model effects the application of discount rates, which leads to an offsetting change in the SCC. The increase in cost from using equity weights is smaller than the impact of discounting (Hope, 2008).

After the update to PAGE 2009, another unique study used the model to show how the social cost of carbon changes based on the length of the time horizon. Some IAMs model the climate and economy to the year 2100 while others extend for another 100 years or more. Determining the SCC requires what is essentially a net present value calculation, and so adding several years of data may change the result. The authors show this result and use it to argue for a consensus time horizon across other IAMs, near either 200 or 300 years (Wong et al., 2015). The PAGE model has also been used to bring attention to some of the more impactful tipping point scenarios. One of these is the melting of arctic permafrost. Some researchers have shown positive effects, such as the benefits to global trade by opening shipping routes and the potential for untapped oil and gas reserves (Whiteman et al., 2013). Despite these, multiple studies have used the PAGE model to show that the melting of arctic permafrost could have dire global consequences. Permafrost soils in the East Siberian Arctic Shelf are estimated to contain around 50 gigatonnes of methane and 1700 gigatonnes of carbon. It is unknown whether this permafrost will melt slowly as the global temperature rises or all at once (Whiteman et al., 2013; Hope & Schaefer, 2016). A study using the PAGE model and IPCC emissions scenario A1B estimated the potential impact of the carbon dioxide and methane released from arctic permafrost to have a net present cost of $43 trillion. These emissions would increase the global mean temperature by 0.17°C, leading to higher damages across the world. In addition, there would be a higher likelihood of other tipping point events, such as the melting of the Greenland ice sheet or the West Antarctic ice sheet (Hope & Schaefer, 2016).

In addition to the numerous analyses already mentioned, one of the most well-known economic studies of climate change is closely associated with the PAGE model. This study is the Stern Review. Sir Nicholas Stern, then Head of the Government Economic Service in the UK and Advisor to the British Government on the economics of climate change, was commissioned to do an independent review on the economics of climate change. Stern and his team used the PAGE integrated assessment model as the basis for their analysis. The final report was over 550 pages and was released in October 2006 (Stern, 2007). The Stern Review was one of the first major studies to recommend immediate and drastic measures to mitigate the effects of climate change and it received widespread attention, both in the form of praise and scrutiny. The viral nature of the Review led to sharp critiques, ranging from general denial of anthropogenic climate change to specific disagreements about the input parameters used to get their results (Carter et al., 2006). One of the most substantial arguments against the methodology of the Stern Review is the choice of discount rate. While PAGE selected its PTP rate, a component of the discount rate, to be 2% in baseline scenarios, Stern used a value of 0.1%. This resulted in a much lower discount rate in the model (Hope & Alberth, 2007). A low discount rate for an individual means that they generally value the future more and weight utility then similar to utility now. A high discount rate is the opposite; the future is less valuable to them and they greatly prefer utility now. Costs due to climate change are expected to increase over time, and a high discount rate lowers the valuation of those costs. Stern's use of a particularly low PTP rate led many to claim that his research greatly exaggerated climate damage costs (Carter et al., 2006).

As some of the controversy over the Stern Review led back to the model it relied on, PAGE2002 underwent many revisions and sensitivity analyses shortly after the Review was published. This model helped researchers to actually check the claims both for and against Stern's conclusions. Ackerman et al. (2009) studied the results of the Stern Review along with the most recent climate and economic science in order to revise the PAGE model. This group of researchers found several adjustments to make, such as relaxing the optimistic values for adaptation costs and modifying the shape of the damage functions. Scientists now know a little more about the likelihood of certain catastrophic tipping points, and so the thresholds for these were also changed to reflect recent research. As a result, the PAGE model determined that the Stern Review may have underestimated the true future damage costs from climate change. The updated PAGE2002 found damages in 2100 to be as high as 2.6% of GDP in the United States and 10.8% of total GDP in the world (Ackerman et al., 2009).

4.4 Synthesis Studies

The best-known IAMs have a plethora of works and analyses – including critiques – in the literature. Peer review and a diversity of insights have led to refined and further improved models over time. Integrated assessment models are certainly a place for continuous research and advancement to better understand the impacts of global climate change. While the literature related to individual well-known models has expanded over time, there remains one area that has received limited attention. Among all of the prominent integrated assessment models used today, few have studied the benefits of choosing one model over another. If, for example, the results in the FUND model hinged on the equilibrium climate sensitivity being within a narrow range of values while DICE did not, it would be beneficial to run a scenario with a very high ECS on the DICE model instead of FUND. Otherwise, the results might not be valuable. It could also be true that the choice of such parameters has a far greater impact than the choice of IAM. When making policies based on the results that come from these models, it is imperative that they are not misunderstood. One of the ways to prevent this is through analysis of integrated assessment models collectively, not just individually. There are a handful of papers that compare multiple models or address further research related to IAMs as a whole.

It is first worthwhile to address some of the analyses of integrated assessment models that focus on their limitations. Negatively connotated research is legitimate, and it offers insights into the most productive ways to improve upon the models of today. One of the critiques of IAMs in general addresses the lack of precision and abundance of uncertainty in their forecasted outcomes. Robert Pindyck (2013) concludes in his research that the models "are of little or no value for evaluating alternative climate change policies and evaluating the SCC." Part of his support for this vivid argument is the degree to which outcomes can be affected by a potentially "arbitrary" choice of input parameters. In addition to this, Pindyck finds that modelers do not know enough about damage functions or the likelihood of catastrophic outcomes to come up with reliable estimates of costs (Pindyck, 2013). Despite the claims against the usefulness of IAMs, the author writes that he does not suggest ignoring the climate issue altogether out of uncertainty. He even goes so far as to recommend using the US Interagency Working Group's estimate of $33, a value for the SCC found by using several integrated assessment models, as a baseline SCC for policymaking (Pindyck, 2013). This shows that Pindyck's goal in this paper is not to discredit IAMs, but rather to demonstrate the need for improvement. If researchers focus more efforts on the factors that make these models less reliable, they could soon become nearly as precise as they sometimes appear. The more climate scientists learn about how the Earth responds to temperature increases and the more economists learn about how to correctly model these climate damages, the more precise the leading integrated assessment models will become.

