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UTILIZING SYSTEM DYNAMICS MODELING FOR THE ANALYSIS OF A MIDWEST REGIONAL CARBON CAP AND TRADE PROGRAM

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Quae sursum volo videre

“I long to see what lies beyond.”

Motto of the Minnesota Territory, 1849

Abstract

As global climate change is increasingly recognized as an important problem in the United States, many state governments and regional organizations are considering the implementation of policies designed to reduce carbon dioxide (CO2) and other GHG emissions from energy production. *Cap and trade* is an important and potentially effective policy tool designed to curb emissions from electricity producing firms through the use of an emissions credit trading scheme. By utilizing conventional linear mathematical models, however, it has remained difficult to quantify the economic and financial impacts of credit trading. Cap and trade systems involve dynamic feedback relationships among factors such as credit prices, mitigation investments and emission rates. System dynamics modeling provides a new perspective and unique methodology that may aid in more accurate tracking and projection of the results of a cap and trade system. In this paper, a system dynamics model is designed and constructed to evaluate the behavior of multiple electricity and emissions producing firms under a simple cap and trade system. By modeling the effect of cap and trade on the price of emissions credits and abatement options, the change in financial incentives for investing in renewable energy is examined. The effect of physical constraints on renewable energy capacity and energy efficiency improvements on the results of this simulation are also analyzed. This study's simulation results indicate that a firm's renewable investment depend on the share of fossil fuels in its energy production portfolio. These results provide insightful conclusions on the use of models in policy making and help determine the effectiveness of using cap and trade policy to combat global climate change.

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Chapter 1. Introduction

Global climate change is one of, if not the most, important issues of the 21st century. If nothing is done to curb anthropogenic increases in the atmospheric concentration of carbon (C) or carbon dioxide (CO2), governments and societies around the world will be unable to address other priorities due to massive abatement costs (IPCC 1995). Most developed and western nations have acknowledged this dilemma and, thus, have worked to develop agreements or plans to reduce greenhouse gas emissions over the next century. For example, the United Nations Framework Convention on Climate Change adopted the Kyoto Protocol in 1997, committing its signatories to reduce greenhouse gas emissions to 5.2 – 7% below 1990 levels by 2012 (UNFCC 1998). Additionally, to avoid drastic and irreversible climate change, the IPCC has reported that an 85% reduction below 1990 levels may be necessary by 2050 (IPCC 1995).

Carbon emissions are one type of greenhouse gas (GHG), named for the atmospheric "greenhouse effect" which is causing global temperature increases (IPCC 1995). In this paper, the terms *carbon emissions* and *greenhouse gases* may be used interchangeably. Both GHGs and CO2 emissions will be considered using *carbon dioxide equivalence* (CO2e), a physical unit which quantifies greenhouse gases by their global warming potential (GWP) (Reilly, et al, 2003). Because popular support for greenhouse gas regulation exists in many regions, state governments throughout the United States are currently considering adopting regional or local emissions agreements. For instance, ten eastern states created the Northeast Regional Greenhouse Gas Initiative (RGGI) and seven western states, with three Canadian provinces, are currently developing a regional, multi-sector market program called the Western Climate Initiative (WCI) to achieve a regional emissions cap in the west (RGGI 2007, WCI 2008).

On November 15th, 2007, nine states and one Canadian province signed the Midwest Governors Association's Greenhouse Gas Accord to establish targets for GHG reductions and develop a cap and trade agreement (MGA 2007). As the accord and its programs are still in the work group stage, there is still debate about the most effective and efficient way to formulate the resulting policies and cap and trade programs.

In his speech to a joint session of Congress on February 24, 2009, President Barack Obama issued an appeal for Congress to establish a "market based cap on carbon" (Whitehouse.gov 2009). President Obama did not specify the nature of such a program in his speech, and at the time of this writing there has been no successive action in Congress regarding the President's appeal. However, two pieces of evidence imply that this legislation will likely use a cap and trade approach. In November, 2008, then President-elect Obama posted his proposal for a cap and trade system on the website of the Office of the President-elect. Essentially following the IPCC's emission reduction recommendations, the plan called for a return to 1990 emission levels by the year 2020 and an 85% reduction on those levels by 2050 (Office of the President-elect 2008). In 2007 Senators Lieberman and Warner drafted S.2191, or *The Climate Security Act of*

2008. The act proposes a national cap and trade program that reduce US emissions by 56% in 2050 (110th United States Congress).

Early cap and trade systems, such as the Acid Rain Program created under the Clean Air Act of 1990, sought to reduce local environmental hazards (like acid rain) by reducing emissions of sulfur dioxide (SO2) and nitrogen oxides (NOx) from point sources, such as a coal-fired electricity power plant in the region where acid rain occurred (EPA 2007). Today, the European Union's Emissions Trading Scheme regulates the trading of carbon credits to reduce economy European CO2 emissions in line with the IPCC recommendations (Ellerman and Buchner 2007).

Cap and trade is just one of a variety of polices which aim to curb greenhouse gas emissions. The policies generally fall under one of the following categories: carbon tax; carbon cap (with or without credit trading); carbon intensity; and energy efficiency. These policies are often designed to correct the environmental externality of GHG emissions. Economically speaking, GHG emissions are considered environmental externalities because they impose a social cost on an economy. The social cost is derived from a combination of environmental damage, mitigation and abatement costs, and other direct or indirect opportunity costs imposed by global climate change (Azar and Sterner 1996, Ayers and Walter 1991, Hope and Maul 1996). Most peer reviewed economic valuation papers have set the price of carbon emissions between US$0 and US$100 per ton CO2e (Tol 2003)

A carbon tax directly accounts for GHG externalities by taxing some or all transactions and activities which produce GHG emissions. The tax can be imposed on a specific sector or across an entire economy. By directly taxing emissions, the externality is internalized within the economy and government tax revenue can then be used to mitigate the effects of GHG emissions. Alternatively, firms and individuals may respond to the tax with less consumption or increase efficiency, effectively avoiding both the tax and the emissions. A carbon tax is one of the more administratively efficient and implementable policies listed here, but is often not socially or politically feasible due to the effects of taxation on industry and the economy (Johnson, et al., 1990).

A carbon cap sets a limit on the amount of emissions produced in a sector or economy. The cap can be imposed on either energy producers or consumers, and can be incrementally reduced to cause continuous decreases in GHG emissions over time. Enforcement of a carbon cap is often through violation fees or through voluntary participation. Alternatively, an emissions credit trading system can be established to track emissions and allow highly emitting firms to buy credits from lower emitting firms in a simulated marketplace. The buying and selling of emissions credits may have a similar economic effect as a carbon tax and rebate system, but is more similar to a capitalist based market system and therefore often more politically feasible in the United States, despite being more administratively burdensome (Colby 2000).

Rather than setting the amount of emissions, a *carbon intensity* policy sets the rate per use of an energy consuming or producing activity. For instance, a low carbon fuel standard for electricity production would set the amount of carbon emissions *per* megawatt-hour (MWh) of electricity produced. Low carbon fuel standards (LCFS) are currently being considered for the transportation sector in a number of states, such as California and Minnesota (CARB 2009).

A renewable portfolio standard (RPS) mandates that renewable energy must provide a specific portion of a region's electric generation portfolio. Renewable portfolio standards are often seen as the most direct policies to encourage renewable energy development, as they rely on mandates rather than market based incentives (Pew 2007). In 2007, Minnesota passed a RPS that requires 25% of its electricity from renewables by the year 2025, making it one of the most stringent standards in the nation (Corey and Swezey 2007).

Finally, *energy efficiency* policies aim to increase the efficiency of energy consumption from buildings and appliances. Through building and HVAC renovation, appliance standards and consumer education, these policies reduce the amount of energy used per effort or utility from an appliance or building. Many states have energy efficiency policies targeted at electric utilities, such as Minnesota's Conservation Improvement Program (CIP) program (Office of Energy Security 2009).

As many local and regional governments in the United States have only recently begun to consider GHG emission regulations, there is still a great amount of uncertainty regarding the effectiveness and efficiency of each type of policy. In light of this, many studies and working groups have been formed to project and model the effect of each policy on the environment and economy. For instance, the Midwestern Governors Association has formed a number of working groups to quantify and analyze the local effects of its 2007 Greenhouse Gas Accord (MGA 2007). Along with the Great Plains Institute, the MGA's Tier II Working Group is developing a model to project the effects of MGA policies in the 12 member states and Manitoba. Tentatively titled The Midwest Tracker, the model uses a system dynamics modeling framework to track energy production, purchasing and consumption, then calculate the resulting costs and emissions. Currently, the model has been able to accurately quantify many of the policies involved with the MGA accord, such as a carbon tax, a low carbon fuel standard, or a renewable portfolio standard (RPS). However, because of the dynamic nature of carbon credit trading, modeling a cap and trade system has proven more elusive. This is primarily because credit trading involves a simulated market involving decision making and possible gaming (Haurie and Viguier 2003). System dynamics modeling may provide an opportunity to more accurately model this.

Modeling has been commonly used in prospective policy analysis, as well as other social or economic analyses, to project the outcomes of possible policy alternatives. Generally, modeling and projecting have often been performed in a *linear* fashion, on paper or in computer programming, to calculate specific outcomes based on specific inputs. This has been appropriate for analyses regarding economic or scientific data, where a model is based purely on equations from economic theory or scientific relationships. However, socioeconomic phenomena, such as microeconomic business decisions or an individual's participation in social programs, are often not based on strictly linear mathematical relationships. To model such phenomena, a more complicated model of the relevant relationships is needed. A linear model uses exogenous inputs to directly calculate its data output, but does not use this output for further calculation. Thus, linear modeling disregards the concept of *feedback*, where the output of an equation may in turn affect the input into the equation. Further discussion on modeling, feedback, mathematical equations and social relationships takes place in Chapter 2.

In the mid-1950s, a type of modeling called *system dynamics* was developed to simulate nonlinear relationship models using concepts such as feedback. Arising from the field of Electrical Engineering, from which the notions of state space and systems control were developed, system dynamics uses traditional engineering theory to help understand social systems. Jay W. Forrester, a professor at the Massachusetts Institute of Technology, used his experience as an electrical engineer to make connections between the fields of systems control and corporate management.

> Forrester's experiences as a manager led him to conclude that the biggest impediment to progress comes, not from the engineering side of industrial problems, but from the management side. This is because, he reasoned, social

systems are much harder to understand and control than are physical systems. (System Dynamics Society)

One of the earliest applications Forrester's development were stock-flow-feedback diagrams and hand written models of General Electric plants which demonstrated the effect of managerial decisions on employment stability (System Dynamics Society).

By design, system dynamics modeling provides an opportunity for policy analysts to simulate dynamic social and economic systems more realistically than traditional linear programming models. Additionally, more recent system dynamics software provides users with an easy to understand graphical representation of model relationships through the use of symbols and diagrams. By using symbols and visual connections to represent entities and the relationships between them, computer programs such as Vensim by Ventana Systems, Inc., offer greater comprehension of both models and the relationships they are simulating. As before, a more detailed discussion of system dynamics modeling, the Vensim computer software and its *symbology* occurs in Chapter 2. This paper will primarily utilize Vensim for its model construction and analysis.

Policymaking often entails risk and uncertainty while predicting the outcome of a policy alternative. Not only must the *type* of outcome be determined, but the magnitude of that outcome must also be estimated. In environmental and energy policy, it is important for policymakers to choose an alternative which is both efficient and effective in achieving an environmental goal. When comparing policies like carbon tax or carbon cap and trade, it is first important to ensure that each policy results in a reduction of carbon emissions. Secondly, it is desirable to predict which policy might have a greater magnitude of emissions reduction. However, as the two policies are very structurally dissimilar, the models of each policy will be structurally unique. A carbon tax may be easily simulated using a linear model, as it is a classic economic concept easily represented by linear equations. Cap and trade, on the other hand, presents a dynamic system of carbon credits and the behavior of multiple firms trading within the carbon market. Because of its incorporation of feedback, nonlinear systems simulation and symbolic relational representation, system dynamics and Vensim may provide an opportunity to develop a realistic model of a cap and trade system. This paper explores the use of Vensim in designing such a model and utilizing it to run simulations of scenarios for prospective policy analysis.

It is expected that a modeling analysis of cap and trade programs will provide useful projections of firm behavior, CO2 emissions and investment decisions over the course of the program. By allowing variations of the policy to be simulated, a system dynamics model can help analysts discover and demonstrate the most important factors for crafting effective and equitable policy. By observing the projected outcomes for phenomena such as CO2 emission trends and renewable energy investment decisions, models can help gauge the impact, whether positive or negative, of proposed climate change policy. This paper first discusses the conceptual framework of system dynamics modeling, then presents the methodology for developing the cap and trade model designed for this analysis. Then, a series of *scenarios* are laid out in order to demonstrate the range of quantitative model inputs used to explore a number of research questions, including: How does a cap and trade program influence the development of carbon-neutral renewable electricity capacity?; Which formulations of cap and trade policy have the most impact on CO2 emissions?; and, Do unique firms behave differently under cap and trade programs? This paper then aims to answer these questions, among others, by presenting the modeling results of a number of scenarios and discussing their interpretations and limitations. Finally, a number of conclusions and policy recommendations are made to help policymakers formulate the most effective cap and trade program for the Midwest region.

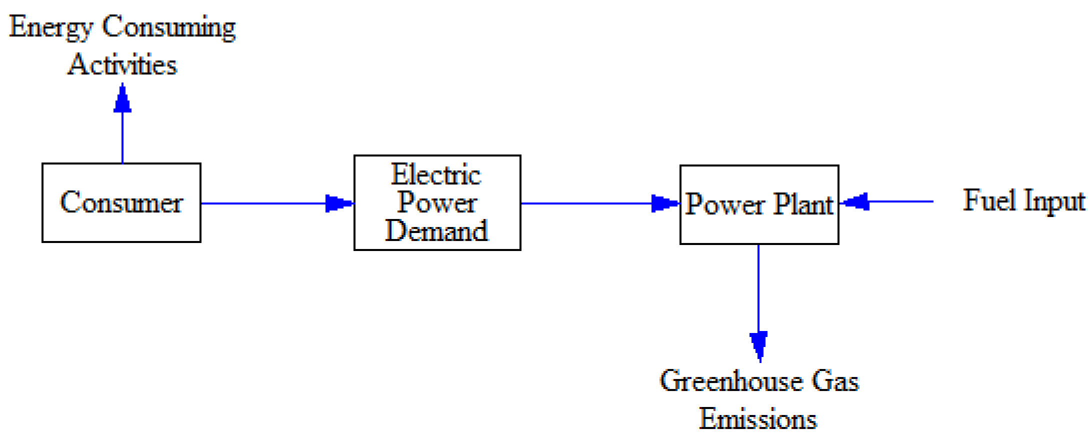
Chapter 2. Conceptual Framework

Explanation of Terms

This section lays out the conceptual framework that is being used in this paper to discuss the role of system dynamics (SD) modeling in policymaking. Because the SD field may not be universally well known, many of the terms and concepts used fluently by SD practitioners must be defined and explained. In addition to serving as an introductory list of definitions, the discussion of modeling concepts also introduces the broader consideration of the strengths and weaknesses of modeling within a policy context.

A model is an abstracted representation of a real entity or phenomenon. By acting as an analogue for an object, system or process, a model is "designed to reproduce as faithfully as possible in some new medium the structure or web of relationships in an original" (Black 1962). In this context, for example, an entity may be an electric power producer or an individual who consumes electric power through various activities. Likewise, a phenomenon may be the emission of greenhouse gases from that power plant or the activities through which that individual consumes power. Whether developed in one's head, written on paper or simulated in a computer program, models are used to conceptualize a set of relationships between entities or phenomena and to quantify the causality between the properties and functions of each entity or phenomenon (Black 1962). The realm or domain within which entities and phenomenon occur may be considered a *system*. A system contains a set of interacting entities which combine to form an integrated whole, such as the system of energy production and consumption, with a set of exogenous inputs, internal processes, and both exogenous and endogenous outputs. Therefore, a *system model* is a representation of a set of entities and phenomena which together may form one whole process or behavior (Churchman 1968). A system model of electricity production and consumption, for example, might look like that shown in Figure 2.1

Figure 2.1 A simple model of an electricity production and consumption system



In this simplistic model the relationship between a power plant and a consumer is demonstrated by a third entity, electric power. Depending on the behavior of the consumer, a certain amount of electric power is demanded from the power plant, which consumes fuel and other input to produce the power and, simultaneously, greenhouse gas emissions. In this demonstration, a box represents an entity while an arrow signifies a relationship between entities. In Vensim, models are a combination of a system's visual structure and the background computer code which runs the simulation of the system. The software tracks entities or phenomena through *variables*, which can be defined by a single value, a series of values, or an equation or relationship based on other variables. The present level of a variable's value may be termed as that variable's *state*. In Vensim models, arrows generally show the flow of information from one variable to another. In Figure 2.1, the direction of the arrows imply a causal relationship, such as the relationship between the consumer and the electric power demanded by the consumer. Despite its simplicity, there may be a variety of ways to conceptualize the relationships in this system besides the method shown in Figure 2.1. For instance, the direction of each arrow is based on the assumptions of the functional relationships one is attempting to model. In this example, the arrow between "Power Plant" and "Electric Power" demonstrates the assumption that the power producer responds to an existing level of demand. However, this could be reversed depending on how one defines the relationship, such as one where "Electric Power" is a level of available electricity into which a producer supplies and out of which a consumer draws. Thus, models are not inherently based on existent physical relationships, but rather on how the individuals developing a model (modelers) have chosen to conceptualize those physical relationships. Multiple and unique models of one single system may be developed by unique modelers, so it is important for a modeler to adequately explain the assumptions under which their model is operating.

The system modeled in Figure 2.1 is a *linear system*. This means that the relationships described by the model are made strictly out of linear operators, such as addition and multiplication, and that the model generally satisfies the superposition principle. In mathematics, the superposition principle states that a system is linear if it is has both the properties of *additivity* and *homogeneity* (Ogunfunmi 2007). A function in the model is additive if the output from two added inputs is equal to the addition of the outputs from each individual input.

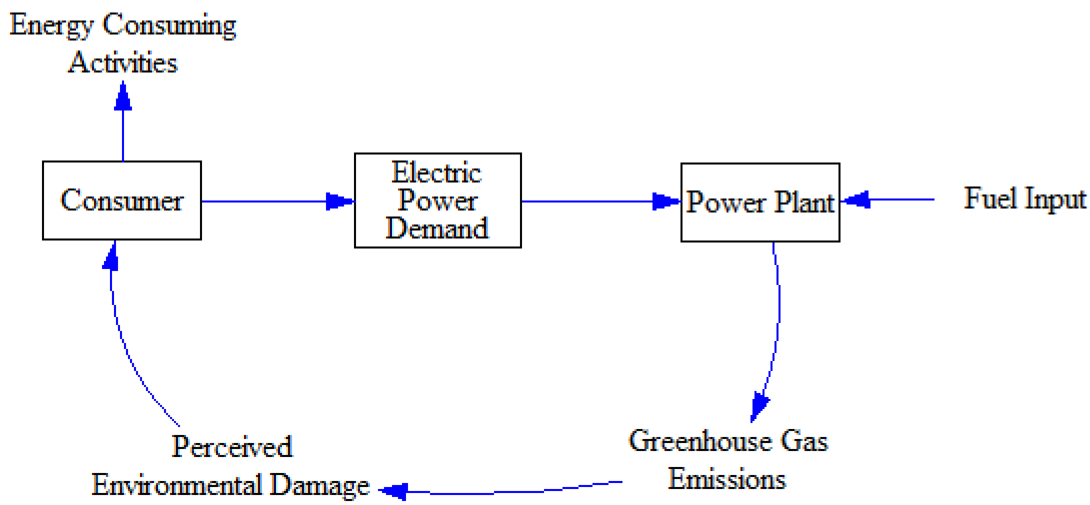
Generally, a linear system is a system in which cause and effect are proportional to each other (Harris, et al, 2002). For the simple conceptualization of an energy production and consumption system, such as the one in Figure 2.1, the relationships between entities are adequately described by functions which adhere to the superposition principle. Simply put, the levels of energy production and consumption are directly proportional to the state of the inputs on which they are based. This entire system could be described by a discrete number of equations and may not even need the help of a complicated program like Vensim to be accurately modeled. In this instance, Vensim simply aids in the visualization of the model.

One could develop a more advanced model, based on more complicated assumptions, that would more precisely simulate the same system and in which case the use of strictly linear equations may less accurately represent the assumed physical relationships. Additionally, many systems are much more complicated than that described above, so one may be unable to develop a useful model by utilizing only linear relationships and representations. A system which cannot be represented by strictly linear relationships, or which does not satisfy the superposition principle, is a *nonlinear system*. Large, complex systems which contain nonlinearity are often colloquially referred to as *dynamic* systems, as well (Sterman 1993). It is in this sense that the name of the field of System Dynamics was derived (Forrester 1971).

Feedback, a concept that is often present in dynamic systems, is one source of nonlinearity. Feedback occurs when the output of a system has an effect on an input into that system (Richardson 1999). The presence of feedback in a system may introduce unexpected behavior or complicated cause and effect relationships. In the field of electrical engineering, feedback is an important feature of circuit design and system control (Spencer, 2003). Feedback is necessary for an electronic control system to track the present state of an entity it is trying to control. System dynamics and related computer software, such as Vensim, were designed to confront the notion feedback and directly incorporate it into system calculations by using concepts and tools developed in Electrical Engineering.

The model shown in Figure 2.1 is quite simple and involves no feedback. However, a reconsideration of the assumptions on which this model is based might lead to an expanded and more complicated model. Figure 2.2 shows an alternative model of the same system which uses feedback to show the effect of emissions on an environmentally conscious consumer.

Figure 2.2 A more complicated model of electricity consumption and production



Whereas the model in Figure 2.1 presented an *open-loop* depiction of energy consumption where possibly occurrent feedback mechanisms were ignored, Figure 2.2 presents a model with a *closed-loop* system where the consumer's energy consumption is affected by the environmental damage they perceive as a result of their most recent energy consumption. While some factors may still depend on exogenous input, the system of feedback has been adequately incorporated into a closed-loop model. The inclusion of feedback in the model, while seemingly simple, might actually have noticeable effects on the behavior of the system. In the previous model, a consumer would continue to demand electric power according to their desired level of energy consuming activity. In Figure 2.2, a consumer would also respond to their perceived level of environmental damage by adjusting their electric power demand. Thus, the number of influential factors on each entity in the model is increased and the overall behavior of the system becomes more complex.

The direct relationships present in a linear model are generally easy for a human observer to comprehend. Nonlinear models with feedback loops, on the other hand, present challenges to one's comprehension of the cause and effect relationships in a system. The presence of feedback can quickly make a model's functionality become unclear to a user, but the real world mechanisms that feedback represents are often very important to consider when building a system model. Therefore, despite the added difficulty, it is important for modelers to incorporate nonlinearity to accurately model a real system when the presence of feedback is apparent. System dynamics modeling programs like Vensim are designed to explicitly confront feedback and model complexity by making model design, configuration and simulation clear and convenient.

It is clear that system dynamics presents an opportunity to build models of energy and environmental policies, such as a cap and trade program, which might be conceptualized as nonlinear systems. As a method that relies on diagrammatical visual structure, system dynamics contains a variety of symbols and organizational techniques that aid in interpreting the dynamics of nonlinear systems. Therefore, there is clear potential for SD modeling to be used as a tool for those seeking to model complex systems like energy production, climate science and the policy mechanisms related to these areas.

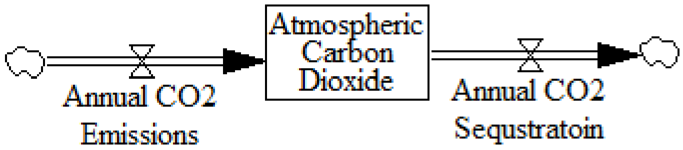
Indeed, system dynamics modeling has often been used to simulate the interaction between energy, policy and emissions. The Massachusetts Institute of Technology's System Dynamics Group constructed *A Simple Model of Energy Dynamics* to illustrate the aggregate dynamics of an energy supply transition (Want, et al., 1983). Other important models from the MIT System Dynamics Group include the WORLD, COAL and FOSSIL models. William Nordhaus' *Dynamic Integrated Climate Economy* (DICE) model simulates global energy production by utilizing a single producer-consumer macroeconomic model that is subject to global population and economic conditions (Nordhaus 1992). Thomas Fiddaman's *aNother Integrated Climate Economy* (NICE) model expands on Nordhaus' DICE by making structural changes to include more explicit carbon flows, path dependant energy sector, and rational decision rules (Fiddaman 1995). The TRACKER model, built for the Midwest Governor's Association, is programmed to simulate the interactions between a wide array of state, regional, and federal energy policies (GPI 2009).

Although these important models establish a precedent for using system dynamics to model energy systems, they do not explicitly confront market-based climate policies such as cap and trade. Whether due to cap and trade's irrelevance to each model's goals or burdensome complexity in simulating within a model's framework, there is a dearth of SD models which incorporate cap and trade programs. In order to forecast the impact of cap and trade, it is important to accurately model the specific dynamics of the policy and determine quantifiable inputs and outputs. This paper aims to address the lack of applicable models by exploring the feasibility of modeling cap and trade using system dynamics.

System models are generally programmed to simulate behavior over a certain length of time. A model runs in cycles, or steps, over this interval (Sterman 2000). Depending on the model, this step could simulate one second, one day, one month or one year, etc. Different types of models require different resolutions of time, depending on the nature of the phenomena they represent. Many political or economic models only need to calculate values annually, while more specific models might need to model decisions which are made on a daily basis. The minimum resolution of time may be an important piece of the analysis done in this paper. While seeking an accurate model of a cap and trade program, the effect of different units of time will be explored during model construction.

The combination of *stocks* and *flows* is another important concept used in system dynamics. Certain entities are best represented as stocks of some quantity, with flows going into and out of the stock at a specific *rate* per time unit (Sterman 2000). For instance, the cumulative amount of carbon dioxide emissions present in the atmosphere can be considered a stock with a certain level of emissions. Each year, humanity produces new CO2 emissions at a certain rate which flow into the total stock of atmospheric carbon. Additionally, the earth absorbs and sequesters some of that carbon at a different rate. The flows into and out of the atmospheric stock of carbon dioxide are shown in Figure 2.4. Stocks and flows will be used throughout the cap and trade model developed in this paper.

Figure 2.4 Stock and flow diagram of atmospheric CO2



As demonstrated above, the assumptions on which models are built are as important to simulation results as the inputs and internally calculated values that are built into the models. Therefore, it is important for a modeling effort to have its assumptions clearly laid out. The model developed here will imply a number of assumptions in each of two areas: *how* to model and *what* to model. In other words, how to properly represent the entities that are involved in a cap and trade program within the model, and what to include in the cap and trade program being simulated (as there are a variety of ways to implement a cap and trade system). These will be referred to as modeling assumptions and policy assumptions, respectively.

Modeling Assumptions

This model simulates the behavior of electric utilities producing electricity under a cap and trade system. It operates on the assumption that these firms will respond to consumer demand by producing electricity (for simplicity, consumer demand must always be met). The production of electricity results in greenhouse gas emissions that will be regulated by the cap and trade program. The cap and trade program may incur a cost to each firm, depending on the level of their emission. Thus, the model is built around three main quantities: electricity, emissions and money.

The primary unit of electricity in this model is the watt-hour (Wh), a measure of energy equal to 3600 Joules (J). Depending on the position of its occurrence, electricity will be presented in various orders of magnitude, such as kilowatt-hours (KWh) for one thousand watt-hours, megawatt-hours (MWh) for one million watt-hours and gigawatt-hours (GWh) for one billion watt-hours. Energy demand has an exogenous constant rate of growth, as determined by consumption trend data from the Energy Information Administration (EIA). This isthe only representation of a consumer in this system.

To assess the environmental impact of cap and trade programs, carbon dioxide (CO_2) emissions are tracked in this model. Metric tons of CO_2 (tCO_2) will be the primary energy unit for emissions. When needed, megatonnes ($MtCO_2$) and gigatonnes ($GtCO_2$) will be used to represent one million metric tons CO_2 and one billion metric tons of CO_2, respectively. Although CO_2 emissions are the primary mechanism by which global climate change occurs, the environmental damage caused by atmospheric CO_2 will not be modeled here. Thus, CO_2 emissions may be considered one of the primary outputs of this model. For simplicity, other greenhouse gases are not modeled here. However, they can be easily included by adjusting the emissions factors used as inputs into the model (as explained in Chapter 4).

US Dollars ($) for the year 2009 are the primary economic unit in this model, which assumes real prices with no inflation. While there will likely be some level of inflation (or deflation) during the time frame projected in this model, using flat prices allows the results of this analysis to be adjusted by whichever rate of inflation actually occurs. A sensitivity analysis that observes the effects of a high and low inflation or discount rate is conducted in Chapter 6. The price of carbon is a very important component of cap and trade programs. Here, the price of carbon occurs as dollars per metric ton of CO2 ($/tCO2). When modeling the cost of new construction, both the capital cost and operating cost of new electric production facilities are integrated into a levelized cost per annual electric generation ($/GWh). The levelized cost is a method of accounting for the total costs of operating an electric plant over its entire lifetime. The calculation of specific levelized costs are shown in the Data Sources and Methodology section of this paper.

This model only simulates new plant construction using renewable energy (such as wind power) as an alternative to buying carbon credits or reducing demand. Therefore, the cost of fuel will not be used in the levelized cost. Additionally, to prevent scope creep, the collection and purchasing of fossil fuels and other materials (such as transmission lines) for energy generation will be placed outside the boundary of this system. Instead, this model assumes that a sufficient amount of fuel and infrastructure are available for the firm to operate. As wind turbines present no fuel costs, this does not impact the financial investment decisions made in this model. Finally, it is assumed that a firm can construct additional renewable energy production plants at a rate equivalent to a two year construction period for each turbine.

The model presents a range of variables that are calculated in a variety of ways. Some of these variables are held constant throughout the various simulations involved in model analysis. Others, however, are utilized to construct different scenarios in which to run the model. This is done by changing the values or deterministic rules of a variable to alter an assumption of the model. Observing the effect of changing a variable's value is a primary method of this analysis. Additionally, a more in depth sensitivity analysis is conducted for some variables in Chapter 6. Examples of such variables include a firm's carbon credit allowance, its fossil fuel electric production portfolio, and the price of renewable or energy efficiency investments, among others. A list of each variable, its definition and its quantitative units is provided in Appendix 1.

Variables like the credit allowance are also closely tied to the cap and trade program modeled in this analysis. There have been a variety of cap and trade programs implemented around the world in the past few decades. The SO2 cap and trade program implemented by the EPA's Acid Rain Program in 1990 provides a major milestone for this type of policy (EPA 2008). While the abatement technology and specific greenhouse gas (CO2) are different in this case, the benefits and effectiveness of cap and trade programs may be transferred to the abatement of CO2 emissions, as many of the emitting firms and economic factors remain the same (Svendsen 1998). Additionally, the European Union Emissions Trading Scheme (EU ETS) provides a modern day example of a CO2 cap and trade program (Ellerman and Buchner 2007). Each program has been unique in the combination of rules and methods employed by its regulators (Colby 2000).

The assumptions made by this analysis regarding the type of cap and trade system being modeled are explained in the next section.

Design of a Cap and Trade System

A cap and trade system for emissions control is comprised of a variety of components. Each component will be discussed in detail on the following pages. As its name implies, cap and trade involves a *cap* that imposes a maximum amount of emissions than can be produced by each firm in the system. An *implementation scope* must be set to determine which firms are responsible for complying with the cap (by industry, geographic area, etc.). *Credits* are used to account for each firm's performance and to track the magnitude by which its emissions are above or below the cap. *Trading* is used to provide incentives for firms to meet the cap by forcing firms with emissions exceeding the cap to purchase allowances from those whose emissions remain below the cap. A number of considerations must be made when configuring of each of these components for a new cap and trade system. This chapter will list many of these considerations and discuss them in the context of a cap and trade system for CO2 emissions from Midwestern electricity producers.

Emissions Cap

Early cap and trade systems, such as the Acid Rain Program created under the Clean Air Act of 1990, sought to reduce local environmental hazards (like acid rain) by reducing emissions of sulfur dioxide (SO2) and nitrogen oxides (NOx) from point sources, such as a coal-fired electricity power plant in the region where acid rain occurred (EPA 2007). In these cases, there was a clear basis for emission limits based on the direct relationship between local SO_2 emissions and acid rain. Because the scientific link between emission levels and acid rain was known, a specific amount of emissions could be set to prevent acid rain from occurring (EPA 2007). However, as the analysis conducted for this paper is done within the context of CO_2 emissions and global climate change, the link between the emission cap and environmental damage is not as clear because local emissions do not have local effects. Instead, local emissions are added to a global aggregate of atmospheric CO_2 levels which have environmental impacts throughout the world (IPCC 1995). A local cap on carbon emissions would therefore be based on a region's contribution to a collaborative worldwide effort to combat global climate change. In their assessment, IPCC lays out a series of emissions benchmarks that must be met to prevent considerable damage from climate change. In short, the benchmarks result in an 85% reduction of 1990 emissions levels by the year 2050. If a region were to participate in the global effort, it could simply base its emissions cap on the recommended percentage reduction as applied to its own historical emissions.

A reduction of emissions on the magnitude that the IPCC recommends implies a very large effort and cost for firms who currently produce CO_2 emissions. These firms need time to plan and invest in ways of reducing their electricity production or emissions intensity. Therefore, a CO_2 cap that is implemented gradually with annual emissions targets that decrease each year to eventually reach the final goal may lessen the burden on firms while still providing an adequate emission reduction. The modeling and analysis process conducted for this paper assumes that a regional cap and trade system will set a final emissions target in 2050 based on an 85% reduction of their 1990 regional CO2 emissions, with annual emissions targets set by a linear reduction from their baseline year to the 2050 target. The emissions baseline for this model is based on data from EPA's eGRID (EPA 2009) and the Department of Energy's Energy Information Administration (EIA 2008). Emissions are accounted for by using metric tons of atmospheric CO2 as a unit. Therefore, the emission cap is also in metric tons of CO2 (tCO2).

Implementation Scope

Cap and trade systems must have a defined scope to determine which firms will be included in emissions cap enforcement and credit trading. First, a geographic area must be established based on the jurisdiction of the cap and trade policy or enforcement organization. Second, the *point of obligation* must be set to assign the responsibility to the types of firms which cause CO2 emissions (EPA 2003). While emissions are produced by the combustion of fossil fuels from a set number of firms, there are a variety of other firms and individuals which are responsible for the amount of combustion. An *upstream* approach to cap enforcement would hold accountable the firms that are responsible for fossil fuel extraction, distribution and processing (essentially, those that provide fuel inputs to the firms that combust fossil fuels). A *downstream* approach would place the responsibility on those who cause the emissions indirectly through energy consumption, such as households and businesses. For the purpose of this analysis, a *point of emissions* approach is used to place the enforcement of an emissions cap on those who directly emit CO2 by the combustion of fossil fuels for electricity generation. Depending on the scenario, this analysis models one or multiple electric utilities or firms that generate electricity in the Midwest. The theoretical firms in this model reflect realistic electric utilities in the region using electric generation portfolios based on data from eGRID and EIA.