A 2014 paper by Bonen et al. goes into some depth on one area pointed out by Pindyck, the damage functions. This paper is meant to shed light on the damage functions used in the DICE, FUND, and PAGE integrated assessment models. Bonen et al. (2014) explain, in detail, just how each model portrays climate damages and how this relates to the calculation of the social cost of carbon. This determines which features may be more or less reliable than others. For example, the FUND model's use of the willingness-to-pay approach is found to create downward bias in the SCC calculation. The authors conclude by calling for several improvements in damage functions of IAMs, including a method which accounts for nonlinear climatic tipping point scenarios (Bonen et al., 2014). In a similar style, Alex Marten (2011) shows the limitations of the same three models in their temperature response specifications.

Marten finds that the function(s) used to model temperature response have a significant impact on the SCC outcomes of each model by comparing the temperature responses to two more detailed models meant to accurately represent the diffusion of energy in the deep oceans. These errors occur most commonly with high values for the equilibrium climate sensitivity parameter (Marten, 2011). In this study, it is determined that FUND underestimates the SCC by 10-75%, while DICE overestimates by 10-110% and PAGE by 40-260%. Marten suggests that these models update their models to reflect the most recent climate research on temperature response. Though IAMs cannot use the most complex models for each component due to computational costs, the author suggests that these changes are necessary and achievable because of technological improvements in computing power (Marten, 2011).

Diverging from analyses of a single component of several IAMs, one could also look at the entire group of uncertain inputs and seek to understand which are most impactful. A study by Anderson et al. (2014) takes this approach by analyzing uncertainty in the DICE model. There are several controversial input parameters in integrated assessment models that must be chosen at the discretion of the modeler, but in some cases, not knowing much about the correct value to select has no bearing on the model's outcome. A global sensitivity analysis is a way to determine the most relevant uncertainties. The authors' results are primarily meant to emphasize the importance of this type of analysis for IAMs. Sensitivity studies such as this one can establish a deeper understanding of these integrated assessment models and provide a path forward with which to focus further research (Anderson et al., 2014).

One of the only studies to conduct global sensitivity analyses across multiple integrated assessment models is the Rose et al. paper (2017). This study breaks down the components of the DICE, FUND, and PAGE models in order to study their similarities and differences. The authors determined the key drivers of model variation and how these affected resulting SCC estimations. The FUND model was found to have a lower incremental response to temperature and damage than DICE and PAGE. DICE was most sensitive to emissions, while PAGE was most sensitive to equilibrium climate sensitivity and temperature (Rose et al., 2017). The authors show that uncertainty causes PAGE to have the largest spread of calculations and a higher probability of catastrophic outcomes, while DICE and FUND have less spread. The temperature and damage response in FUND is partially responsible for its low estimation of the SCC relative to the others. To define uncertainty in these models more concretely, the authors recommend future researchers work to define distributions for input parameters. Doing so would facilitate a method for explicitly defining sensitivity to uncertain parameters in IAMs. This is strongly encouraged by the authors as a way of furthering the work of integrated assessment modeling and the economic study of climate change (Rose et al., 2017).

The literature surrounding integrated assessment models is growing quickly around the most prominent IAMs but lacks in cross-model comparisons and analyses. The studies that have been done on these three models or IAMs in general reveal the need for much more research and understanding. While these models do not create precise forecasts of the future climate-economy, they are still instructive as modelers continue to adjust to the newest research developments. One major step in this direction is through uncertainty analysis. The knowledge of which uncertain parameters are most influential in integrated assessment models allows researchers to concentrate efforts on understanding these factors. This in turn can make IAMs more accurate and increasingly beneficial for policymaking. The method of quantifying uncertainty for key input parameters as suggested by Rose et al. (2017) is the subject of the remainder of this paper.

Chapter 5

Methodology

5.1 Purpose and Models Included

The overall goal of this research is to study the effect of uncertain input parameters on estimates of the social cost of carbon within well-established integrated assessment models. While there has been plenty of debate surrounding choices of the discount rate, clearly a significant factor in net present value calculations, this parameter is primarily determined by preferences and the objectives of the modeler (Stern, 2007; Hope & Alberth, 2007; Carter et al., 2006). Rather than discussing further the merits of a higher or lower discount rate, this paper seeks to elucidate the impacts of observable parameters on the SCC. There are many parametric values used as inputs for integrated assessment models, and their forward-looking nature produces considerable uncertainty in their forecasts. However, if varying one unknown parameter within its feasible domain produces nearly constant output results, the uncertainty in this parameter might not be very important. On the other hand, if varying a parameter just slightly changes the output by a lot, uncertainty in that parameter should become a much higher research priority.

This analysis involves three prominent integrated assessment models, DICE, FUND, and PAGE. These IAMs are among the most cited models in the literature and are the three main models used by the US Interagency Working Group for estimating the social cost of carbon (IWG, 2013). Each model includes the necessary exogenous parameters for this study and a full range of output values typical to integrated assessment models. These outputs include annual results for temperature, CO_2 emissions and concentrations, population, per capita consumption, economic output, damages, and the social cost of carbon. These three models have many distinctions, assessing different levels of global or regional aggregation, taking unique approaches to the economy, and differing in their models of climate damages. These details, as well as influential studies and critiques of each model are examined more fully in chapter 4.

DICE, FUND, and PAGE were also chosen for this analysis because of their accessibility. Each model has a complete open-source implementation in the Julia programming language, which can be freely accessed online. This makes it possible to run each model repeatedly with code and efficiently conduct sensitivity analyses. While these models are known to produce very different evaluations of the social cost of carbon, this study abstracts from these differences to assess within-model variations based on a grid of calibration runs for each IAM. The resulting outputs can be analyzed to determine the significance of changes in uncertain inputs on the specific outcome of the social cost of carbon. Due to the policy significance of SCC estimates, these results will be beneficial for directing future research and narrowing the focus on the actual social cost of carbon.

5.2 Primary Approach and Grid Design

The first portion of this analysis involves using all three integrated assessment models to produce a dataset of several important outputs by variations in input parameters and by model. In their Julia implementations, the command to run each model passes in an optional parameter designating which file or directory to read as inputs for the model. By creating copies of input files and editing the desired parameters, a model can be run with identical baseline values except for changes in a select number of inputs. Each uncertain parameter is given five values centered around the default value from the model's baseline scenario. The baseline scenarios are reliable for assessment because they are thoroughly scrutinized and checked by peer-reviewers as well as organizations like the Stanford Energy Modeling Forum and the IPCC (Gillingham et al., 2018). Therefore, each model's baseline scenario is a dependable standard upon which to conduct sensitivity tests. Output values for each IAM are time-dependent, so this study measures results for temperature, CO_2 emissions and concentrations, population, per capita consumption, economic output, and damages as their respective values in 2100. The social cost of carbon is assessed as its value in 2020.

The grid design for this study was constructed to match the method used by Gillingham et al. (2018) in a similar sensitivity analysis of six IAMs. With a set of three uncertain parameters and five values per parameter, the complete domain for our study becomes $5 \times 5 \times 5 = 125$ individual calibration runs for every IAM. Increments for the parameter grid were chosen to span most of the probable parameter space without pushing too far into distribution tails as to create unreliable outcomes. The Gillingham et al. study analyzed distributions for all three uncertain parameters in order to determine the best choices for this parameter grid (2018). The authors found that the growth rates of both population and total factor productivity closely resemble normal distributions. The equilibrium climate sensitivity was well approximated by a log-normal distribution (Gillingham et al., 2018). The points for calibration runs are all derived from these approximate distributions and centered around the default scenarios. The adjustments to baseline values are treated identically for each model. When analyzing results for this study, it is important to recognize that there is more uncertainty surrounding some parameters compared to others. A change of 1% in total factor productivity is much more likely than a change of 1% in population growth, for example. Therefore, standard deviations of each parameter will be used to compare the impact of a consistent amount of uncertainty in each input. Research by Gillingham et al. (2018) found the standard deviations to be 1.12%, 0.22%, and 0.843 for total factor productivity growth, population growth, and climate sensitivity, respectively.

5.3 Choice of Uncertain Parameters

The uncertain parameters selected for this study are the growth rate of total factor productivity, the population growth rate, and the equilibrium climate sensitivity parameter. Gillingham et al. (2018) selected these same parameters for uncertainty analysis because they can be changed without significantly altering the mechanics of the models and because each uncertain parameter can be easily represented by an estimated probability distribution, which was another component of that study. These were also good choices because they represent some of the most important uncertainties in climate change economics. Per capita GDP growth impacts the total welfare for individuals in the world economy and is also related to emissions rates in the short run. Population growth affects energy and land use, migration, and has many other implications surrounding development and welfare. Equilibrium climate sensitivity determines the increase in temperature in response to emissions. Each of these has a large role in the impacts of climate change as well as the estimation of the social cost of carbon.

Total factor productivity (TFP) growth is the rate at which economic productivity grows over time. Not every economic growth model separates growth based on total factor productivity, but TFP is a major driver of the total growth rate. For these situations, the uncertain parameter was replaced with GDP growth. The grid for TFP growth first takes the baseline value for each model, and then makes four additional assumptions to create a five-point set for calibration runs. These adjustments add -1%, -0.5%, 0%, 0.5%, and 1% to the baseline value of TFP growth. If a model were to have a constant default GDP growth rate of 1.6%, the five values would become 0.6%, 1.1%, 1.6%, 2.1%, and 2.6%. The actual models included in this study do not have constant growth rates over time. All three models' baseline scenarios include an entire set of growth rates that vary by year and by region, if applicable. To create the calibration runs, the same values $(0\%, \pm 0.5\%, \pm 1\%)$ were added to each annual and regional growth value. Each default path of growth was shifted up or down by a constant amount for each assumption.

The population growth rates were treated similarly to the TFP growth rates. Each value was adjusted by adding -1%, -0.5%, 0%, 0.5%, or 1% to the baseline scenario to create a set of five different population growth paths. DICE, FUND, and PAGE all use non-constant population growth rates, so the values were adjusted individually for each time period and region. One intricacy for both growth rate adjustments is that the DICE model does not use annualized rates. This model runs in five-year timesteps and uses one rate to calculate the change between each period. To achieve consistency between analyses of all models, the assumptions were converted for the DICE model to adjustments of $\pm 5.101\%$ and $\pm 2.525\%$ to the baseline five-year rates. All modifications to baseline scenarios were only made to the period between 2010 and 2100 in order for transformations to be consistent across models. Population and TFP growth rates after 2100 (and before 2010, if applicable) are the same as the modeler's base scenario for every calibration run.

The equilibrium climate sensitivity (ECS) is a single parametric input to climate models that represents the increase in global temperature in response to a doubling of CO_2 (or CO_2-equivalent) in the Earth's atmosphere. It is also sometimes called the temperature sensitivity coefficient, or more simply, climate sensitivity. A high value of the ECS means that as emissions increase, temperature will increase by larger amounts, while a low ECS means emissions are not quite as potent. The grid of calibration runs for this parameter adds -3, -1.5, 0, 1.5, and 3 to the baseline value in each model. Note that this value represents the constant level, not a set of annual rates like previous uncertain parameters, so the assumptions create a set of five one-dimensional parameters for calibration runs. In the FUND model, the baseline value for the climate sensitivity is small enough to make the lowest assumption negative. This lowest value was replaced with 0.001 to produce similar results without violating assumptions in the mathematical components of the model which require a non-negative value.

5.4 Regression Specification

After collecting data by running each model using the three-dimensional grid of calibration runs, the next step is to evaluate the results. The impacts of parametric uncertainty on the social cost of carbon can be studied in general terms by determining a closely fitted model for the dataset. Gillingham et al. (2018) analyze several different regression specifications for modeling the impacts of the same uncertain parameters, focusing on outputs other than the social cost of carbon. They find that the ideal approach is a linear quadratic interactions, or LQI specification, because it produces a high R-squared value without becoming too complex or overfitted (Gillingham et al., 2018). The present study briefly assessed and confirmed that this model provides a strong fit for the data. Linear quadratic interactions takes the form:

$$Y = \alpha + \sum_{i=1}^{3} \beta_i x_i + \sum_{j=1}^{3} \sum_{i=1}^{j} \gamma_{ij} x_i x_j + \epsilon$$

In this model specification, Y represents an outcome variable such as the social cost of carbon. It would similarly represent temperature increase, CO_2 concentrations, climate damages, or another variable if these were the outcomes of interest. The uncertain parameters x_i and x_j are inputs to the model. The constants $\hat{\alpha}$, $\hat{\beta}_i$, and $\hat{\gamma}_{ij}$ are the estimators from regression. Subscripts for the model are suppressed. This specification states that the social cost of carbon is a function of each uncertain parameter individually, their squares, and interaction terms between each input. By expanding the equation, this specification could also be written as:

$$\widehat{SCC} = \hat{\alpha} + \hat{\beta}_1 TFP + \hat{\beta}_2 POP + \hat{\beta}_3 ECS + \hat{\gamma}_{1,1} TFP^2 + \hat{\gamma}_{2,1}(POP * TFP) + \hat{\gamma}_{2,2} POP^2$$
$$+ \hat{\gamma}_{3,1}(ECS * TFP) + \hat{\gamma}_{3,2}(ECS * POP) + \hat{\gamma}_{3,3} ECS^2$$

In this case, SCC is the social cost of carbon, TFP is the growth rate of total factor productivity, POP is the population growth rate, and ECS is the equilibrium climate sensitivity parameter. Separate regressions are completed for each model, thus controlling for other significant factors like the discount rate, which cause substantial differences in SCC results across models.