Credits: Allocation and Trading

Credits (or *carbon credits)* are the primary currency and resource on which a cap and trade system operates. There are a number of ways to allocate and distribute credits in such a policy. Generally, credits are either allocated to each firm based on emission allowances, allocated based on generation performance (emissions per customer served or emissions per energy generated), or made available to purchase through an open auction. Under allocation, every firm has an emission allowance that it must comply with based on the total emissions cap. While this type of distribution imposes no initial cost on the firms being regulated, it will not provide any initial revenue for the cap and trade enforcement organization (CBO 2001). An auction system for allowance distribution would force regulated firms to compete for credit purchases. Theoretically, the auction market would follow the economic rules of supply and demand, resulting in more expensive credits when faced with a greater demand for credits from regulated firms (Ausubel and Cramton 2002). In this manner, the market would settle on a price for carbon emissions that reflects a consensus between regulators and firms. However, past emissions trading markets have demonstrated a great amount of uncertainty, resulting in volatile credit prices whose fluctuation makes the economic valuation of emissions difficult (Victor and Cullenward 2007).

Currently, much of the industry stakeholders in the U.S. have stated a preference for free allowance allocation over auction based credit purchasing (USCAP 2009). Additionally, the cap and trade system implemented by the successful Acid Rain Program used a credit allocation method based on each firm's emissions baseline. Taking this into consideration, as well as the added complexity of modeling an auction market, this analysis assumes that credits are allocated on a free baseline emissions basis. A theoretical baseline is constructed for each firm based on emission intensity and electricity demand information from eGRID and EIA's SEDS. This baseline, reported in metric tons of CO2 (tCO2), will set the initial allowance and consecutive annual emissions caps with which each firm must comply.

Following the initial year, firms will need to meet energy demand by producing electricity. Assuming a linear reduction of emissions, where annual emissions allowances are determined by drawing a straight line from the baseline year to the final goal, each firm will face a stricter cap each year. If a firm emits less than the cap allowance, it receives an amount of credits equal to the difference between the cap and their actual emission. If a firm emits more than the cap allowance, it must purchase an amount of credits equal to the difference between their actual emissions and the cap.

This analysis uses metric tons (tCO2) as a unit of measurement for carbon credits, so one carbon credit is determined by one metric ton of atmospheric CO2 emissions. If a firm receives credits in a given year, it sells the credits to firms on the carbon market who have emitted more than their cap allowance. While in this analysis the initial allocation avoids an auction-type market place, the price of a carbon credit in successive years is determined in certain scenarios by the interaction between those who supply carbon credits and those who demand them. This is explained further in Chapters 4 and 5.

Each unique firm in the electric industry may face a unique abatement cost for reducing carbon dioxide emissions. This is a result of unique portfolios of energy generating technologies, electricity and emissions generation levels, and available capital and financing options. For example, a small utility with aging electric production plants would likely face a higher abatement cost than a large utility with newer and more efficient equipment. Theoretically, all firms will face an equal market price for carbon credits but a unique cost of abatement. Therefore, it may be less costly for one firm to simply purchase a carbon credit from a firm whose abatement cost is lower than the market cost. If a firm is influential enough to set the market price of carbon, its unique abatement cost determines its willingness-to-pay (WTP) for carbon credits. As discussed in Chapter 4, this analysis explores using a firm's WTP to calculate the market price of carbon.

Chapter 3 Methodology and Modeling Assumptions

The previous sections of this paper outlined the policy and modeling framework employed by this analysis. With the assumed worldview defined for this analysis, a model can be built to simulate the interactions of entities and phenomena based on the relationships described previously. This section presents a detailed methodology for this research. First, the goals for modeling a cap and trade system are discussed. Then, an overview of the method for modeling firms, policies and decisions is provided. Finally, the actual construction of the system dynamics model, as well as its data inputs, is presented in descriptive and graphical form.

Goals of Modeling

While addressing the dearth of cap and trade SD models is a primary goal of creating a new model, the modeling process itself must also have clearly outlined goals. One goal of this model is to simulate electricity producing firms who are faced with a carbon emissions cap with a market-based credit trading system. Accurately depicting the decision making process of a firm under credit trading conditions is an important segment of this analysis. Another goal of this analysis is to observe how a firm behaves when faced with varying costs of abatement or trading, and how this affects investment in abatement strategies such as energy efficiency or renewable energy investment. Policymakers might wish to encourage the development of renewable electricity generation technology, such as wind turbines and photovoltaic solar panels, or increased energy efficiency. If simulated accurately, this model can help policymakers determine how a cap and trade system can encourage such developments.

The primary modeling goal will be achieved by constructing an accurate model based on realistic assumptions and decision rules. Upon model completion, however, the secondary modeling goal must be achieved through multiple simulations based on *scenarios* that act as inputs into the model. A scenario is built from a set of data and assumptions for energy demand, emission intensity profiles, investment costs and other factors that would accurately reflect a variety of possible conditions. The process for determining scenarios and their inputs is presented in Chapter 4.

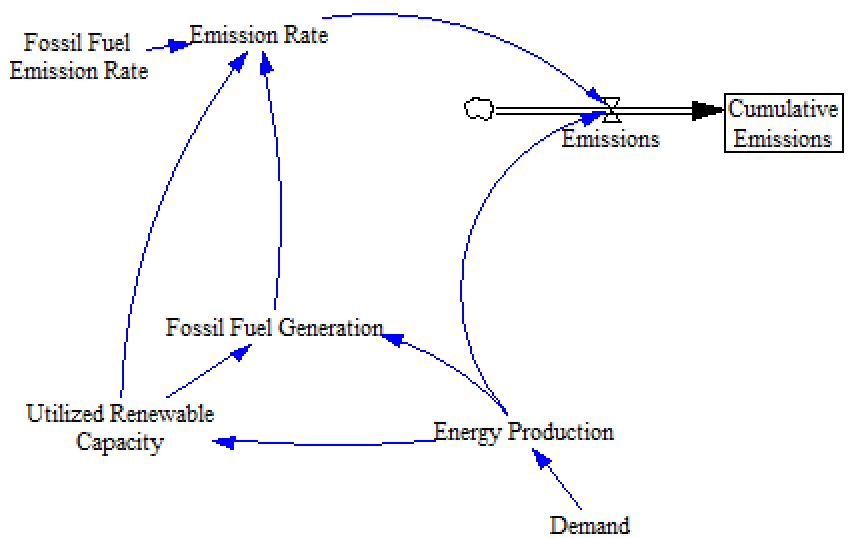
Modeling Assumptions & Policies: Firms and Decisions

The model developed here simulates electricity producing firms whose production level must meet consumer demand. The firm must also comply with policies that regulate its generation and emissions levels. To build a practical model, a system boundary must be established to demarcate which phenomena are explicitly simulated within the model (endogenous), and those that are represented only as inputs into the system (exogenous). It is assumed here that each electricity producing firm, though simplified to model only those aspects of the firm that are relevant to this study, is contained entirely within the system as an endogenous entity whose states and actions are simulated through model programming. In contrast, the policies and demand levels that each firm faces will only be partially endogenous with some factors integrated as exogenous inputs. This section explains the methodology for simulating a firm and the breakdown between endogenous and exogenous inputs. In the text, model variables are defined using a bold font in the following manner: [**variable name**]. All model variables and equations are listed in Appendix 1.

System dynamics models run in cycles whose progression represents the passage of time (Randers 1980). In this model, each time cycle represents one consecutive year in which the properties and levels of each variable change to reflect the evolution from one year to the next. Although a smaller time step would provide greater fidelity in simulating the results of each scenario by providing smaller intervals for changes to take effect, an annual time step is compatible with the decision-making calculations used for each firm (defined in Appendix 1) A firm begins each year by establishing a level of electricity production [**Electricity Production**] that is equivalent to the amount of consumer demand [**Demand**]. The firm generates this electricity using a portfolio of production technology that includes both renewable and fossil fuel based energy sources. Here, all fossil fuel generation technologies are converted to one aggregate energy source with a calculated carbon emission intensity [**Fossil Fuel Emission Rate]**. This emission rate will be calculated explicitly for each firm based on a realistic set of fossil fuel technologies in Chapter 4 of this paper. All renewable source are aggregated in the same manner, to a single plant, but are assumed to have zero direct carbon emissions (a reasonable assumption for wind and solar energy technologies during operation).

Figure 3.1 shows the electric production and CO2 emissions portion of the model. The amount of electric demand determines the amount of energy the firm must produce. Then, the amount of fossil fuel generation and utilized renewable capacity are calculated to meet the electric demand, with renewables chosen first (to maximize renewable utilization). The proportion of fossil fuel to renewable generation determines the total emission rate, which, when multiplied with the total energy production, determines the amount of CO2 emissions each year. A figure which depicts the interconnection between this and other sections of the model is given later in this chapter.

Figure 3.1: Model of Demand, Production and Emission



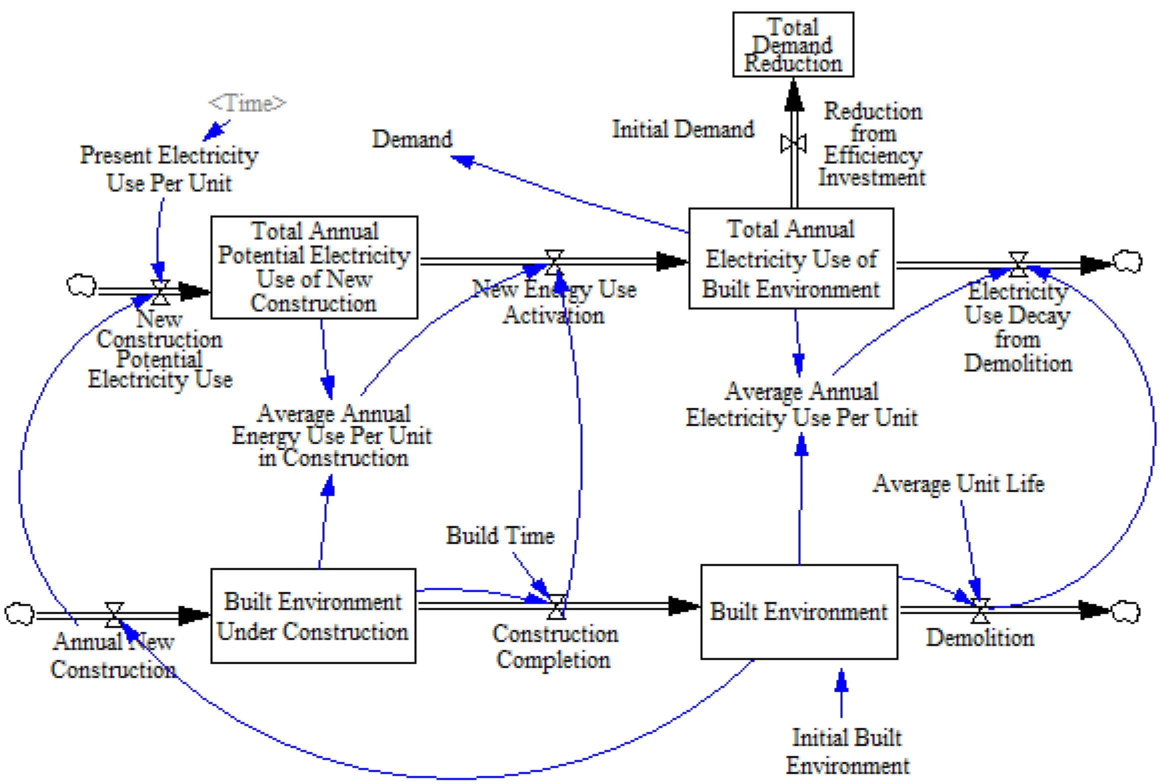
The division of a firm’s production portfolio between fossil fuels and renewables is handled by *shares* which represent the percentage of the firms portfolio held by each source. It is assumed that each firm starts out with a majority of fossil fuel production with enough capacity to meet a base load of energy demand. If a firm invests in wind energy, for example, its share of renewables [**Renewable Production Share]** increases. The share of fossil fuels [**Fossil Fuel Production Share**] is determined by the amount of production that remains after the renewable share [**Fossil Fuel Production Share = Electricity Production – Renewable Production Share]**.

A firm's fossil fuel production share and fossil fuel emission rate determines its total emission rate [**Emission Rate**]. A firm's annual CO2 emissions [**Emissions]** are calculated by the emission rate multiplied by the level of electricity production. Annual emissions are used both as flow into a firm's cumulative emissions level [**Cumulative Emissions**] and as an input into the cap and trade policy portion of this model. The equations for these calculations are given in Appendix 1.

Electric demand is modeled endogenously using a system dynamics co-flow structure, where the flow between one chain of stocks is determined by the flow of another (Ford and Sterman 1998). One flow models the built environment as the aggregation of all residential, commercial and industrial buildings that account for the electricity consumption in Minnesota. The built environment is tracked in terms of total area (square feet) with an annual growth from new building construction and a decay caused by an 85 year lifespan. The data used for this section was derived from the Midwestern Governors' Association's Energy Efficiency Advisory Group dataset (EEAG 2008).

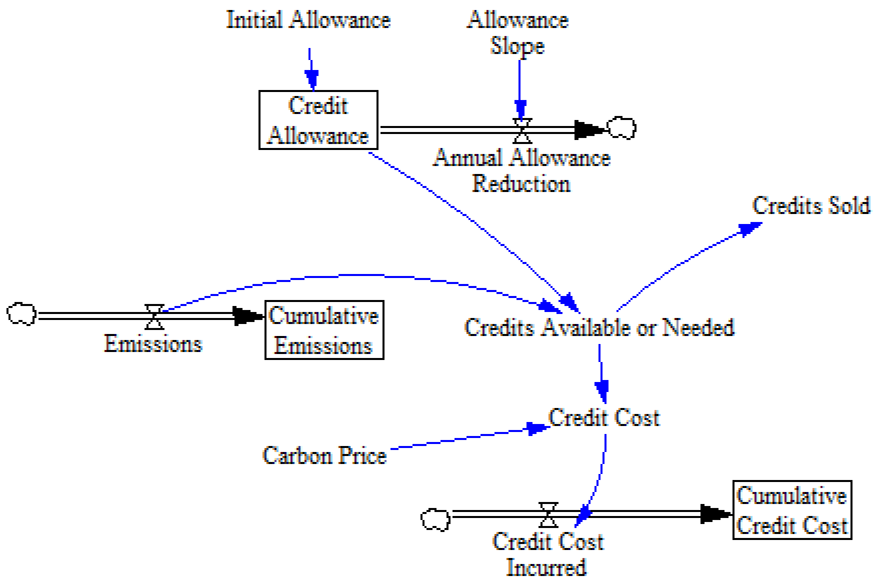
A co-flow is formed with the total built environment's stock and flow chain to track its total and average rate of electricity consumption. Electricity consumption data from EIA was used to align the state of Minnesota's built environment with its energy demand by finding the average annual electric demand per square foot (GWh/SqFt). While in reality, electricity consumption does originate from a variety of sources, the built environment accounts for the majority of electric demand in developed countries (Langston, et al, 2001). Utilizing a co-flow with the built environment allows the model to accurately simulate efficiency improvements, as well as track present electric demand and potential additional demand from newly constructed buildings. A full depiction of this co-flow is provided in Figure 3.2.

Figure 3.2: Built Environment Energy Consumption Co-Flow



The policy portion of this model relies on both exogenous input and endogenous modeling. It may be useful to alter a number of the components of the simulated cap and trade program to model different scenarios and compare their outcomes. In this model, the method of credit allocation [**Credit Allowance**] is used as an exogenous input which may be set at a constant or decreasing level, determined by a firm's energy production baseline or set at specific benchmarks determined by the cap and trade policy. A firm's annual CO2 emissions [**Emissions**] are used as an endogenous input into the policy section of this model. By comparing a firm's actual emissions to its credit allowance, the model determines whether the firm has additional credits remaining or must buy additional credits as a fee for its excessive emissions [**Credits Available or Needed**]. There is no "banking" decision making in the model, so if a firm has additional credits available it will choose to sell them in the carbon market. Since some cap and trade programs allow credit banking, this may be an important feature to consider and future revisions of this model may attempt to simulate banking. However, given the investment decision programming in the current version of this model, a long-run banking decision rule would require significant additional research and possibly a reformation of many of the model's forward-looking components. This carbon price then determines the amount of revenue a firm receives from selling its additional credits or the cost incurred by purchasing additional credits [**Credit Cost**]. Figure 3.3 depicts the portion of the model described in this paragraph.

Figure 3.3: Cap and Trade Program Emission Allowances and Credits

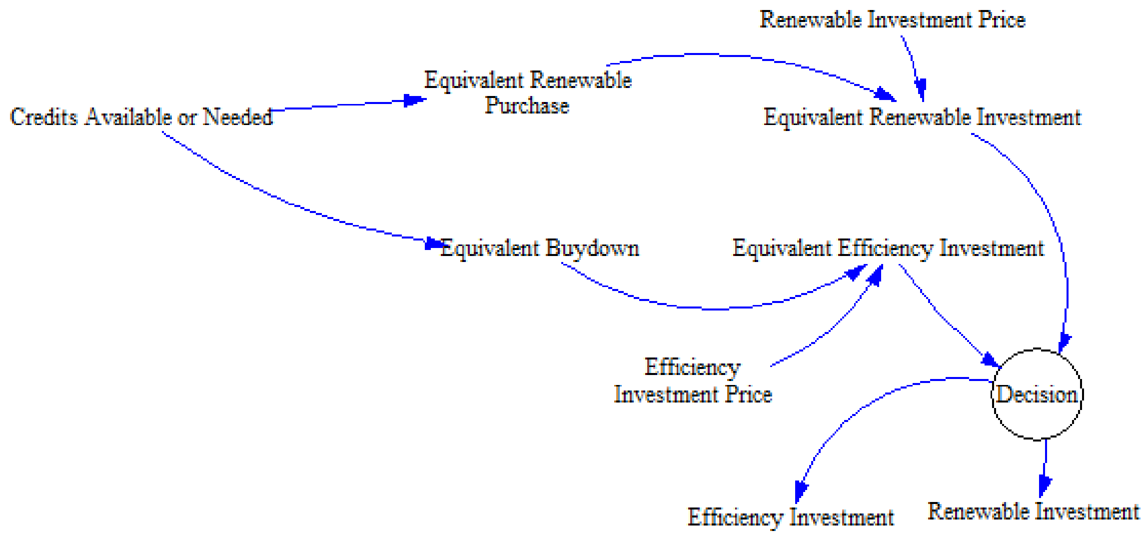


If a firm needs additional credits from producing more emissions than its allowance, it must buy the credits from the market and face a cost [**Credit Cost Incurred**] which adds to the total amount that a firm spends on credits for the entire run of the model [**Cumulative Credit Cost**]. However, while it purchases the credits, the firm also makes a decision regarding its behavior in the next year. While there are a number of methods and resources for a firm to invest in to reduce its emissions (Grubb 1997), for practicality this model assumes that a firm will choose to invest in either renewable energy or energy efficiency. First, the firm calculates how much electricity production it must reduce or replace to avoid exceeding its emission allowance (based on its existing generation portfolio's emission intensity) [**Equivalent Buydown**]. Then, it calculates the cost of an investment in renewables or efficiency equivalent to that production amount [**Equivalent**

Efficiency Investment and **Equivalent Renewable Investment**]. Here, the price of each investment is determined by exogenous inputs (shown in Chapter 4) [**Renewable Investment Price** and **Efficiency Investment Price**].

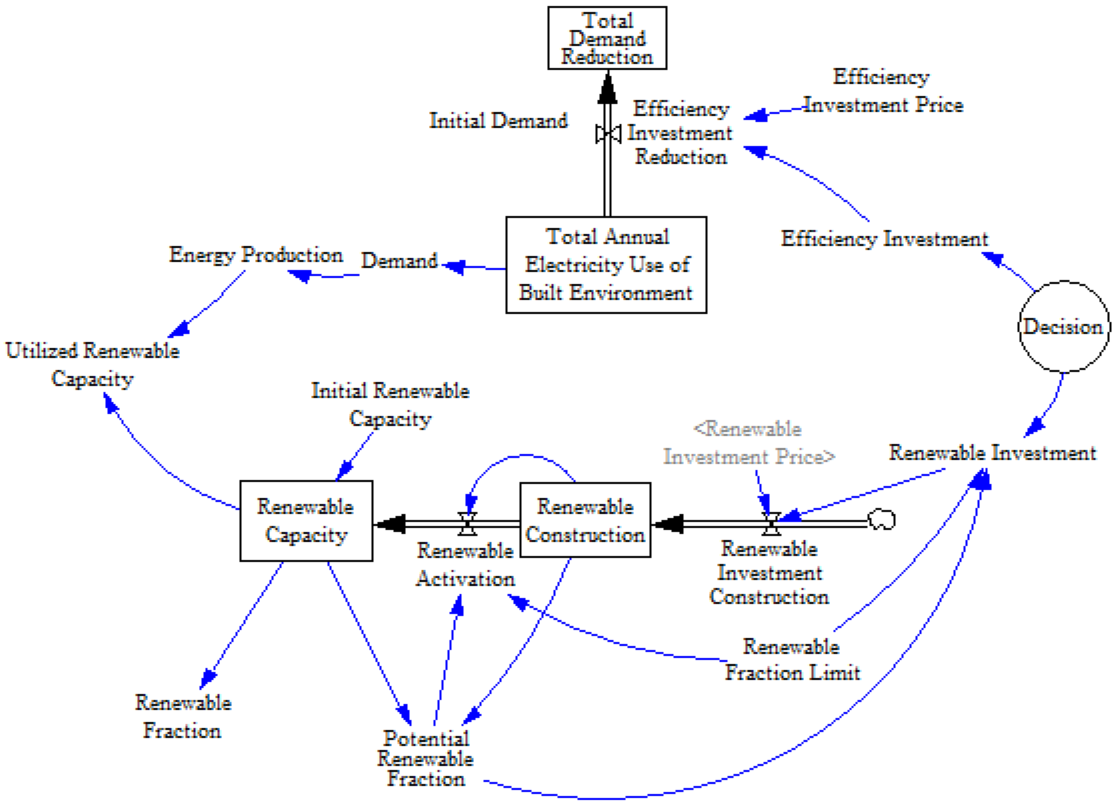
Additionally, each investment is limited by an exogenous maximum annual amount that a firm can invest in each area (by default, a certain percentage of a firm's annual electricity production). For instance, a firm may need to replace 10% of its fossil fuel production with renewables in order to meet an emissions cap. It may be unrealistic, however, for the firm to replace that portion of its existing production before a turbine's two year construction period allows. Likewise, the firm may only be able to increase energy efficiency by 3% each year by providing consumers with incentives for building renovation and energy efficient product purchases. Figure 3.4 depicts this modeled investment calculation and decision.

Figure 3.4: Investment Decision Calculation



After the firm determines the equivalent amount of renewable or efficiency investment, it compares the costs of each with the cost of simply purchasing more credits [**Decision**]. The firm then chooses the least costly option of the three (do nothing/buy credits, invest in renewables [**Renewable Investment**], or invest in energy efficiency [**Efficiency Investment**]). If the firm chooses to invest in efficiency, it may also invest in renewables if there is a gap between the maximum efficiency investment and the equivalent amount of energy production necessary to meet the emissions cap. The amount of efficiency investment determines the next year's demand reduction [**Demand Reduction**], while the amount of renewable investment determines the increase in the next year's renewable energy supply [**Renewable Production Share**]. The increase in electric demand from its baseline is determined by a combination of the percentage of demand growth and the annual energy efficiency investment. These items are depicted in Figure 3.5

Figure 3.5: Effect of Investment Decision

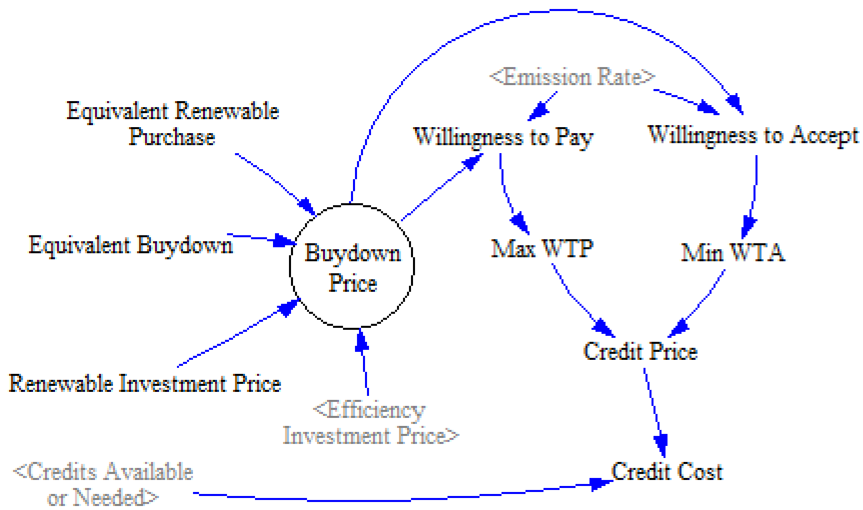


For accounting purposes, this model maintains a number of cumulative or total levels to track the overall behavior of the model over the course of its entire simulation. These levels, which do not affect the behavior of the model but serve as indicators of the impact on firms, include the following variables: **Cumulative Emissions; Total Demand Reduction; Cumulative Efficiency Investment; Cumulative Renewable Investment;**

Cumulative Credit Cost; and **Total Cumulative Cost** (which is the summation of all investments and costs).

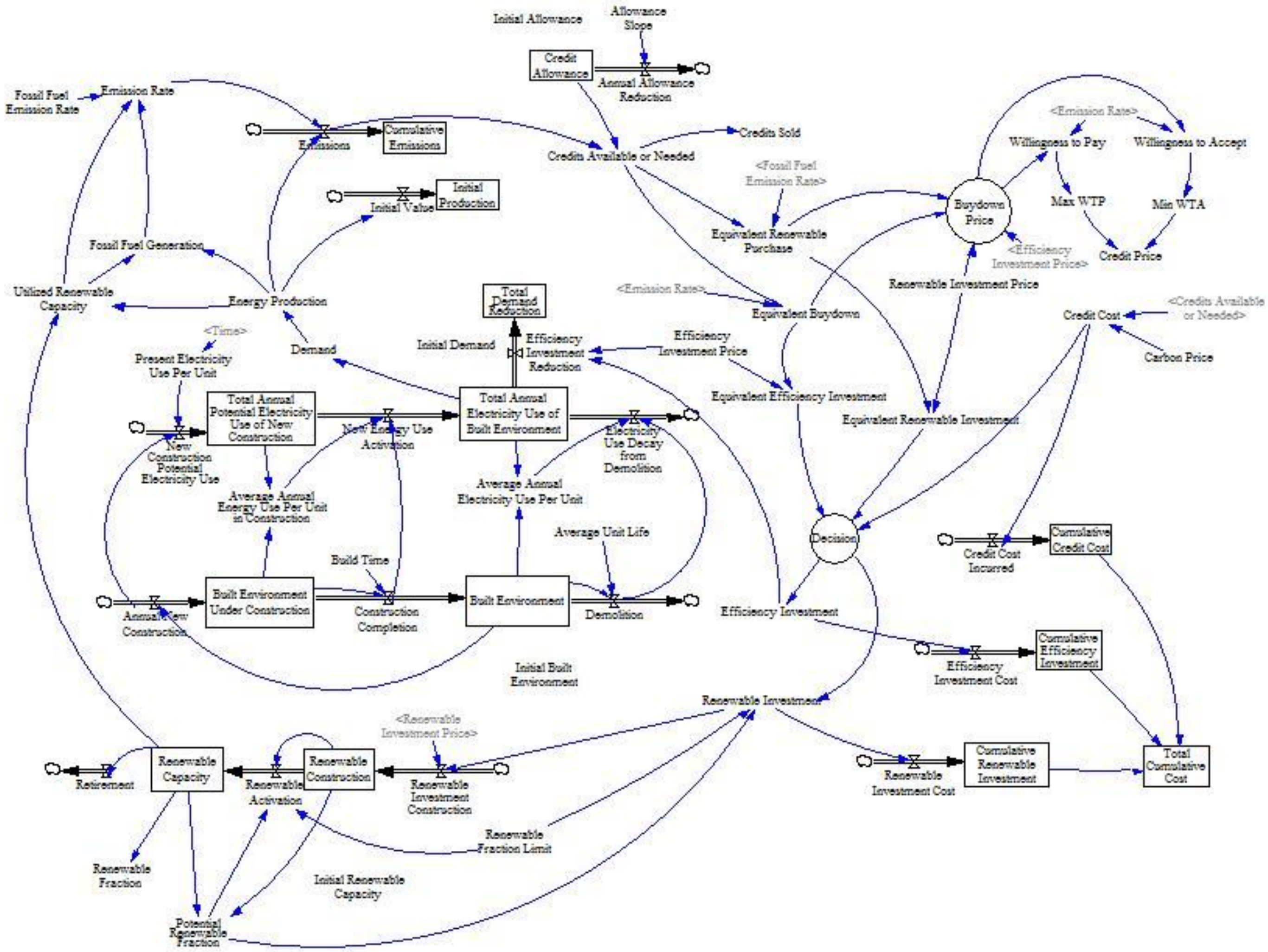
The portions of the model discussed in this chapter are in general well developed and founded on real data. One portion of the model that could be developed further might be the calculation to determine a dynamically changing carbon credit price. In this model, the carbon price is regulated by the cap and trade program authority and is assumed to be set at $50 per ton of CO2. As described in the next two chapters, however, this analysis does study a theoretical scenario in which the endogenous firm is influential enough to set the price of carbon. Figure 3.6 demonstrates the experimental carbon credit price calculation section of this model. This calculation assumes that the credit price is determined by the firm with the highest willingness-to-pay (WTP) for credits. Here, the WTP is calculated by the firm's marginal cost of meeting its carbon cap. By taking the average price per energy equivalent ($/GWh) of its two investment options, efficiency and renewables, a unique WTP is calculated for each credit buying firm. If a firm is a credit seller, a similar calculation is used to determine its willingness-to-accept.

Figure 3.6: Determining the Carbon Credit Price



Because of its scope, there is a number of items that this model is not meant to simulate. For instance, this model does not simulate the cost of producing electricity seen by each firm, or the revenue made by selling this electricity to consumers. Additionally, the decision making programmed in this model looks only at the short term (from year to year), rather than taking long term considerations which may include opportunity costs, inflation and discount rates. Other models, such as those listed earlier in this chapter, have been developed to take closer looks at these issues. The intent of this paper is to develop a model to examine cap and trade programs and the resultant decisions of regulated firms. As such, this model is meant to complement, not supplant, those models which might include many financial and political considerations but not cap and trade programs. Figure 5.7 displays the model in its entirety.

Figure 3.7: System dynamics model of a regional cap and trade program



Data Input and Assumptions

Emissions data for fossil fuel electricity generation is taken from EPA's eGRID 2007 (EPA 2009). The electricity producing firms in this model are assumed to be electric utilities in the state of Minnesota. These firms will produce electricity based on the fossil fuel technologies listed by eGRID, which provides the CO2 emission rate for coal, oil and natural gas electricity plants in Minnesota. For this study, only CO2 that was emitted directly as a result of each unit of electric generation were tracked (lifecycle emissions are ignored). These are:

Coal:	2,326.15 lbs CO2/MWh
Oil:	2,174.30 lbs CO2/MWh
Natural Gas:	1,251.13 lbs CO2/MWh

Source: EPA's eGRID 2007

To reflect the resources in Minnesota, it is assumed that all new renewable energy is produced by wind turbines with no direct CO2 emissions. Although, on a lifecycle basis, CO2 emissions may occur during the manufacture, transportation and construction (*upstream emissions*) of wind turbines, the carbon intensity of electricity generated from wind relative to that generated from coal would still be substantially smaller, as a lifecycle assessment of coal-fired electricity would also add an additional amount of upstream emissions. The Pacific Northwest National Laboratory (PNL) estimates that Minnesota has about 657,000 GWh of annual wind energy potential (Elliot, et al., 1991). Because of transmission, distribution and interconnection concerns, however, this analysis assumes that wind energy can contribute no more than 45% of a firm's total electricity production. This model accounts for the cost of wind energy investment on a levelized basis, which considers the capital, operation and maintenance cost of a electric production over the entire life a wind turbine. A National Renewable Energy Laboratory (NREL) assessment has found that the levelized cost of wind energy is about $0.0476 / kWh, or $47,600 / GWh (Fingersh, et al., 2006).

As an alternative to renewable development, a firm can also choose to spend capital to increase the energy efficiency of the existing built environment of its customers. In Minnesota, the Conservation Improvement Program (CIP) requires utilities to commit a certain portion of their revenue to consumer outreach, education, rebate programs and other investments that can increase consumer side conservation or energy efficiency (MN DOC 2009). It is assumed that every dollar invested into this program results in a stated amount of annual electricity demand reduced. The MGA Energy Efficiency Advisory Group (EEAG) has estimated this investment ratio to be about two cents for every kilowatt-hour reduced, or $0.02/kWh (EEAG 2008). Using this, the model will assume that for every two cents a firm invests in energy efficiency, the annual electricity demand seen by the firm will be reduced by one kilowatt-hour.

When compared to the cost of investing in renewables, energy efficiency is a relatively inexpensive alternative that is less than half the cost of wind, according to the sourced cited above. Therefore, it is expected that each firm would choose to invest in efficiency instead of renewables. It is unreasonable to assume, however, that a firm can continuously invest in efficiency to perpetually reduce electricity consumption despite a growing economy with increasing demand and an increasing intensity of electricity use per capita or per square foot (Reddy 1990). Because technological change provides a moving target for energy efficiency improvements, it is hard to determine the true potential for consumption reduction through efficiency (Newell, et al, 1999). Here it is assumed that investments in energy efficiency through building renovation can achieve a maximum 35% reduction in annual energy demand before the cost of efficiency improvements becomes significantly larger. While this number is a reasonable estimate for the inexpensive, "low hanging fruit" of easily accessible efficiency improvements, this does present some limitations in accurate cost modeling (Mallett, et al, 2008). A research project with greater resources than this one could conceivable produce an cost curve which increases the price of efficiency gains as the overall system efficiency improves.

Given this, when faced with credit fees for emitting more than its cap, a firm may be expected to invest in the cheaper option, energy efficiency, until the maximum investment is made. When the efficiency limit is reached, the firm will likely begin to invest in renewable energy. The date of incidence, rate and overall magnitude of these investments are an important result of this analysis.

The data inputs discussed here provide a consistent baseline environment for each scenario to operate from. Factors such as physical constraints, emission rates, economic growth and investment costs provide a constant basis from which to analyze the simulation results. Table 3.1 provides a summary of the data inputs which are held constant across all scenarios.

Table 3.1 Baseline Data Input

Variable	Value	Units
Efficiency Investment Limit	35	%
Renewable Investment Limit	45	%
Annual Demand Growth	1	%
Fossil Fuel Emission Rate	1035.64	tCO2/GWh
Efficiency Investment Price	20000	$/GWh
Renewable Investment Price	47600	$/GWh
Energy Use per SqFt	.075	MWh/SqFt

This section has provided a narrative of the overall structure and behavior of the system simulated by this model. For more detailed information, Appendix 1 lists definitions for each model variable and its data input. Appendix 2 provides a complete listing of each model scenario and its run results. Some limitations and areas of improvement of this model are discussed in Chapters 6 and 7.