The dataset created for this analysis normalizes each uncertain parameter to its baseline values. This is done in order to study the impact of changes to each parameter rather than the specific values that the parameter takes on. With two parameters representing growth scenarios for 90 years, recording a single value for a nonconstant growth path is infeasible. Since constant adjustments were made for each calibration run, these delta values can be recorded and accurately represent the data. As such, setting a parameter in the regression equal to zero does not mean that this variable is actually zero. Instead, it means that the parameter is unchanged from its baseline state. This is useful for analyzing changes in one uncertainty at a time; setting two parameters to zero produces a quadratic equation for the SCC. This process also gives meaning to the constant term α, which is equal to the social cost of carbon when all parameters are zero. If all parameters are equal to their baseline scenarios, then $\hat{\alpha}$ is the estimated baseline SCC for that model.

Chapter 6

Results and Analysis

The LQI model specification fits the social cost of carbon results well, with a R-squared value that is greater than 0.96 for all three models, though it is important to note that this result is expected. The output SCC relies solely on the three chosen inputs by construction, so the only error in the model comes from the choice in model specification. A high R-squared result shows that the LQI model specification is a suitable choice. This chapter will present selected results from the regression analyses of each integrated assessment model. The reader is encouraged to reference the complete regression results, which are presented in Appendix B. Nearly all coefficients for the model are significant at a high level, with the exception of the quadratic term on total factor productivity growth. Linear terms, which tend to dominate the quadratic components of each parameter, move in the same direction for each IAM. The following analysis of each uncertain parameter takes the other two as given to create a simple quadratic model with one independent variable. This exercise is the equivalent of analyzing one uncertain parameter while setting the other parameters equal to zero, an action that is economically reasonable because the regressors are defined as changes from the baseline value.

In general, higher rates of total factor productivity growth lead to decreases in the social cost of carbon. Elevated population growth rates cause increases in the calculated SCC, and high values for the equilibrium climate sensitivity parameter also raise the social cost of carbon. There are differences in concavity across integrated assessment models. Sometimes, the effect of an uncertain parameter becomes stronger as it increases further. For other IAMs, the impact of the same parameter decreases as it grows. This can be inferred directly from the coefficients on the quadratic regressors. In analyzing the magnitude of each parameter's impacts on the SCC, this study weighs the extent of current uncertainty against the impact of a deviation from the baseline. Using the standard deviations referenced by Gillingham et al. (2018), uncertainty in the equilibrium climate sensitivity parameter is found to be the most influential on the social cost of carbon, though all three parameters impact the SCC calculation substantially.

6.1 Outcomes from the DICE Model

The regression for the DICE model has the best fit of the three IAMs, with an R-squared of 0.9745. All estimators are significant except for the squared term on total factor productivity growth, which is not found to be significantly different from zero. The baseline DICE model produces a social cost of carbon estimate of 24.51 dollars. By varying one uncertain parameter at a time and holding the other two constant at their predicted baseline values, the following estimates of the SCC are created using the DICE model:

$$\widehat{SCC}_{DICE} = 24.51 - 6.024 * TFP - 0.148 * TFP^2$$

$$\widehat{SCC}_{DICE} = 24.51 + 22.278 * POP + 8.573 * POP^2$$

$$\widehat{SCC}_{DICE} = 24.51 + 11.629 * ECS + 0.494 * ECS^2$$

If baseline predictions are accurate about population growth and climate sensitivity, then the impact of total factor productivity on the SCC is nearly linear. TFP growth that is higher than the baseline path by one standard deviation (1.12 percent per year) will reduce the social cost of carbon by 6.933 dollars, and if it is one standard deviation lower each year, the cost will increase by 6.561 dollars. In contrast, the population growth rate and the ECS have a positive correlation with the SCC estimate. Though the estimators are larger for population growth, the uncertainty is not as substantial, so one standard deviation (0.22 percent) in either direction affects the SCC slightly less for population growth than for TFP growth. The positive sign on the squared term indicates that larger increases in population growth over the baseline scenario increasingly inflate costs. This accurately reflects the expectation that significant warming of the atmosphere can lead to more catastrophic climate impacts in a nonlinear fashion. The equilibrium climate sensitivity parameter is much more potent than both TFP growth and population growth. If the current estimate of ECS is too low by one standard deviation (0.843), the true SCC would be 10.154 dollars larger than predicted by the baseline scenario. Uncertainty in equilibrium climate sensitivity in the DICE model, holding the other parameters constant, is the most impactful of the three uncertainties.

Both estimators for the interaction terms involving total factor productivity are negative and significant. The simplest conclusion to draw from this is that positive changes to population growth and the ECS reinforce movements in TFP growth. When population growth is high, an increase in TFP growth drops the SCC by even more and a decrease in TFP growth increases the SCC further. The same applies to larger than expected climate sensitivity parameters. However, low values for population growth and ECS lead to a smaller impact from changes to TFP growth. The estimator for the population growth and climate sensitivity interaction term is positive and highly significant. This can be described as a synergistic relationship. If both parameters are greater than expected, the growth in the social cost of carbon would be higher than the combined impact of each being increased separately. The opposite is true for low values of climate sensitivity and population growth. If these two uncertain parameters move in opposite directions, each limits the impact of the other.

6.2 Outcomes from the FUND Model

The regression for the FUND model is similarly well fit, producing an R-squared value of 0.9616. Like the DICE model, all estimators are statistically significant except for the squared term on TFP growth. The FUND model has a baseline social cost of carbon that is much lower than the DICE model, estimating the 2020 cost to be a relatively low 2.14 dollars. By varying one uncertain parameter at a time and holding the other two constant at their predicted baseline values, the following quadratic models are fit to predict the SCC in the FUND model:

$$\widehat{SCC}_{FUND} = 2.14 - 0.898 * TFP + 0.230 * TFP^2$$

$$\widehat{SCC}_{FUND} = 2.14 + 1.720 * POP + 0.711 * POP^2$$

$$\widehat{SCC}_{FUND} = 2.14 + 1.299 * ECS - 0.290 * ECS^2$$

With the assumption that population growth and climate sensitivity are equal to their baseline values, and thus zero in this model, total factor productivity has a negative relationship with the social cost of carbon. An increase in TFP growth reduces the SCC, but due to the positive coefficient on the squared term, there is a diminishing marginal benefit to high levels of growth. Population growth impacts the FUND model in the same way that it affects the DICE model. The quadratic model is positively sloped near zero and increasing faster for higher rates of population growth. The impact of uncertainty in climate sensitivity, all else equal, is similar to that of uncertainty in growth of total factor productivity, but with the opposite sign. A higher level of ECS increases the social cost of carbon but does so at a diminishing rate due to the negative quadratic term. This means the FUND model estimates that a lower climate sensitivity causes a more dramatic change than a higher value. As the ECS increases, it raises the social cost of carbon less and less per unit of sensitivity increase. The FUND model is known to value the agricultural benefits of high atmospheric carbon concentrations and increasing temperatures, but the existence of nonlinear and discontinuous damages suggests that these benefits would at some point be surpassed by the growing costs for high levels of ECS. The impact of potential climate tipping points at high levels of temperature anomaly further indicate that the model of equilibrium climate sensitivity should have a positive concavity. Increasing the climate sensitivity parameter above the baseline value should cause more extreme damages the more it is increased. The FUND model does not seem to do this, which may be a fault in its method of calculating damages. This observation is similar to other studies that have critiqued the calculation of damages in this integrated assessment model. It is possible that the same issues pointed out by Ackerman and Munitz (2012; 2016) are the root cause of the diminishing effect of high climate sensitivity. Even though the IAM might underestimate damages in response to high levels of the ECS, the uncertainties in total factor productivity and equilibrium climate sensitivity have the largest impacts on the FUND model's estimation of the social cost of carbon.

Estimators for all three interaction terms are significant and of the same sign as those in the DICE model results. Scenarios with higher levels of population growth and equilibrium climate sensitivity are reinforcing for TFP growth and make changes in this parameter more impactful. Low population growth and ECS lead to total factor productivity growth being less important in determining the SCC. These interaction estimators also mean that high levels of TFP growth make changes in population growth and climate sensitivity less significant, while low TFP growth reinforces the other two parameters. Population growth and equilibrium climate sensitivity once again are synergistic; their combined impact on the SCC increases when they both move in the same direction.

6.3 Outcomes from the PAGE Model

The LQI specification is a good fit for the PAGE model as well. The regression results in an R-squared value of 0.9606, just slightly below the FUND model's result. However, the model's estimators are not uniformly significant. All four coefficients for terms that include total factor productivity are found to not be statistically different from zero at a reasonably high level. This is particularly the case for the estimator for the quadratic term on TFP, which is to be expected after being the least significant value on the previous two models. PAGE produces the highest baseline estimate of the social cost of carbon, generating a value of 56.47 dollars. By varying one uncertain parameter at a time and holding the other two constant at their predicted baseline values, the following representations of the SCC are created using the PAGE model:

$$\widehat{SCC}_{PAGE} = 56.47 - 7.560 * TFP + 0.817 * TFP^2$$

$$\widehat{SCC}_{PAGE} = 56.47 + 133.357 * POP + 56.266 * POP^2$$

$$\widehat{SCC}_{PAGE} = 56.47 + 89.039 * ECS + 20.876 * ECS^2$$

Total factor productivity growth clearly has smaller estimators than population growth or climate sensitivity, but the overall effect of the parameter still moves in the expected direction. Much like the FUND model, a high level of TFP growth reduces the SCC, but by smaller amounts as it increases more. Population growth increases the social cost of carbon when it is higher than expected and reduces the cost when it is lower than expected. High levels of population growth have a particularly potent effect on the SCC. If the population growth rate is one standard deviation lower each year than predicted, the social cost of carbon will be 26.615 dollars lower. If population growth is one standard deviation larger than the baseline scenario, the cost increases by 32.062 dollars to 88.53. Despite the population growth having such a large effect on the social cost of carbon within the PAGE model, uncertainty in the equilibrium climate sensitivity parameter is more impactful. The ECS is increasing around zero and concave upward as expected. An increase in this uncertain parameter by one standard deviation, with the other two parameters set to their baseline values, increases the social cost of carbon to 146.37 dollars. According to the PAGE model, the climate sensitivity parameter is the most important uncertainty by a large margin.

All three interaction terms behave in the same fashion as in the other IAMs. Estimators for TFP's interactions with population growth and climate sensitivity are both negative so high values for these two parameters reinforce impacts of TFP growth while low values dampen them. High values for TFP growth reduce the effect of population growth changes and ECS changes, and low total factor productivity growth increases the impact of population growth and climate sensitivity. It is important to note that these two interaction terms are relatively small and are not as significant as in other models, but they still move in the same direction. The estimated coefficient on the interaction term between population growth and equilibrium climate sensitivity is 66.055, a value that is significant and comparable to the values found in the analysis of both DICE and FUND models. This supports the conclusion that population growth and ECS reinforce each other in their impacts on the social cost of carbon, raising it dramatically when they are both above baseline scenarios and reducing it more quickly when they are both low.

6.4 Discussion

Many of the results found in this study support expectations of how the social cost of carbon would behave in response to changes in the three uncertain parameters. In general, high rates of TFP growth lead to greater welfare in the future, welfare that can theoretically be used to offset costs from climate change. If society has more wealth, some of it can be spent on adaptation to high temperatures or rising sea levels. Some of this wealth could also potentially be redistributed to those who experience the highest costs, creating the potential for Pareto improvements in response to total factor productivity growth. In theory, high TFP growth should lower costs, but looking at past data may appear to indicate the opposite relationship. Rates of economic growth and greenhouse gas emissions growth have both grown exponentially. However, economic growth is not coupled with emissions growth in the long run. This is particularly the case because of total factor productivity growth, which is sometimes described as improvements in technology. Such technological advancements are why mitigating climate change does not require stunting economic growth. By these arguments, it should be expected that higher rates of TFP growth will cause the SCC to decrease, and vice versa.