Chapter 4 Scenario Design

The entities and values contained within a system dynamics model change over the course of the model to reflect a simulated system behavior. However, the nature of the change and behavior depends on the initial state of the model's inputs and assumptions. The entire set of inputs can be altered to reflect a unique context or *scenario* that is meant to model a real world situation. Here, a model scenario can reflect a series of specific values in the following areas: the level of consumer demand and growth faced by an electricity producing firm; a firm's existing level of fossil fuel and renewable energy production technologies; the specific make up of the modeled cap and trade program, including its method of credit allocation and the nature of its resulting credit market; and the cost of various actions and investments available in the model, such as renewable energy or energy efficiency investment. This chapter discusses the design of each scenario utilized by this analysis and the data used in its construction.

Scenario Methodology

This paper invents three scenarios to test the behavior of the cap and trade SD model developed here. The first two scenarios are meant to simulate two separate and unique firms to examine the differences in the behavior of each under a cap and trade system. In these scenarios, the cap and trade system is assumed to be large enough to model the firms as price takers. The third scenario will allow these firms to trade carbon credits with each other in a market where they may be price setters. A projection of emissions for each scenario *without* the cap and trade program will baseline by which to compare the results of each scenario. Aside from the data input detailed in table 3.1, each scenario will operate on unique values for many of the variables within the model.

Much of the unique data used for each scenario will be based on calculations derived from the electric industry in Minnesota. The goal for this is to establish estimations of firm behavior and emissions that would be likely in a state similar to Minnesota. For example, data from EPA's eGRID and EIA's SEDS were used to determine Minnesota's emission level and rate in 1990 and 2004. This is then used to determine an 85% emissions reduction (from 1990 levels) goal for the year 2050 according to IPCC's climate change guidelines. The Minnesota-derived information that provides the basis for the data in each scenario is detailed in table 4.1.

4.1 Minnesota Values (Year 2004)

Variable	MN Value (2004)	Units
Initial Electric Demand	52,381	GWh
Initial Renewable Capacity	3667	GWh
Initial Renewable Fraction	7	%
Fossil Fuel Emission Rate	1035.64	tCO2/GWh
Initial Total Emission Rate	963.15	tCO2/GWh
1990 Emissions	48848153	tCO2
2004 Emissions	54,248,344	tCO2
2050 Emissions Goal (IPCC)	7327223	tCO2
Initial Building Stock	698,416,584	SqFt
These values are provided with as much detail as possible to provide a transparent description of model inputs		

Scenario 1: A large, conventional electric utility

The first scenario developed here is meant to simulate the behavior of a large electric utility, *Firm 1,* which provides a substantial portion of a state's electricity. This firm, which meets 80% of the state's electricity demand, relies primarily on fossil fuels for its electric generation with seven percent (7%) of its electric production coming from renewables. Thus, the total emission rate for Firm 1 is about 963 tCO2/GWh, much like the total emission rate for Minnesota (eGRID 2009).

If it were to have produced 80% of Minnesota's electricity in the year 2004, Firm 1 would have emitted over 40 million metric tons of CO2. Under a cap and trade system with an emissions goal similar to IPCC's 2050 goal, Firm 1 would need to reduce its emissions to 5 million metric tons of CO2 in the year 2050. This determines the equation for Firm 1's annual emissions cap over the course of the simulation. A summary of all unique data inputs for each scenario, such as the 2050 cap goal and annual reduction slope, is provided in table 4.2.

Scenario 2: A small, primarily renewable electricity provider

The second scenario is meant to simulate the behavior of a firm (*Firm 2*) which owns a moderately sized renewable source of electricity. An example of such a firm might be a company that owns a large wind farm. Firm 2 meets 20% of the state's electricity demand and produces 90% of its electricity from carbon-neutral sources such as wind turbines. Thus, its total emission rate is about 104 tCO2/GWh. Since Firm 2 met only 20% of the total state demand by using 90% renewables, Firm 2 only emitted an estimated 1.08 million metric tons of CO2 in 2004. This also means that Firm 2's 2050 goal is about 146 thousand metric tons. The implications of a cap this strict will be discussed with the scenario's results.

Scenario 3: Firms 1 and 2 trading as price setters

A third scenario creates a theoretical carbon market that is small enough for Firm 1 and Firm 2 to become *price setters*. The two firms may trade credits with each other, or they may trade with a theoretical third firm which represents an aggregate of all other firms in the market. The three firms can freely trade emission credits with each other while the firm with the highest *willingness to pay* is the price setter. To ensure unlimited availability of credits in the market, it is assumed that Firm 3 produces no emissions and generates many credits. Although this is not very realistic for single, large electric utility, Firm 3 is only a theoretical firm used by this model to produce a market with many carbon credits. In this scenario, the data input for Firm 1 and Firm 2 is identical to that in scenarios 1 & 2. For simplicity, the data input for Firm 3 is set to be identical to the Minnesota state data. This data is summarized in Table 4.2.

Table 4.2 Exogenous Data Input Summary

Variable	Units	Scenario 1 (Firm 1)	Scenario 2 (Firm 2)	Scenario 3 (Firm 3)
Initial Electric Demand	GWh	41,905	10,476	52,381
Initial Renewable Capacity	GWh	2,933	9,429	52,381
Initial Renewable Fraction	%	7	90	100
Fossil Fuel Emission Rate	tCO2/GWh	1035.64	1035.64	1035.64
Initial Total Emission Rate	tCO2/GWh	963.15	103.56	0.00
1990 Emissions	tCO2	36,343,026	976,963	48,848,153
2004 Emissions	tCO2	40,360,768	1,084,967	54,248,344
2050 Emissions Goal	tCO2	5,451,454	146,544	7,327,223
Annual Cap Reduction	tCO2/year	758,898	20,400	1,020,024
Credit Price	$/tCO2	50	50	Endogenous
Efficiency Investment Price	$/GWh	20,000	20,000	20,000
Renewable Investment Price	$/GWh	47,600	47,600	47,600
Efficiency Investment Limit	%	35	35	35
Renewable Investment Limit	%	45	100	100
Demand Trend	%	1	1	1
Initial Building Stock	SqFt	558,733,267	139,683,317	698,416,584
Building Energy Use	kWh/SqFt	75	75	75

These values are provided with as much detail as possible to provide a transparent description of model inputs and exact data values collected from EPA and EIA.

Because the most consistent and reliable state data is only available up until the year 2004, this model starts in the year 2004 and runs for 46 years until the year 2050. The end date of 2050 was chosen to measure the policy's effectiveness in achieving IPCC climate change goals. New datasets are frequently released from federal agencies such as EIA and EPA, however, so altering the model to run with more recent data and more recent (or future) years is not difficult. To keep this theoretical model clear and simple, however, this analysis instead aligns the model with the most reliable data. The model is run once for each scenario and simulated until the year 2050. The primary results of each scenario are presented in Chapter 5. A complete listing of results is provided in Appendix 2.

Chapter 5 Model Simulation Results

Table 5.1 Scenario Emissions Results (thousand tCO2)

Annual	**2020**	**2030**	**2040**	**2050**
Scenario 1	29,000	22,000	18,000	20,000
Baseline 1	39,100	39,100	39,400	39,900
Scenario 2	776	597	402	190
Baseline 2	776	770	841	978
Scenario 3	38,100	28,100	23,000	25,200
Baseline 3	39,900	39,800	40,200	40,900
Cumulative	**2020**	**2030**	**2040**	**2050**
Scenario 1	565,000	824,000	1,080,000	1,200,000
Baseline 1	632,000	1,020,000	1,420,000	1,810,000
Scenario 2	14,000	20,900	27,200	28,800
Baseline 2	14,000	21,700	29,600	38,600
Scenario 3	641,000	973,000	1,220,000	1,460,000
Baseline 3	646,000	1,040,000	1,450,000	1,850,000
Thousand Metric Tons of CO2. Results Reported to three significant figures.				

The results of each scenario demonstrate a reduction in carbon emissions over each firm's baseline emissions projection. Table 5.1 provides a summary of benchmark annual cumulative emissions for each scenario and its baseline. For the years 2020 to 2050, model simulation projected a decrease from 29 to 20 million metric tons of annual CO2 emissions from Firm 1, and a decrease from 776 to 190 thousand metric tons from Firm 2. This results in a net avoidance of about 616 million metric tons of CO2 for Firm 1 and about 9.83 million metric tons for Firm 2, as shown in Table 5.2.

Table 5.2 CO2 Emissions Avoided by 2050

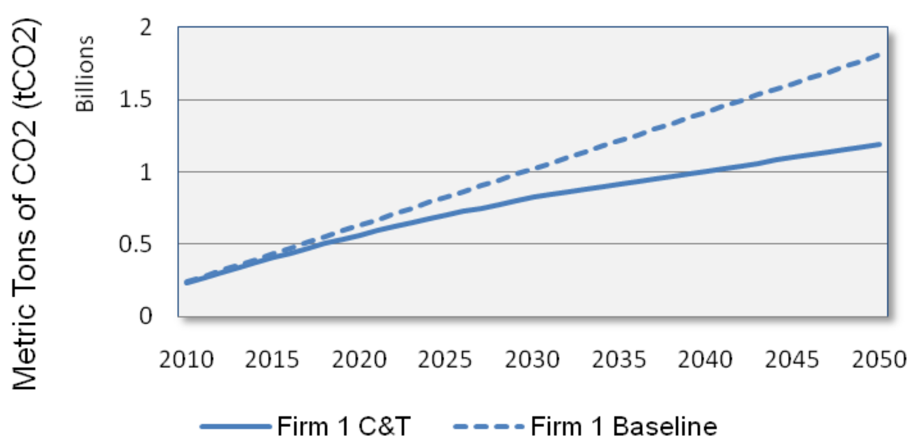
	Annually	**Cumulative**
Scenario 1	20,200	616,000
Scenario 2	788	9,830
Scenario 3	15,700	387,000
Thousand Metric Tons of CO2, 3 sig figs; Avoided emissions are the difference between the results of a scenario and its baseline		

The detailed results for each scenario are presented and discussed on the following pages.

Scenario 1 Results: A large, conventional electric utility

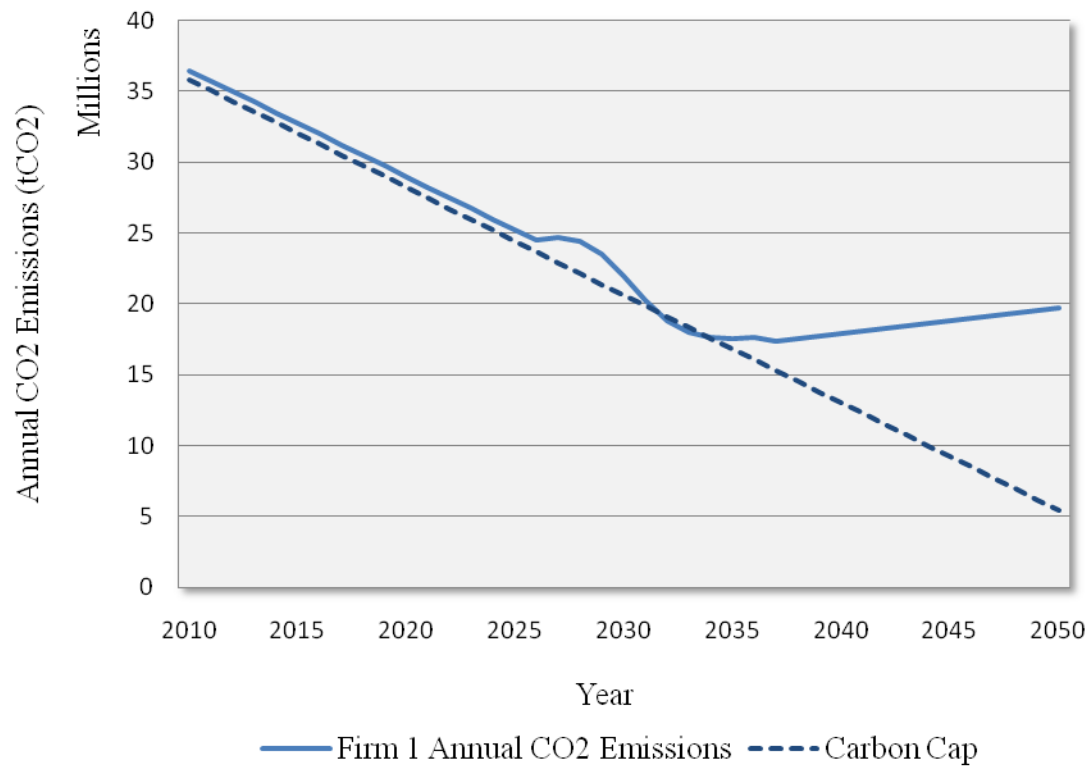
In this scenario, Firm 1 represented a very large and traditional electric utility that provided a theoretical 80% of the electricity in Minnesota, or 41.9 TWh in 2004. Its electric generation was derived from 93% fossil fuels with a total emission intensity rate of about 963 metric tons of CO_2 per GWh (tCO_2/GWh). If it were to reduce its emissions by the year 2050 to 85% below its 1990 levels, Firm 1 would need to emit less than 5.45 million tons of CO_2. Given its annual CO_2 emissions of about 40.4 million tons in 2004, this equates to an annual reduction of about 759 thousand tons per year. This amount, a linear reduction over 46 years, is set as the annual carbon cap for Firm 1. Figure 5.1 presents the resulting cumulative emissions from Firm 1 for the first model simulation scenario.

Figure 5.1: Scenario 1 Cumulative CO2 Emissions of Firm 1



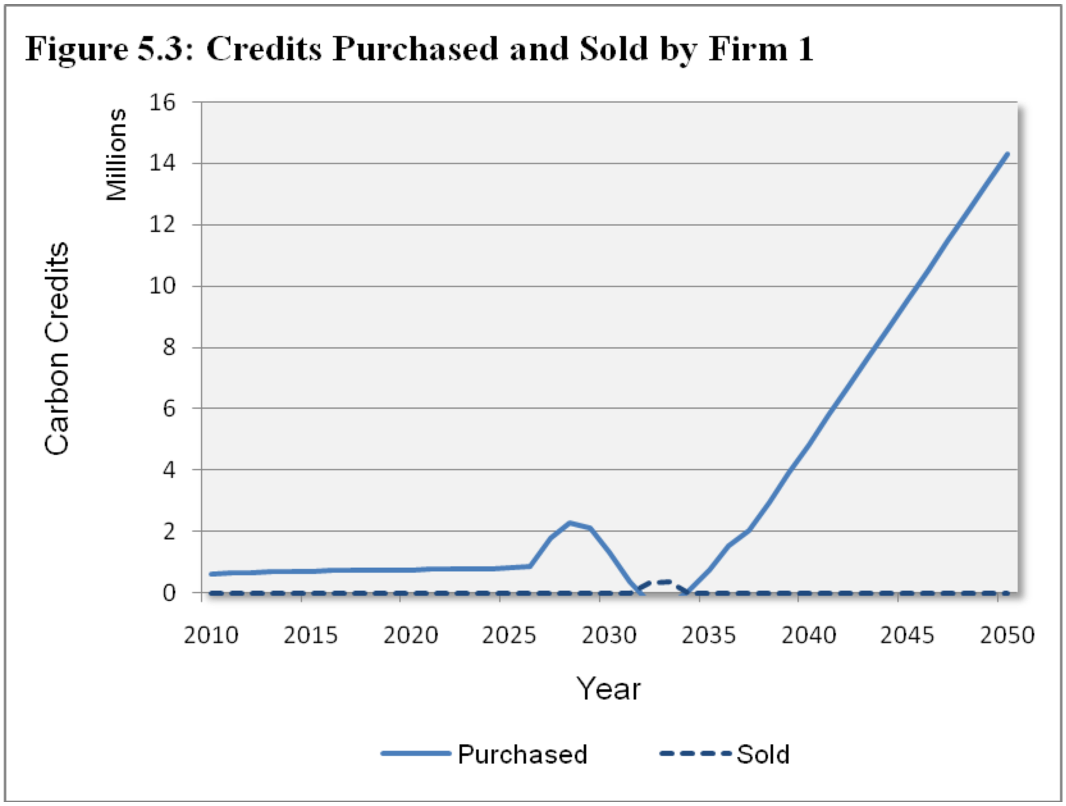
The results presented in Figure 5.1 demonstrate a clear reduction of cumulative CO_2 emissions over the 40 year simulation. By 2050, the model projected that a total of 616 million metric tons of CO_2 are avoided. It is clear from these results that cap and trade has a positive effect, but a more detailed observation of Firm 1's behavior would help determine whether the program is reaching its potential and goals. Figure 5.2 presents Firm 1's annual emissions over 40 years. The emissions in the graph are actual emissions, rather than net emissions after a firm's allotment of credits.

Figure 5.2: Scenario 1 Emissions of Firm 1



For the first 15 years, Firm 1 approximately follows the carbon cap implemented by the cap and trade system. Although it is clear that Firm 1 emits slightly more than the cap for each of these years, its declining shape demonstrates effort by the firm that may be deemed adequate for the cap and trade program, as significant emission reductions are achieved. However, following the year 2025, Firm 1's annual emissions begin to show what appears to be erratic behavior with an initial increase in emissions followed by a reduction to a level *below* the cap, and finally an apparent breakdown of emission reductions with a continually increasing emission rate until the model ends. While this trend seems chaotic based on Figure 5.2 alone, a closer look at Firm 1's behavior, including its financial investments and renewable energy development, may show a clear reason for these results.