Similarly, logic would suggest that high rates of population growth increase the costs of climate change. Many of the densely populated regions of the planet are near coastlines, places that are most at risk to sea level rise and extreme weather events like hurricanes. Poorer populations tend to have higher fertility rates, so increased population growth might unequally impact these regions and groups who do not have the means for as much climate change adaptation. In a general sense, high rates of population growth means that there will be more people, and so the same effects of climate change will impact more humans. This suggests that population growth will be positively associated with the social cost of carbon. The logical connection between costs and the equilibrium climate sensitivity parameter is even more straightforward. ECS represents the amount of global temperature increase for a doubling of carbon dioxide in the atmosphere. Given a single level of greenhouse gas emissions, this parameter determines how much hotter the planet gets in response. For the most part, higher temperatures will have a negative impact, leading to higher sea levels, increases in extreme weather, and many other types of climate damages. A large value for the ECS leads to a higher temperature, which leads to more damages. Thus, changes in climate sensitivity should be positively associated with the social cost of carbon.

Across all three IAMs, the sign of the relationship between each uncertain parameter and the social cost of carbon was the same, matching the expected result. For population growth, each model also produced the same concavity. Changes in the population growth rate caused more extreme increases in the SCC as they moved further from the baseline population growth scenario, regardless of which integrated assessment model is analyzed. The concavity was more ambiguous for total factor productivity growth. Two models showed a positive coefficient on the quadratic term, while one IAM had a negative one. All three coefficients were found to not be statistically different from zero, so it is possible that the relationship between total factor productivity and the social cost of carbon is nearly linear. Otherwise, a larger sample size might lead to more consistent and significant results. In fitting a quadratic approximation to the effect of the ECS, the models were again split between a positive and negative concavity. In this case, however, there is strong theoretical support for the relationship to have a positive second derivative. As pointed out in section 6.2 and described in detail in Chapter 2, higher temperatures are expected to cause damages at increasing rates. There are many climate feedback systems in which temperature increases cause further emissions and subsequently amplify the existing climate change. Scientists also understand there to be several major tipping points regarding climate change where passing an unknown threshold leads to a significant increase in costs, often irreversibly so. The DICE and PAGE models both found this to be the case in our analysis, but the FUND model did not.

The dissimilarity of the FUND model from other IAMs in this case becomes one of the most noteworthy consequences of this study. In all likelihood, FUND's misrepresentation of social cost of carbon sensitivity to the ECS parameter is a result of faulty calculations of climate damages. The FUND model, which has already been criticized for over-discounting and producing too low an estimate for the social cost of carbon (Guo et al., 2006; Weitzman, 1998), may not be correctly calculating damages in the first place before any discounting. The present study provides supporting evidence for the arguments of Ackerman and Munitz (2012; 2016), who found that many of the damages categories within the FUND model produced particularly small cost estimates. If damages in several relevant categories like sea level rise and extreme weather are overshadowed by benefits in the agricultural category, then increases in global temperature could show limited changes to the social cost of carbon where they should show increasing impacts. Regardless of how carbon fertilization is expected to impact the agricultural sector, nonlinearities in climate damages through feedbacks and tipping points should increase in magnitude faster than the former benefit. A negative quadratic coefficient on the equilibrium climate sensitivity parameter does not accurately reflect the current state of scientific knowledge and theory about the impacts of future climate change.

6.5 Application for Climate Change Research

This study finds two major results that affect the need for future research on the economics of climate change. The first is a potential inaccuracy in the FUND model's calculation of damages as described above. This integrated assessment model is integral to the study of climate change and is referenced by the IPCC and the US IWG for research on the social cost of carbon. Therefore, the model needs to be continually updated to reflect recent research and critiques in order to most accurately reflect economists' best forecasts of future climate change. Specifically, further research into the IAM's damages components could determine where the model can be adjusted to increase the plausibility of its calculations. A more accurate damages model would heed the suggestions made by Ackerman and Munitz (2012; 2016) and be able to produce a social cost of carbon with a positive slope and concavity near the baseline scenario.

In addition, our sensitivity analysis found that the equilibrium climate sensitivity parameter is the most important uncertain input of the three in determining the social cost of carbon. Variation due to uncertainty in the ECS leads to larger changes in the SCC than variation in the growth rates of both total factor productivity and population. Of course, any reduction in uncertainty will increase the accuracy of the social cost of carbon calculation. This analysis finds that the marginal benefit of uncertainty reduction is largest with respect to climate sensitivity. If researchers were to focus on this problem with more intensity, future calculations of the SCC would become more accurate at a faster rate. The uncertainty in total factor productivity may have the second-most room for improvement, but at this point it is worth clarifying that the uncertainty in all three chosen parameters is quite significant and relevant to the social cost of carbon. Limiting the uncertainty in social cost of carbon estimates helps policymakers to focus in on a feasible range of true social costs upon which to create policies for climate change mitigation. The ultimate purpose of integrated assessment modeling is to serve policymakers and mitigate the impacts of future climate change, so making adjustments with this goal in mind is conscientious and welfare-improving for both current and future generations.

Chapter 7

Conclusion

Uncertainty is one of the most significant issues faced by economists when modeling climate change. There have been relatively few studies on the effects of parametric uncertainty on integrated assessment models. This analysis aims to build upon the work by Gillingham et al. (2018) to explore uncertainty and its effects on the calculation of the social cost of carbon within integrated assessment models. Beginning from a background description of the processes and impacts of climate change, this paper has demonstrated the importance of integrated assessment modeling as a means for quantifying the costs of climate change and comparing the implications of mitigation policies. Government and international policymaking organizations such as the IPCC rely on integrated assessment models for their climate change assessments. One of the major issues with IAMs is the uncertainty involved in their calculations. These models rely upon many simplifying assumptions which make the models bounded and solvable, but some of which also introduce uncertainty to the results. One of the primary goals of this paper is to seek out the most influential uncertainties among three major integrated assessment models, DICE, FUND, and PAGE.