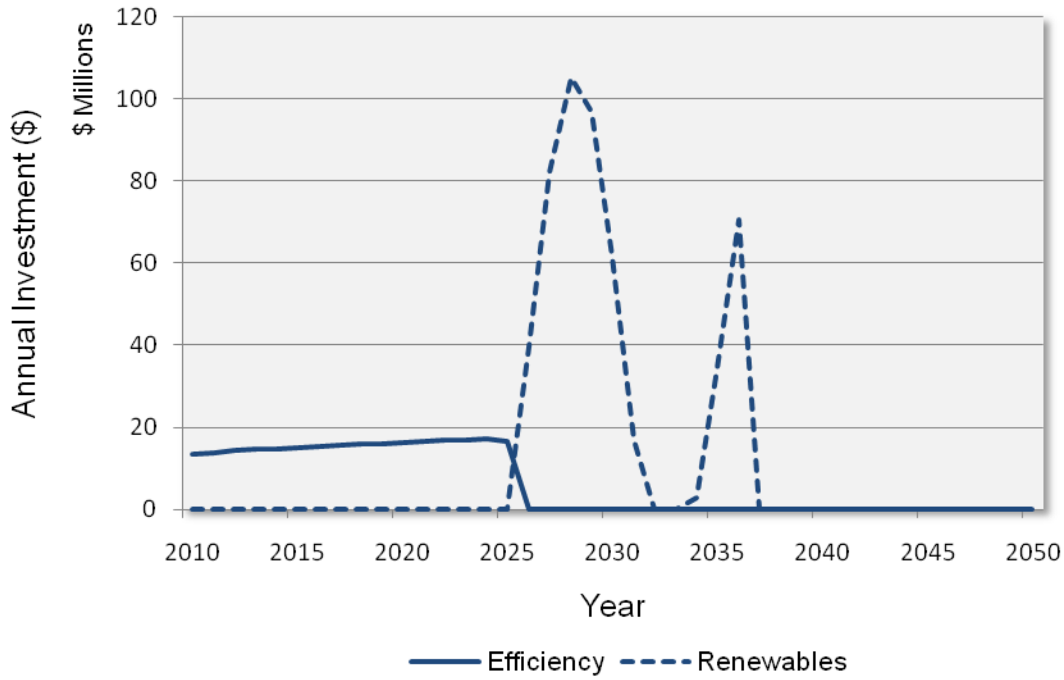
Under a cap and trade system, a regulated entity must pay for every unit of emissions that it produces over its cap by purchasing credits. Depending on the price of carbon, a firm that continuously exceeds its carbon cap is incurring a great cost. Theoretically, there would be an incentive to reduce its emissions to meet the cap, if possible. To consider Firm 1's incentive to invest in emission reduction, Figure 5.3 presents the amount of carbon credits that are purchased or sold by Firm 1 through the model's 40 year run.



As shown in Figure 5.3, Firm 1 must purchase carbon credits, equivalent to just under one million tCO2, until just after the year 2025. At this point, the amount varies significantly by more than doubling through the year 2030, then decreasing to a point where Firm 1 can sell credits around 2033. Then, after 2035, Firm 1 must buy an increasingly large amount of credits each year until the end of the model run. In total, Firm 1 was required to purchase over 125 million carbon credits over the course of the simulation at a cost of $50 per credit, or $6.28 billion total. In comparison, the years in which Firm 1 emitted less than its cap resulted in the sale of only about 697 thousand credits for a revenue of only $34.8 million. While it is clear that Firm 1 has a moderate incentive to invest in alternatives, its behavior is still not directly apparent.

The truly interesting results of this analysis are shown in the financial investment behavior of Firm 1. Given the context of the cap and trade system and the disincentive to emit presented by the cost of carbon credits, Firm 1 can invest in either renewables or energy efficiency to reduce its emission to its cap. As discussed before, energy efficiency is generally a less expensive alternative than renewable investment, so it is expected to be a firm's first choice. However, both efficiency and renewables have physical constraints which limit maximum investment. Figure 5.4 reports the investment decisions made by Firm 1 over the course of the simulation.

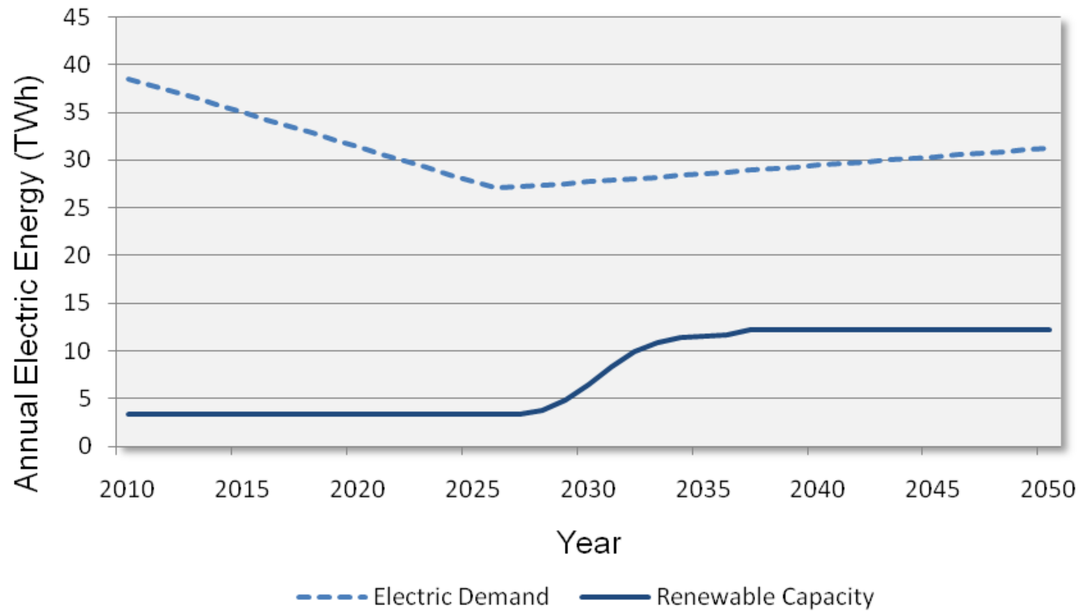
Figure 5.4: Investments of Firm 1



As expected, the firm first chooses energy efficiency, investing between $15 and $20 million each year between 2010 and 2025. Once a 35% reduction of electric demand has been made, Firm 1 can no longer invest in efficiency. At this point, the firm must determine whether it is less costly to pay for credits or invest in renewables to meet its cap. Although it must pay for the emissions that exceed its cap regardless of its investment efforts, the firm looks to the next year and compares the cost of another year's credits with the cost of investing in enough renewable energy to avoid exceeding its cap. After the efficiency maximum is met, Firm 1 decides to invest in renewables, with an annual investment of about $105 million by 2028 (Figure 5.4).

At first puzzling, the increase in Firm 1 emissions shown in Figure 5.2 between the year 2025 and 2030 directly correlates with the period in which the firm transitions from efficiency to renewables as a primary means of emission mitigation. Because the firm has reached the maximum potential allowed by energy efficiency and building renovation, it can no longer reduce its annual emissions with such ease. In fact, after it ceases investment in efficiency, electric demand begins to increase (at 1% annually in this scenario). Although it immediately invests in renewable energy, this model includes a 2 year delay to simulate the construction and interconnection time of wind turbines. Thus, while it was actively investing in renewable energy, Firm 1's renewable capacity lagged behind the increase in electric demand during these 5 years. Figure 5.5 compares the electric demand faced by Firm 1 with its total renewable capacity. The graph shows that from 2010 to 2025, the electric demand decreases due to Firm 1's efficiency investment, then steadily increases during the years in which the firm must increase its renewable capacity.

Figure 5.5: Firm 1 Demand and Renewable Capacity



For a brief time, Firm 1 became a seller of credits. In the years 2032 and 2033 the firm sold a total of 697 thousand credits for a revenue of $35.8 million. In 2032, enough renewable capacity has been constructed to meet Firm 1's emissions cap. However, the firm had invested a substantial amount of capital into construction in the previous six years, much of which hadn't been completed by 2032. Therefore, for a period of two years after its cap has been met, Firm 1's renewable capacity continues to grow and push its emissions below the cap, resulting in a surplus of credits for it to sell to the market. This phenomenon, where Firm 1 *overshoots* its future goals by investing too much in the present, is a result of the model's decision making rules described previously in this paper. The revenue generated here ($35.8 million), however, is many orders of magnitude smaller than the cumulative amount Firm 1 must pay for credits throughout the model simulation (about $6.28 billion).

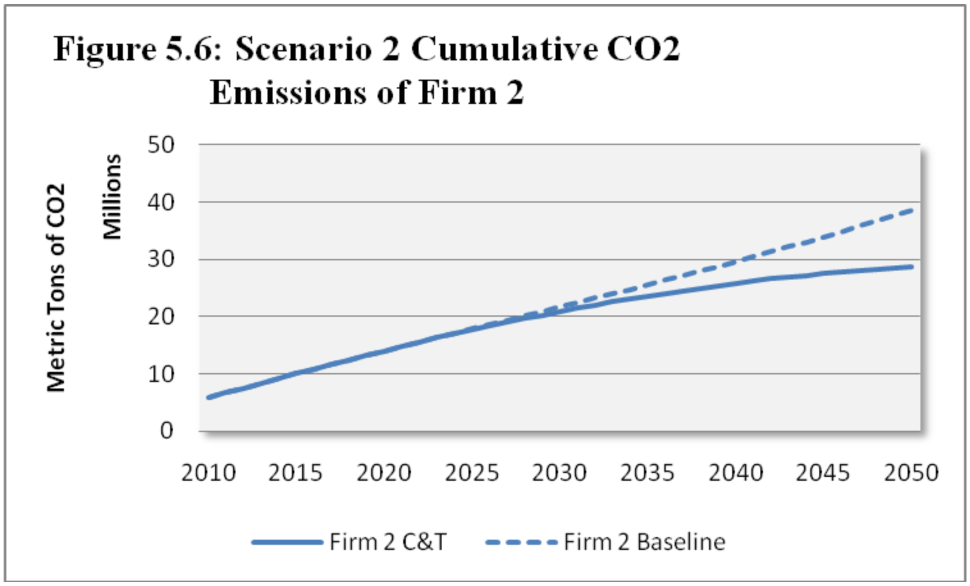
Finally, another spike in renewable investment is seen for the years 2034 through 2036. At this point, the dip in emissions caused by Firm 1's extra renewable capacity has been outpaced by an increase in demand. Once again exceeding its cap, Firm 1 begins constructing additional renewable capacity until 2036 when, at a fraction beginning to exceed 40% of its total generation capacity, renewables cannot be used to provide additional generation to the electric grid. All available mitigation options have been exhausted at this point and Firm 1's ability to meet the goals of the cap and trade program are diminished. Thus, Firm 1's emissions exhibit the significant increase seen for the last fifteen years of this model simulation. In the end, although Firm 1 reduced a tremendous amount of CO_2 emissions from its baseline, 616 million tons, it did not reach the 2050 goal set by the cap and trade program. Table 5.3 provides a summary of the results of this scenario.

Table 5.3 Results Summary of Scenario 1

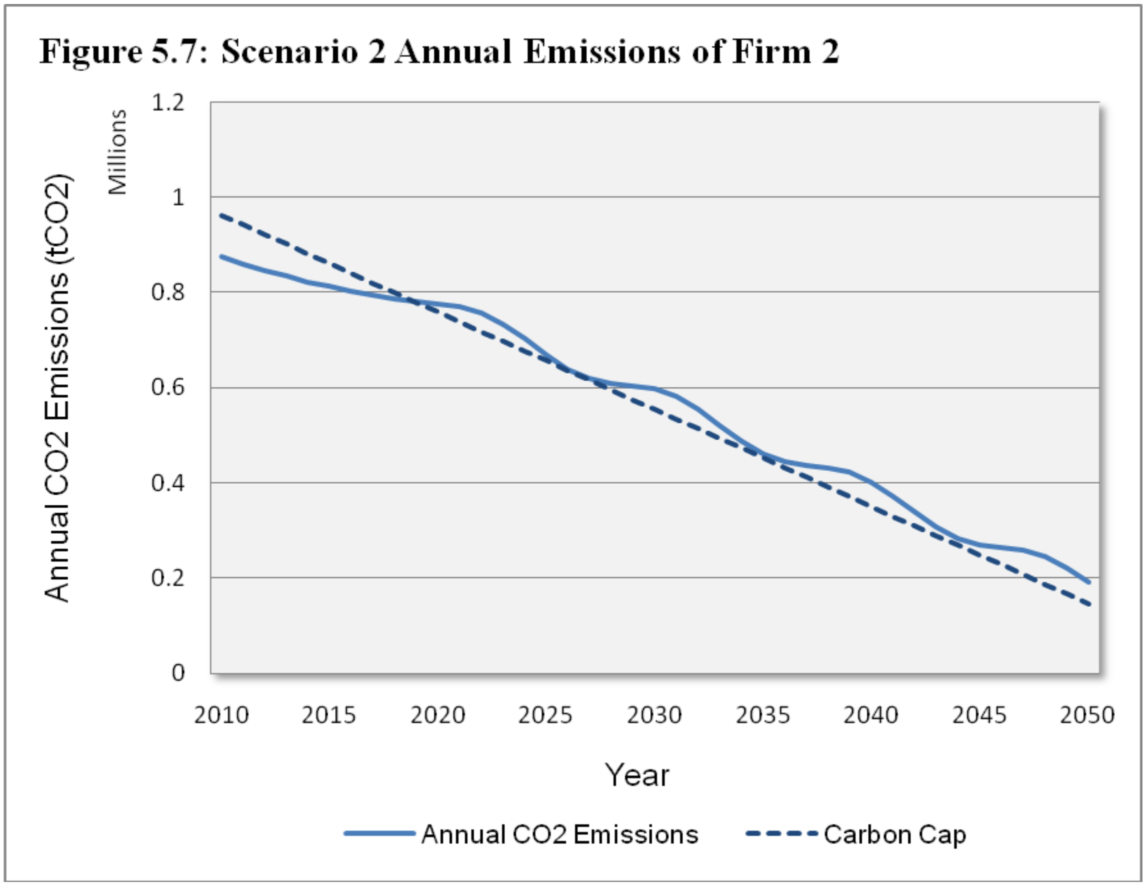
Emissions Avoided	616 million tCO2
Credit Cost Avoided	$32.50 billion
Credit Purchasing Cost	$6.28 billion
Credit Sale Revenue	$35.8 million
Efficiency Investment	$302 million
Renewable Investment	$531 million
Demand Reduction	15.10 TWh
New Renewables	9.24 TWh
2050 Goal Met?	No
All figures provided as *cumulative* totals of 40 year simulation and are not discounted into Net Present Value (NPV)	

Scenario 2 Results: A small, primarily renewable electricity provider

In this scenario, Firm 2 represented a small electricity provider that primarily utilized renewable energy to meet 20% of Minnesota's electric demand, or 10.4 TWh in 2004. Perhaps similar to the owner or operator of a large wind farm, Firm 2 generated 90% of its electricity from carbon-neutral renewable energy, resulting in an emission rate of only 103 metric tons of CO2 per GWh (tCO2/GWh). If it were to reduce its emissions by the year 2050 to 85% below its 1990 levels, Firm 2 would need to emit less than 147 thousand tons of CO2. Given its annual CO2 emissions of about 1.08 million tons in 2004, this equates to an annual reduction of about 20.4 thousand tons per year. Just as in scenario 1, this linear reduction over 46 is set as the annual carbon cap for Firm 2. Figure 5.6 presents the resulting cumulative emissions from Firm 2 for the second model simulation scenario.

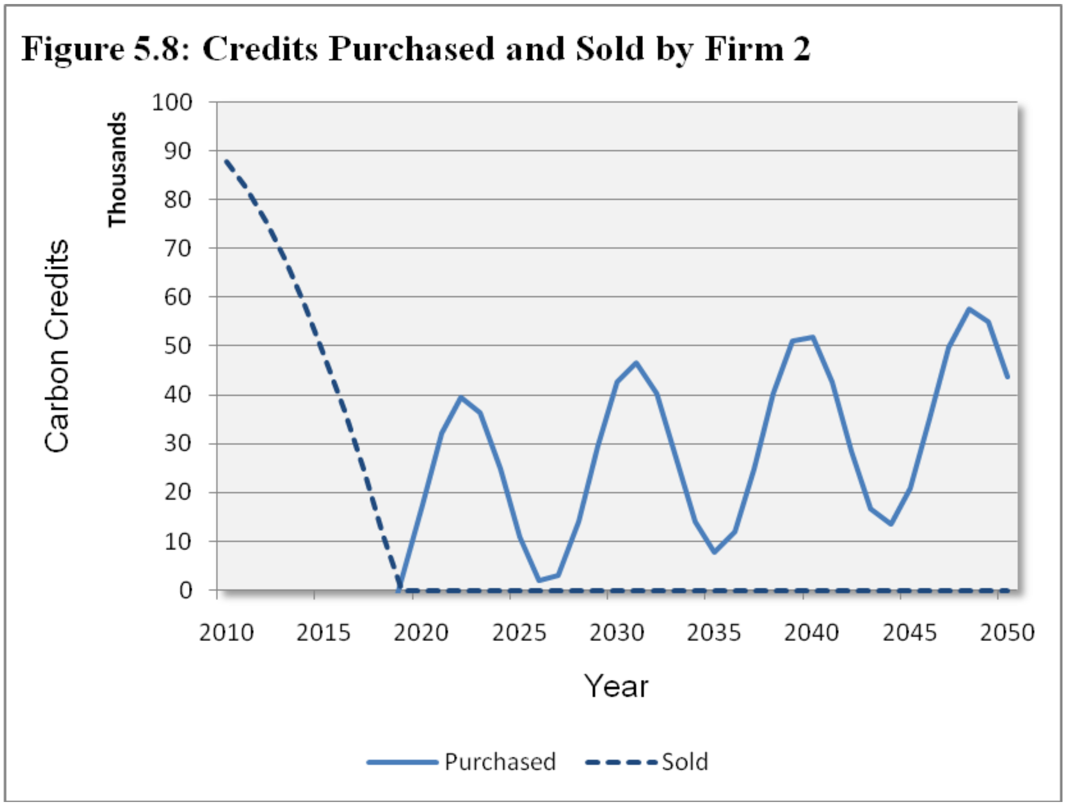


The results presented in Figure 5.6 demosntrate a clear reduction of cumulative CO2 emissions beginning around 2025 and growing in magnitude until 2050. By the end of the simulation, the model projected that a total of 9.83 million metric tons of CO2 are avoided. Though both the results of scenario 1 and scenario 2 demonstrate a reduction in CO2 emissions (a positive outcome), the reductions by Firm 2 seem to be less dramatic relative to its baseline. To determine the source of this difference, a look at the emissions cap seen by Firm 2, shown in Figure 5.7, may be enlightening.



Despite what appears to be a less significant reduction in cumulative carbon emissions when compared to the previous scenario, the behavior of Firm 2, as revealed in Figure 5.7, follows the goals set by the cap and trade program quite faithfully. At first, Firm 2 emits less than its allowance, generating credits to sell to the market, until the year 2020 when its emissions approach its cap. From this point until the end of the simulation, the firm's emissions demonstrate an oscillatory behavior, where the level increases or decreases evenly at a certain frequency. Despite its constant oscillation, the firm's emissions approximately follow the declining annual allowances until 2050 where, although it does not quite get there, Firm 2 nearly achieves its final goal. Thus, whereas Scenario 1 exemplified a failure or breakdown of cap and trade goals, Scenario 2 appears to demonstrate a successful implementation of these goals by a small, primarily renewable electricity generated firm.

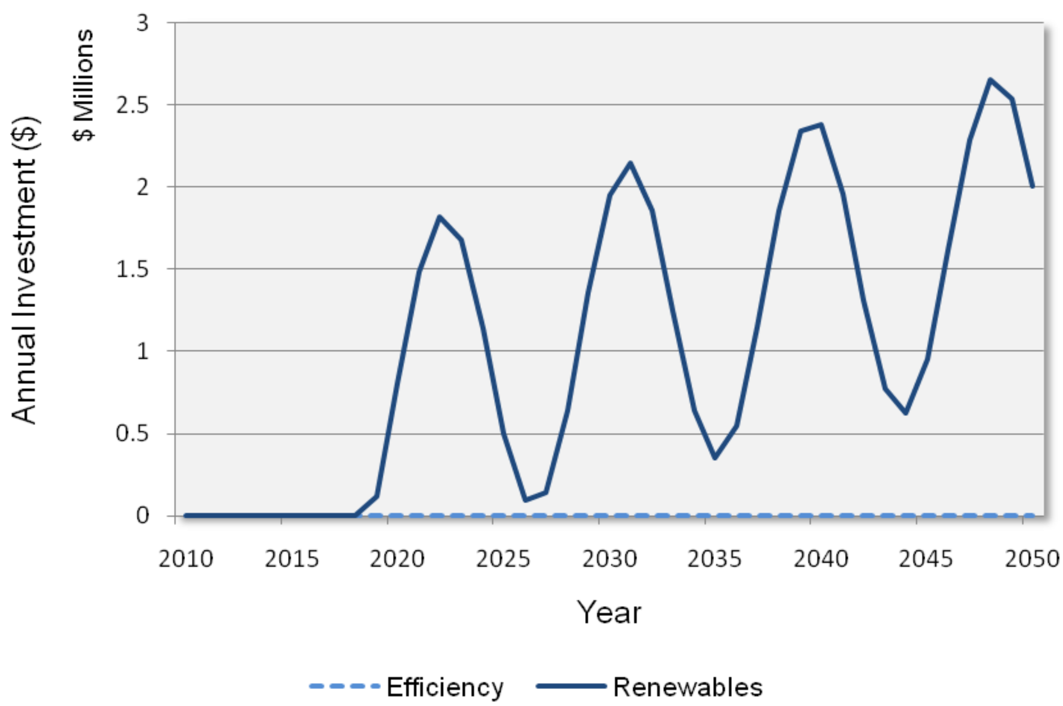
The oscillatory nature of Firm 2's behavior can seem intriguing or unrealistic at first glance, so a more detailed study of its decisions may be fruitful. Figure 5.8 reports the amount of credits that Firm 2 was able to sell or forced to purchase during the entire simulation. A sinusoidal oscillation is once again seen in its credit purchasing behavior. However, the oscillations seen here are an artifact of the mandatory purchase of credits from excess emissions rather than the result of some decision making process. Additionally, despite the oscillation, a linear increase can be seen by observing the relative change of the amount of credits purchased during each period. This reveals that, in the years when Firm 2 is furthest from its annual goal, the firm's emissions are increasingly excessive over time.



As shown in Figure 5.8, Firm 2's credit purchases oscillate up and down. Despite frequent increases in emissions, Firm 2 must also be regularly making the decision to mitigate its emissions through investment in efficiency or renewables. Due to a lag between the time of emission and the time of accounting or decision-making, Firm 2 continues to increase its emissions before it makes enough investments to compensate. While this lag may be realistic (due to actual emission reporting schedules by regulatory agencies) or may simply be the result of model limitations, oscillatory behaviors are a regular feature of SD models of economic markets (Sterman 2000).

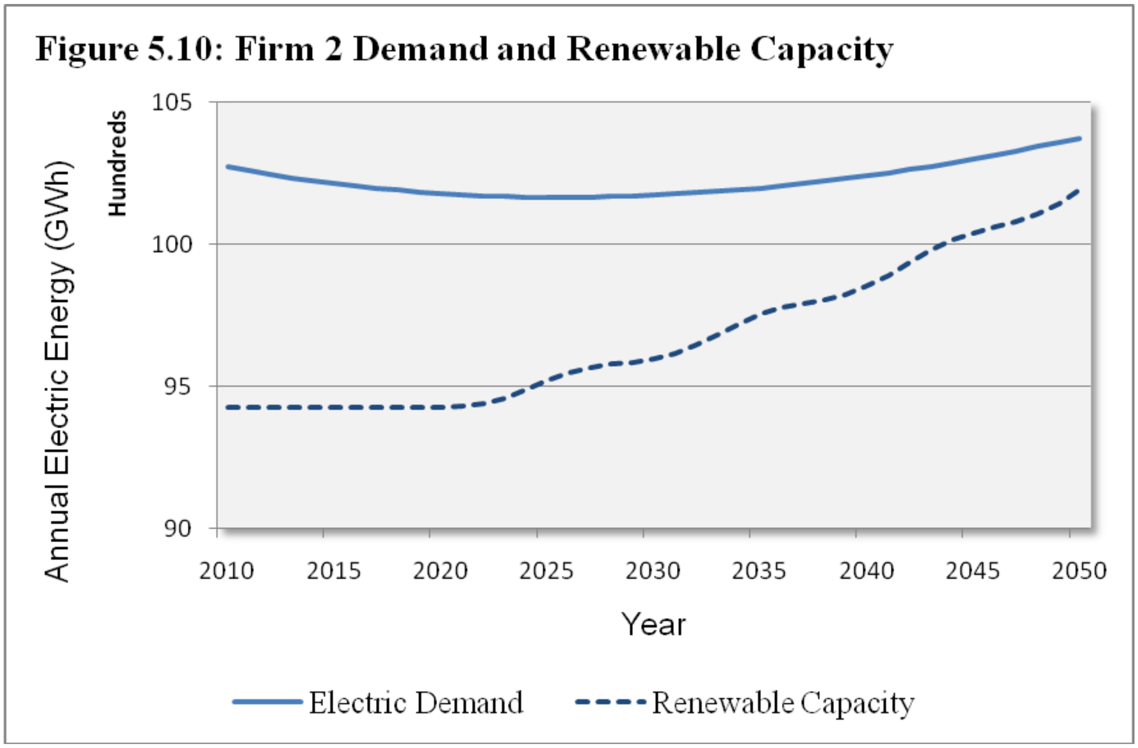
Despite the oscillations, a relative increase in mandatory credit purchasing occurs. This increase over time clearly provides an incentive for this investment. In the first scenario, Firm 1 first chose to invest in energy efficiency, then in the more costly renewable energy after reaching its efficiency maximum. In both cases, the firm reached a maximum barrier where further investment in either arena would provide no additional benefit due to physical constraints or an increasing marginal cost. As revealed in Figure 5.9, the investment decisions made by Firm 2 show dramatic differences from those made by Firm 1. This may be due to a variety of factors, as discussed below.

Figure 5.9: Firm 2 Investments



Because Firm 2 is a seller of carbon credits until around the year 2018, it does not have any immediate incentive to invest in either efficiency or renewables. As it begins to purchase credits for exceeding its cap, however, Firm 2 interestingly decides to invest in renewables first. In fact, the firm never invests in energy efficiency for the entire duration of the simulation. At first this may seem counterintuitive, as energy efficiency is assumed to cost only two cents per kilowatt-hour ($0.02/kWh) while renewables cost $0.0476/kWh. As explained in Chapter 3, however, this cost intensity is not the only factor that firms use to determine their investments. To make its investment decision, each firm calculates the effective carbon reduction made by either investment. Investing in energy efficiency results in lower electric demand, but does not change the carbon emission intensity of the firm's electric generation. Investing in renewables, on the other hand, reduces the firm's carbon intensity but does not reduce demand. Firm 2 is quite small compared to Firm 1, and generates a very large portion (90%) of its electricity from carbon-neutral renewables. Because a very small portion of its generation is derived from fossil fuel combustion, a small absolute decrease in its fossil fuel use would result in a dramatic relative decrease of its emission intensity. In this scenario, Firm 2 has found that this dramatic relative decrease is less expensive to achieve than the equivalent investment in energy efficiency.

It should be noted that since Firm 2 begins with a renewable capacity that provides 90% of its electric generation, it is assumed that the firm is not subject to the physical constraint on renewable capacity seen by both Firm 1 and the regional electric grid. As shown in Figure 5.10, Firm 2's renewable energy capacity starts out quite high and only increases throughout duration of the model simulation. By the year 2050, the model projected that more than 98% of Firm 2's electric demand will be met by renewables. Depending on the size and geographic distribution of the firm, the assumption that Firm 2 is not subject to a constraint on its renewable capacity may hold true in reality. The scenarios developed for this paper are meant to demonstrate two types of firms: a very large electric utility with a diverse portfolio of generation feedstocks; and a small or moderately sized company that owns one or more large wind farms. Firm 1 is large enough to be held to constraints that are similar to those seen by the electric grid as a whole. Here, it is assumed that Firm 2 is small and geographically distributed enough to avoid this constraint. The difference in investment behavior for the two firms raises an important point: assumed physical constraints *do* matter. This issue is addressed in chapter 6.



As it is a level that accumulates over time according to the level of investment, Firm 2's renewable capacity does not appear at first glance to exhibit the same oscillatory behavior shown in previous figures. However, the rate of its accumulation is directly correlated to Firm 2's oscillating investment. During years in which the firm's investments are on the rise, the renewable capacity accumulates at an increased rate. During years in which the firm's investment are on the decline, the renewable capacity accumulates very slowly. Thus, it is concluded that the firm's oscillatory behavior pervades the results of this scenario. This is not necessarily a fault of the model or an unrealistic projection of behavior. Perhaps with a forward-looking decision rule, however, the firm would average its investments to a steady rate for each year. Coupled with the fact that Firm 2 never overshoots its renewable investments, despite being subject to the same decision making rules that resulted in a number of overshoots by Firm 2, the results of this scenario proved to be interesting. A summary of this scenario is provided in Table 5.4, and an analysis of the results of both scenarios is given in the next chapter.

Table 5.4 Results Summary of Scenario 2

Emissions Avoided	9.83 million tCO2
Credit Cost Avoided	$38.6 million
Credit Purchasing Cost	$55.6 million
Credit Sale Revenue	$45.0 million
Efficiency Investment	None
Renewable Investment	$41.0 million
Demand Reduction	None
New Renewables	761 GWh
2050 Goal Met?	Yes
All figures provided as *cumulative* totals of 40 year simulation and are not discounted into Net Present Value (NPV)	

Comparison of Costs in Scenario 1 and Scenario 2

Although Firm 1 mitigated significantly more emissions than Firm 2 during the two model simulations, the firm lost control of its emissions around the year 2035 and was not able to meet the 2050 goal of an 85% reduction from 1990 emission levels. Firm 2, meanwhile, was able to maintain a modest but steady enough investment in renewables to eventually meet the 2050 goal (within a small margin). Therefore, although it avoided less emissions than Firm 1, Firm 2 made a larger *relative* reduction in emissions after 40 years of projection. Three factors likely influenced this outcome: the emission profile of each firm; the physical constraints on efficiency and renewable investments; and the total electric demand seen by each firm. A fourth factor may exist, however, that was not endogenously addressed in the model developed for this paper. Each firm's access to capital may play a crucial role in its investment decisions, but this model assumed that each firm had adequate capital to invest as much as it needed. This may not always hold true, especially for small firms. While it was not factored into this model's calculations, the credit costs and credit sale revenue associated with this simulated cap and trade program can be studied to determine the importance of this issue. Table 5.5 lists the net present value (NPV) of each revenue, cost and investment.

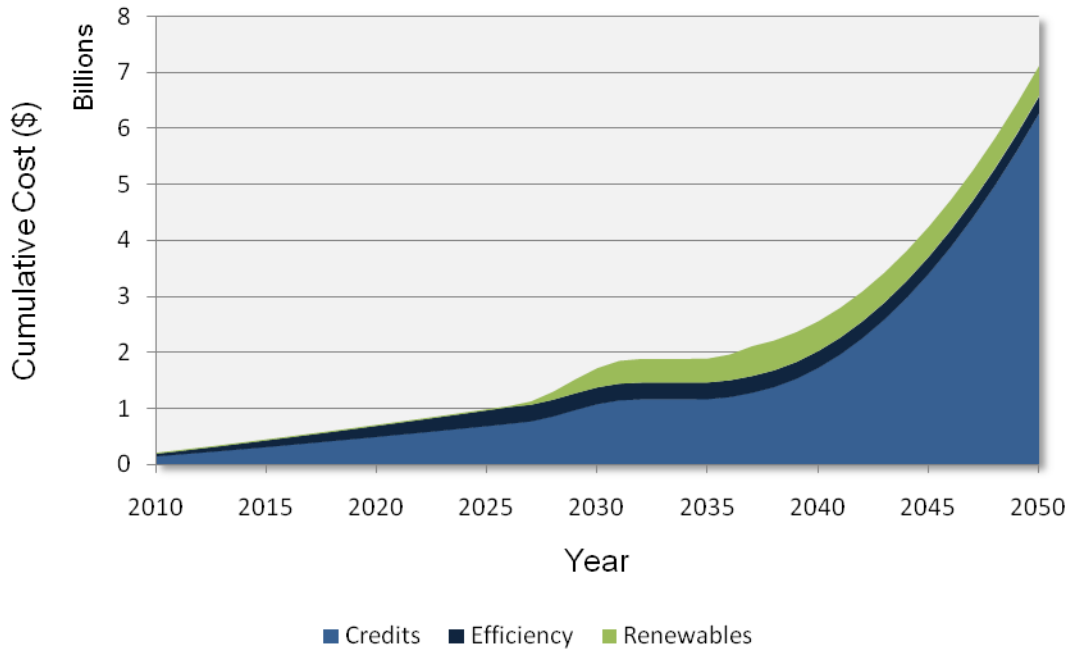
Table 5.5: Total Net Present Value of C&T Costs and Investments

	3%		8%	
Discounted Value	Firm 1	Firm 2	Firm 1	Firm 2
Credit Revenue	14.50	36.40	3.59	26.50
Credit Cost	2,400.00	17.90	608.00	4.46
Renewable Investment	252.00	16.40	84.90	4.10
Efficiency Investment	208.00	--	123.00	--
Total NPV	**-2,850.00**	**2.15**	**-812.00**	**17.90**
Millions of Dollars (2004$)				

Two discount rates were used to present a high and low example of interest when calculating the NPV of each revenue, cost and investment. As shown in table 5.5, the net present values of each item and their total for both firms are listed under two discount rates. A 3% rate mimics the inflation rate often seen by the American economy, while a rate of 8% is sometimes used in the electric industry to determine the levelized cost of new generation plants. In both cases, Firm 1 faces a very large cost of purchasing carbon credits due to its excess emissions. The few years in which Firm 1 generates credit revenue never make up for the amount that the firm must pay or invest, resulting in an NPV of -*$2.85 billion* (at a discount rate of 3%) or -*$812 million* (at a discount rate of 8%). On the other hand, because of a moderate revenue from the sale of credits during the early years of the simulation, and a very modest necessity to invest in renewables, Firm 2 was projected to have a positive NPV for both discount rates. At a discount rate of 3%, Firm 2 saw a net of $2.15 million in revenue, while a discount rate of 8% resulted in a total revenue of $17.9 million. The smaller, more renewable firm is the definite beneficiary of this virtual cap and trade program. Note that as the discount rate increases, the costs seen by the firms decrease. Because many of these costs occur in the later years of the simulation, a large discount rate further diminishes their value.