By creating a three-dimensional grid of calibration runs for each IAM, this study has modeled the impacts of total factor productivity growth, population growth, and the equilibrium climate sensitivity parameter. The findings include some intuitive results, such as the overall direction of the relationship between each parameter and the social cost of carbon. Key results include a critique of the FUND model and the determination of the ECS parameter as the more impactful uncertainty across all three IAMs. The quadratic fit to the climate sensitivity parameter in FUND is found to be concave downward when there is significant theoretical support for a positive second derivative. The model does not seem to accurately represent nonlinearities in climate damages or the increased likelihood of catastrophic tipping point events given high temperature increases, which would indicate that a quadratic representation of the data should be concave upward. The DICE and PAGE models follow this expected trend. This assessment of the FUND model supports other critiques of the damages module in the IAM, described by Ackerman and Munitz (2012; 2016).

By comparing regression results normalized by pre-determined distributions for each uncertain parameter, this paper shows that uncertainty in the climate sensitivity parameter has a larger impact per standard deviation than the other two parameters. This result lends itself to a call for further research. The significance of the ECS on the social cost of carbon across three major integrated assessment models shows how crucial understanding of this climate feature is to accurately assess future warming and costs. At the same time, the uncertainties in all three parameters are substantial in regard to the SCC, so better understanding and forecasting their true values will prove invaluable for future analysis of climate change. This analysis has assessed significant uncertainties across three major integrated assessment models used to calculate the social cost of carbon. In doing so, this paper has contributed to the understanding of uncertainty in the economics of climate change and provided groundwork for future uncertainty analyses to come.

Appendix A

Definitions

Carbon Dioxide (CO_2) – A common gas which makes up the majority of greenhouse gas emissions. Global emissions are often calculated in terms of total CO_2-equivalent emissions instead of each GHG separately. This is referenced in the term “social cost of carbon.” [See Chapter 2, Section 1]

DICE Model – The Dynamic Integrated model of Climate and the Economy, an integrated assessment model created by William Nordhaus. DICE is known for estimating a middle-ground level of the social cost of carbon at $24.51 for the baseline scenario. [See Chapter 4, Section 1]

Discount Rate – The rate of interest used when calculating the present value of future earnings or costs. The discount rate is influential in calculating the social cost of carbon, where a high discount rate produces a lower estimate of the SCC. [See Chapter 2, Section 2]

Equilibrium Climate Sensitivity (ECS) – The increase in global temperature due to a doubling of carbon dioxide in the atmosphere. This is one of the key uncertain parameters in this study. [See Chapter 5, Section 3]

Externality – A positive or negative effect of an economic decision on an uninvolved third party, which is not considered as part of the decision maker’s judgement. Climate change is the negative externality of greenhouse gas emissions because the future damages and social costs of climate change are not accounted for in the emissions decision. [See Chapter 2, Section 2]

FUND Model – The Climate Framework for Uncertainty, Negotiation and Distribution, an integrated assessment model created by Richard Tol and co-developed by David Anthoff. FUND is known for estimating the social cost of carbon to be very low, at $2.14 in the baseline scenario. [See Chapter 4, Section 2]

Integrated Assessment Model (IAM) – Complex mathematical models that scientists and economists use to study the effects of climate change. They combine models of energy systems, economic systems, and climate science to study climate change outcomes such as the social cost of carbon. Examples include DICE, FUND, and PAGE. [See Chapter 3, Section 1]

Intergovernmental Panel on Climate Change (IPCC) – International organization committed to assessing the "science of climate change, its impacts and future risks, and options for adaptation and mitigation." The IPCC released its fifth assessment report in 2013. [See Chapter 2]

PAGE Model – The Policy Analysis of the Greenhouse Effect, an integrated assessment model created by Chris Hope. PAGE is known for estimating a high value for the social cost of carbon, at $56.47 in the baseline scenario. [See Chapter 4, Section 3]

Social Cost of Carbon (SCC) – A calculation that estimates the marginal impact of an additional ton of carbon dioxide emissions (or equivalent) through climate change damages. This is the primary outcome variable studied in this analysis. [See Chapter 2, Section 2]

Stern Review – Famous report led by Sir Nicholas Stern near the end of 2006. This review used a very low discount rate and outcomes determined by the PAGE model. [See Chapter 4, Section 3]

Tipping Point – Nonlinear, unknown, and often dramatic impacts of climate change. Examples include the collapse of the Greenland ice sheet, melting of arctic permafrost, and a breakdown of major ocean currents. [See Chapter 2, Section 2]

Total Factor Productivity (TFP) – The rate at which economic productivity grows over time. This is one of the key uncertain parameters in this study. [See Chapter 5, Section 3]

Appendix B

Full Regression Results

The following results come from OLS regression analysis of the dataset created through the aforementioned calibration grid. These results are discussed in Chapter 6 but presented in full detail in this appendix. Each integrated assessment model is considered separately for analysis. Relative regression outcomes can be compared across models despite the exogenous differences in discount rates which cause each IAM to generate different relative values for the SCC. It is important to not directly compare coefficients across models, as each is starting from a different base-case social cost of carbon.

In each regression, the base scenario occurs when TFP, POP, and ECS are all set to zero. Then the SCC is equivalent to the constant coefficient at the bottom of each table. The three terms above the constant row represent the interaction terms in this analysis. Much like a single variable squared, the interaction terms measure the impact of two parameters multiplied together, searching for impacts of a parameter that differ in response to the levels of other parameters. The coefficient on each regressor represents the change in the social cost of carbon if that parameter were to increase by one, while holding all other regressors steady. Of course, this cannot easily be done with the variables in this regression because increasing TFP would also increase TFP^2, and possibly the $TFP{:}\,POP$ and $TFP{:}\,ECS$ as well. The standard error values reflect the uncertainty or potential error in each coefficient estimator. A regressor is most influential on the dependent variable when the standard error is small relative to the estimated coefficient.

The significance of each regressor is shown through the values in the last two columns. The T-statistic and the values under "$P > |t|$" are both interpreted as measures of significance in opposite ways. For a regressor to be considered statistically significant, the T-statistic should be large, usually greater than two in magnitude. On the other hand, the P value should be as small as possible, preferably less than 0.05. For this analysis, the significant regressors meet these criteria by a large margin so that the P values are displayed as 0.000. Analysis finds that TFP^2 is not significant for any of the three integrated assessment models. For the PAGE model, TFP, TFP^2, $TFP\!:POP$, and $TFP\!:ECS$ are all insignificant. All other regressors across each IAM are found to be statistically significant.

Table 1: Regression Results for DICE Model

Variable	Coefficient	Standard Error	T-statistic	$P > \|t\|$
$\boldsymbol{TFP}$	-6.024104	0.7030274	-8.57	0.000
$\boldsymbol{TFP^2}$	-0.1482225	1.188333	-0.12	0.901
$\boldsymbol{POP}$	22.27839	0.7030274	31.69	0.000
$\boldsymbol{POP^2}$	8.573349	1.188333	7.21	0.000
$\boldsymbol{ECS}$	11.62927	0.2343425	49.63	0.000
$\boldsymbol{ECS^2}$	0.4935531	0.132037	3.74	0.000
$\boldsymbol{TFP\!:POP}$	-5.616793	0.9942309	-5.65	0.000
$\boldsymbol{TFP\!:ECS}$	-2.306667	0.3314103	-6.96	0.000
$\boldsymbol{POP\!:ECS}$	8.829605	0.3314103	26.64	0.000
$\boldsymbol{Constant}$	24.5054	1.142902	21.44	0.000

Table 2: Regression Results for FUND Model

Variable	Coefficient	Standard Error	T-statistic	$P > \|t\|$
TFP	-0.8976221	0.0959679	-9.35	0.000
TFP^2	0.2304702	0.1622154	1.42	0.158
POP	1.720409	0.0959679	17.93	0.000
POP^2	0.7113182	0.1622154	4.39	0.000
ECS	1.298618	0.0319893	40.60	0.000
ECS^2	-0.290293	0.0180239	-16.11	0.000
$TFP:POP$	-0.8625371	0.1357192	-6.36	0.000
$TFP:ECS$	-0.5592701	0.0452397	-12.36	0.000
$POP:ECS$	0.8444657	0.0452397	18.67	0.000
$Constant$	2.144765	0.1560138	13.75	0.000

Table 3: Regression Results for PAGE Model

Variable	Coefficient	Standard Error	T-statistic	$P > \|t\|$
TFP	-7.559675	6.602651	-1.14	0.255
TFP^2	0.8173658	11.16052	0.07	0.942
POP	133.3574	6.602651	20.20	0.000
POP^2	56.26644	11.16052	5.04	0.000
ECS	89.03861	2.200884	40.46	0.000
ECS^2	20.87633	1.240057	16.83	0.000
$TFP:POP$	-8.182604	9.337558	-0.88	0.383
$TFP:ECS$	-3.718723	3.112519	-1.19	0.235
$POP:ECS$	66.05533	3.112519	21.22	0.000
$Constant$	56.47268	10.73384	5.26	0.000

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ACADEMIC VITA

Austin Morey

EDUCATION

The Pennsylvania State University **University Park, PA**
Schreyer Honors College August 2017 – May 2021
Bachelor of Science in Economics

- Modules Awarded: Human Resource and Public Economics; Macroeconomics, Money & Banking

Bachelor of Science in Mathematics, Systems Analysis option
Thesis: *Modeling Climate Change: Sensitivities of The Social Cost of Carbon Under Parametric Uncertainty*

RELEVANT SKILLS AND EXPERIENCE

Bates White Economic Consulting **Washington, DC**
Summer Consultant June – August 2020

- Contributed to multiple matters within the Environmental and Product Liability (EPL) Practice involving asbestos liability and mesothelioma incidence modeling
- Processed and cleaned data using Stata programming and updated Excel files for an internal database
- Collaborated with a team of interns on a price-fixing case study project which required data processing, analysis, a formal report, and a presentation to the firm
- Organized a firm-wide charity event with other interns, raising over $3400

The Pennsylvania State University **University Park, PA**
Undergraduate Student Researcher Spring 2020

- Funded by Bates White REU Program with the Department of Economics at Penn State University
- Worked with a faculty advisor to study survey design and public opinion on global climate change
- Constructed a survey for undergraduate students on the effects of personal experience on advocacy

The Pennsylvania State University **University Park, PA**
Undergraduate Student Researcher Spring 2019

- Funded by Bates White REU Program with the Department of Economics at Penn State University
- Analyzed vehicle list prices and transaction data from Cars.com and the Ohio D.O.T.
- Wrote Python code to process input files and simplify necessary data for future application

Programming and Data Skills: Microsoft Excel, Python, Stata, R, Matlab, Mathematica, Julia

WORK EXPERIENCE

Shipt, Inc. **Pearland, TX**
Shopper May – August 2019

- Served the community by shopping for and delivering groceries from a variety of local stores
- Interacted with customers throughout shopping and delivery process to ensure accuracy and promptness
- Operated as an independent contractor responsible for personal scheduling and workload

Designer Shoe Warehouse, Inc. **Pearland, TX**
Sales Associate May – August 2018
- Organized incoming freight and its timely transfer to the sales floor, marked down clearance items
- Interacted with customers and assisted in locating merchandise, utilized location systems

LEADERSHIP AND INVOLVEMENT

Penn State Blue Band **University Park, PA**
Guide and Squad Leader, Saxophone Section August 2017 – May 2021
- Led the 25-member saxophone section in the University's 300-member marching band
- Taught and demonstrated marching technique for new auditioning musicians
- Communicated with band staff and leadership regularly during four rehearsals each week
- Supported the football team at all home games and travel to additional away games, including bowl games in Phoenix, Orlando, and Dallas

Boy Scouts of America Troop 24 **Doylestown, PA**
Eagle Scout February 2016
- Presented a project proposal and final project review to troop executive board and district representative
- Planted 3 community gardens for endangered Monarch Butterflies, raised nearly $600
- Led troop of 70 boys in various roles such as Patrol Leader and Assistant Senior Patrol Leader

HONORS AND AWARDS

Paterno Fellows Program: Honors program including advanced academic coursework, thesis, internship, ethics study, and leadership/service commitment
Honors Courses: Econometrics, Financial Crisis Economics, Intermediate Microeconomics, Discrete Analysis, Industrialization and Development Economics Seminar, Game Theory
Best Economics Thesis: Voted by 2021 graduating class of honors economics students
Thesis title: *Modeling Climate Change: Sensitivities of The Social Cost of Carbon Under Parametric Uncertainty*
Dean's List: Fall 2017, Spring 2018, Fall 2018, Spring 2019, Fall 2019, Spring 2020, Fall 2020
Other Awards: President's Freshman Award, President Sparks Award, Rosenberg Undergraduate Scholarship in Economics (2x), Department of Economics Undergraduate Award