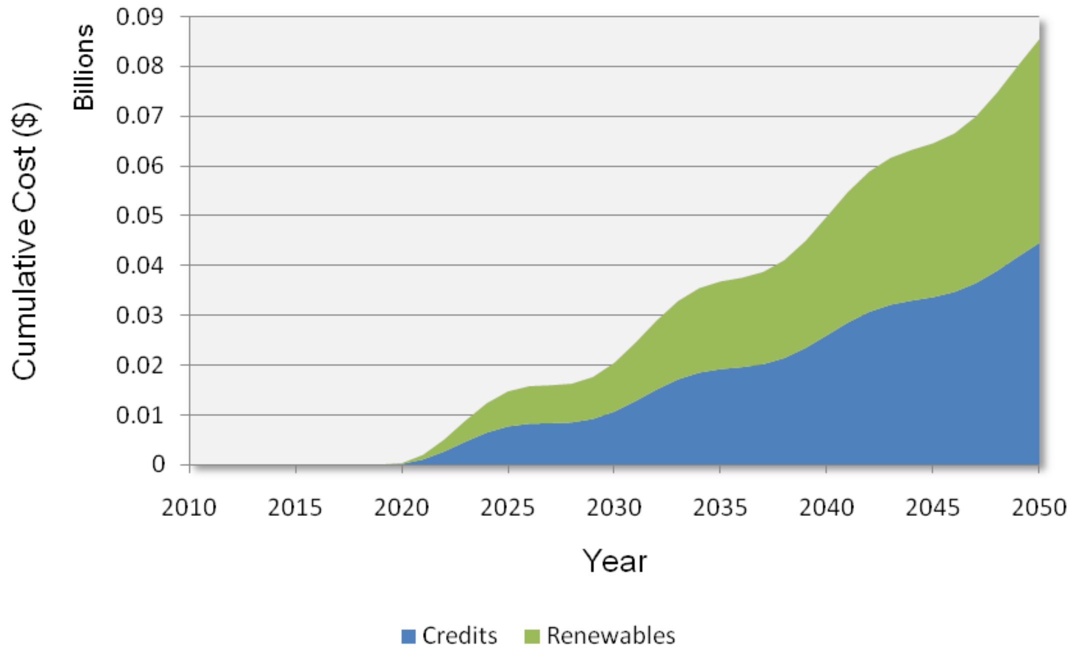
According to these projections, Firm 2's enrollment in the program results in a 2.74% internal rate of return (IRR) for the firm, where the net present value of all cash flow equals zero. Because its investments and mandatory credit purchases significantly outpace its credit sale revenue throughout the model simulation, Firm 1 is never able to break even under this program, under any discount rate, and thus has no internal rate of return. It is clear that each firm is met with a different set of costs under this simulated cap and trade model. Figures 5.11 and 5.12 chart the cumulative cost breakdown for each firm.

Figure 5.11: Firm 1 Cumulative Costs



Clearly, the bulk of Firm 1's costs originate from its mandatory credit purchases. While it also invests in efficiency early in the simulation, renewables receive the bulk of Firm 1's investments by the year 2050. In contrast, Firm 2 faces nearly the same proportion of costs from credit purchases and renewable investment.

Figure 5.12: Firm 2 Cumulative Costs



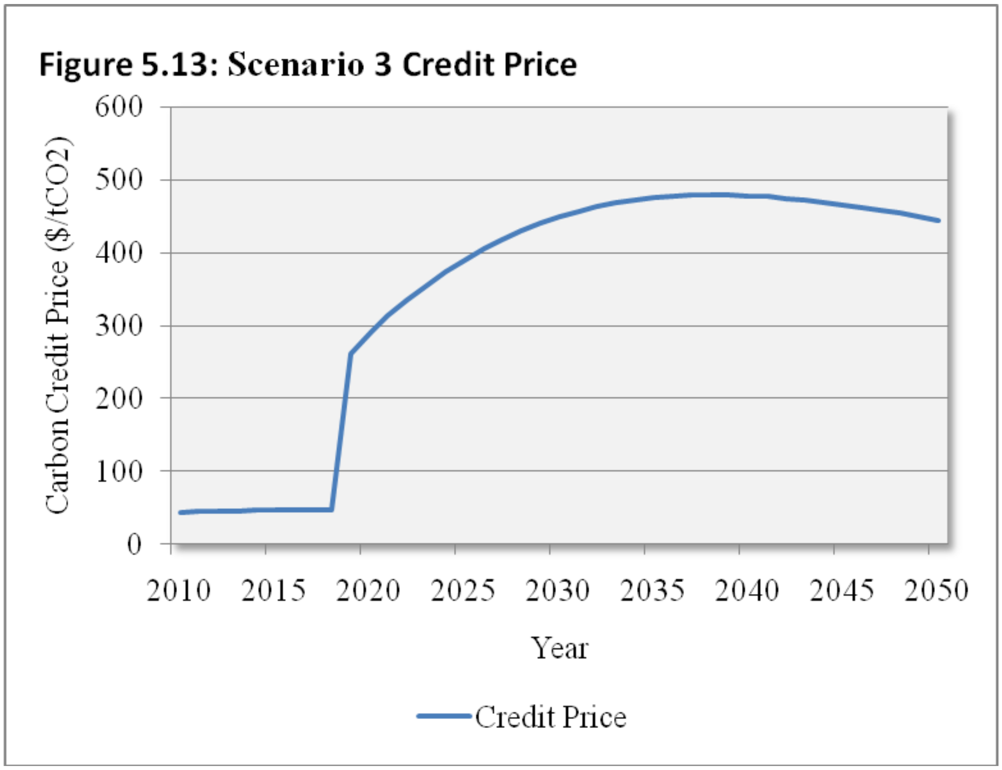
Disregarding discounting, Firm 1 incurred a cumulative total of $7.08 billion in costs in this simulation, while Firm 2 incurred a cost of only $96.6 million. With total cumulative CO2 emission levels at 1.20 billion tCO2 and 28.8 million tCO2 from Firm 1 and Firm 2, respectively. By all accounts, despite the *relatively* equivalent carbon reduction goals (an 85% reduction) and the same costs and prices (for renewables, efficiency, and carbon), the smaller and more renewable dependent firm fares better under this model. The firm that must meet a larger electric demand with a portfolio that relies heavily on fossil fuels faces much greater costs and a larger "tax" on its carbon emissions.

Scenario 3 Results: Firms as endogenous price-setters

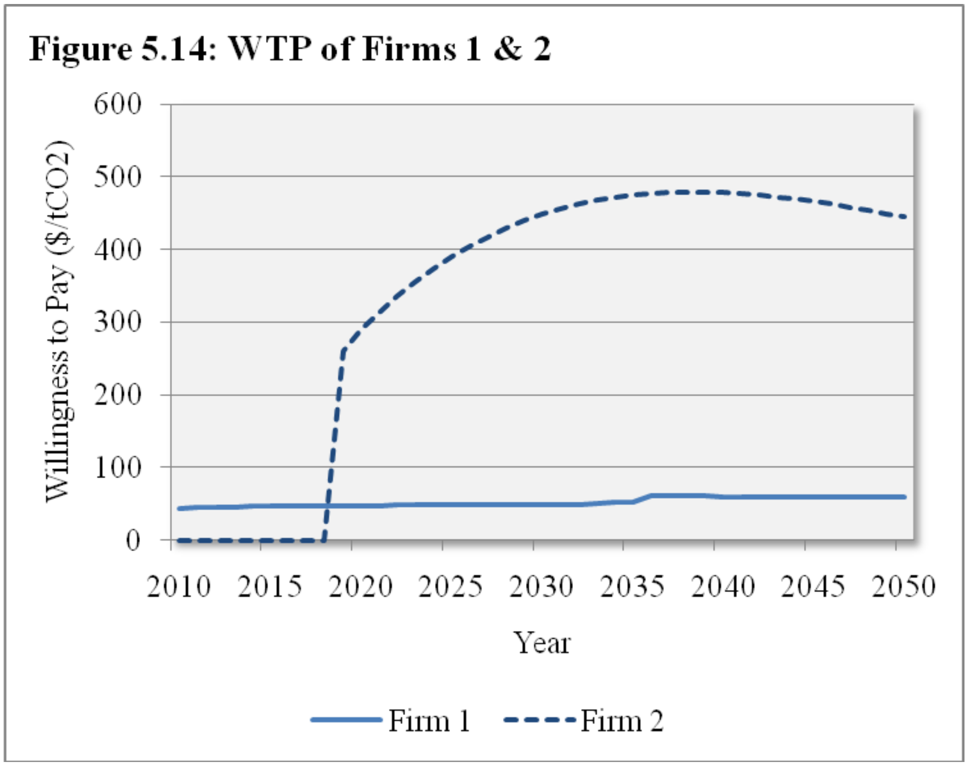
In Scenario 3, both Firm 1 and Firm 2 operated within the cap and trade program just as they did in the first two scenarios. In this scenario, however, the firms were assumed to be large enough (relative to other firms within the carbon credit market) to influence the price of carbon credits. As price setters, their willingness to pay (WTP) for credits determined the carbon price as long as it was greater than the minimum willingness to accept (WTA) for credit payments in the market. As explained in the previous chapter, a theoretical Firm 3 was used to provide an aggregate of firms and their WTA for the collective carbon market. This scenario utilizes a less developed portion of the model, and is meant to observe the dynamics of the carbon price when it becomes endogenous to the model. Thus, the results presented in this section will not focus on the behavior of Firms 1 and 2, but rather the effect of the financial analysis that is part of their decision making process.

Every year, each firm makes the decision to invest or continue purchasing credits by comparing the price of a carbon reduction to an estimate of the price of credits in the next year. Theoretically, each firm is willing to pay for credits if the total cost of those credits is less than or equal to the amount they would need to invest to mitigate an equivalent amount of carbon emissions. As shown in the first scenario, the nature and cost of available mitigation options changes over time. Therefore, each firm's WTP should also change over time. In previous scenarios, the carbon price was set at a constant value of

$50/tCO2. In this scenario, the carbon price is set when the market's maximum WTP exceeds its minimum WTA. For a description of the WTP calculation, see Appendix 1.

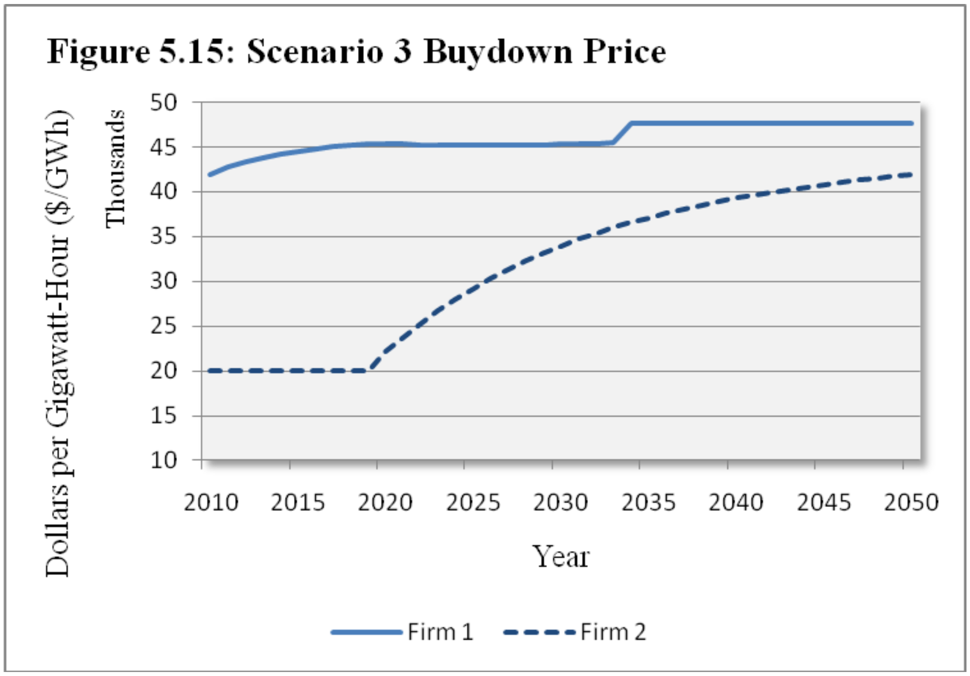


The carbon credit price levels over 40 years for Scenario 3 are reported in Figure 5.13. After starting at the default price of $50 per metric ton of CO2, the carbon price quickly settles at between $45 and $50 per tCO2 for the initial years of the simulation. Then, in the year 2019, the credit price rapidly increases to about $260/tCO2. From here, the price grows to a peak of about $479/tCO2 in 2038, and finally to a final price of about $445 in the year 2050. Aside from the significant rise in price in 2019, the price of a carbon credit does not dramatically fluctuate during the course of this simulation. Since it is determined by a firm's willingness to pay, the carbon price is clearly influenced by the mitigation cost seen by firms who are regulated by the cap and trade system. This cost changes from year to year depending on the resources available to each firm and the investment decision it is choosing to make. As the price is determined by the firm with the highest WTP, it is not immediately clear which firm is influencing the carbon price the most. Figure 5.14 compares the WTP of Firm 1 and Firm 2 over time.



As seen in Figure 5.14, the WTP for Firm 1 remains relatively unchanged, between $40 and $60/tCO2, for the entire duration of the simulation. In contrast, Firm 2 has no willingness to pay until the year 2019, when it exhibits the same curve as the one described in Figure 5.13. Despite being the larger firm, Firm 1 influences the price of carbon only until the year 2019, when a higher WTP makes Firm 2 the price setter. It may seem counterintuitive for the smaller firm to have more influence in the market. However, these results indicate that Firm 2 faces higher costs for every ton of CO_2 it decides to abate. In the previous scenarios, Firm 2 performed better than Firm 1 in meeting the goals of the cap and trade program. Because the carbon price changes significantly over time, this scenario likely induced different behavior for the two firms.

To determine the cause of Firm 2's high WTP, it is helpful to observe the cost of its mitigation efforts. In this model, a firm's *buydown price* is the total cost of a firm's efforts to avoid carbon-producing electricity generation. Whether by reducing demand or replacing fossil fuel plants to meet a carbon cap, a firm is essentially "buying down" electric energy through its investments. The model developed for this paper calculates the buydown price by averaging the cost of the mixture of investments each firm decides to make, where the total the amount invested in both renewables and efficiency are divided by the equivalent buydown achieved by both investments. The programming equation for this variable can be found in Appendix 1. Figure 5.15 compares the buydown prices of Firm 1 and Firm 2 from the results generated in this scenario.



For the duration of this simulation, Firm 1 consistently maintained a higher buydown price than Firm 2. At first glance, this appears to contradict the WTP results from Figure 5.14. There is one other factor, however, which affects a firm's WTP: a firm's CO2 emission rate.

Each firm has a different CO2 emission rate depending on its portfolio of electric generation plants. Firm 1 has a much higher emission rate than Firm 2 because it generates electricity primarily from fossil fuels. Therefore, every unit of electric energy that Firm 1 avoids generating actually prevents more CO2 emissions than an equivalent amount of generation from Firm 2. Table 5.6 compares the average buydown price and emission intensity for Firm 1 and Firm 2. These rates were calculated by averaging the series of values generated for each firm over the course of the model simulation in this scenario.

Table 5.6: Calculation of Average Mitigation Costs

	Firm 1	Firm 2	Units
Buydown Price	46,000	31,600	\$/GWh
Emission Intensity	884	81	tCO2/GWh
Price per Emissions	52	393	\$/tCO2

Table 5.6 makes it clear that even though Firm 2 has a lower average buydown price, its very low emission intensity results in a price per emission reduction that is much higher than Firm 1. Note that when comparing the average price per emission reduction in Table 5.6 to the curves in Figure 5.13 and 5.14, the average price approximates the WTP of each firm, the larger of which determines the carbon credit price in this scenario.

Finally, with an explanation now made for the behavior of the carbon price in this scenario, it is interesting to observe the effect that an endogenous carbon price has on the behavior of the two firms. Importantly, neither firm achieves the 2050 goal of an 85% reduction from 1990 emission levels. Figure 5.16 and 5.17 compare the annual emissions and allowances of Firm 1 and Firm 2, respectively.

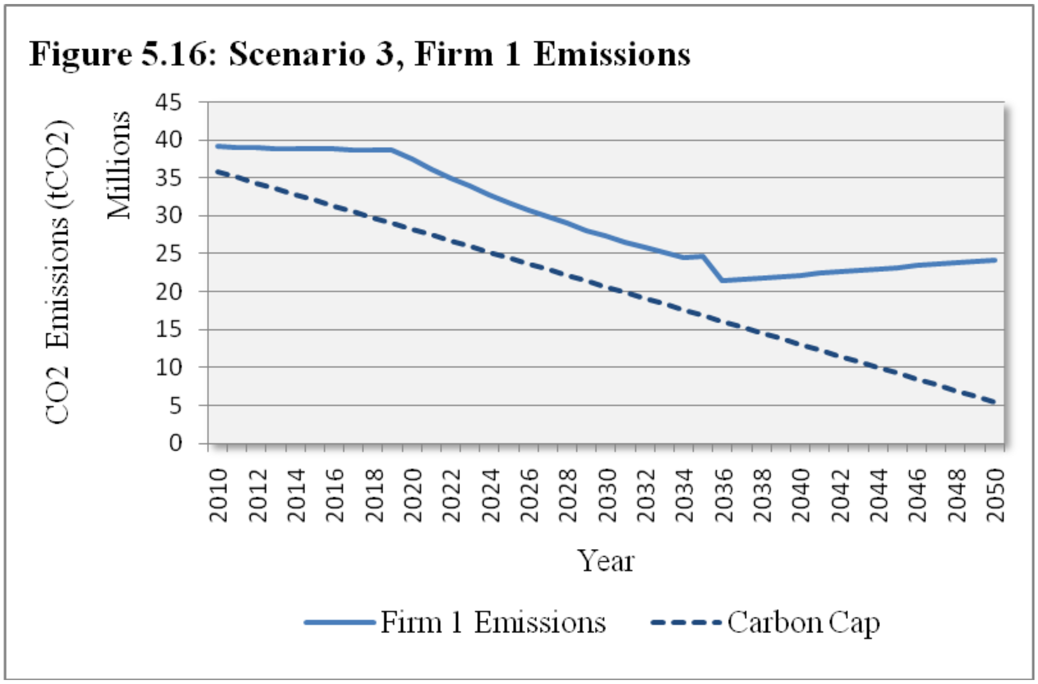


Figure 5.16: Scenario 3, Firm 1 Emissions
CO2 Emissions (tCO2)
Millions
45
40
35
30
25
20
15
10
5
0
2010
2012
2014
2016
2018
2020
2022
2024
2026
2028
2030
2032
2034
2036
2038
2040
2042
2044
2046
2048
2050
Year
Firm 1 Emissions
Carbon Cap

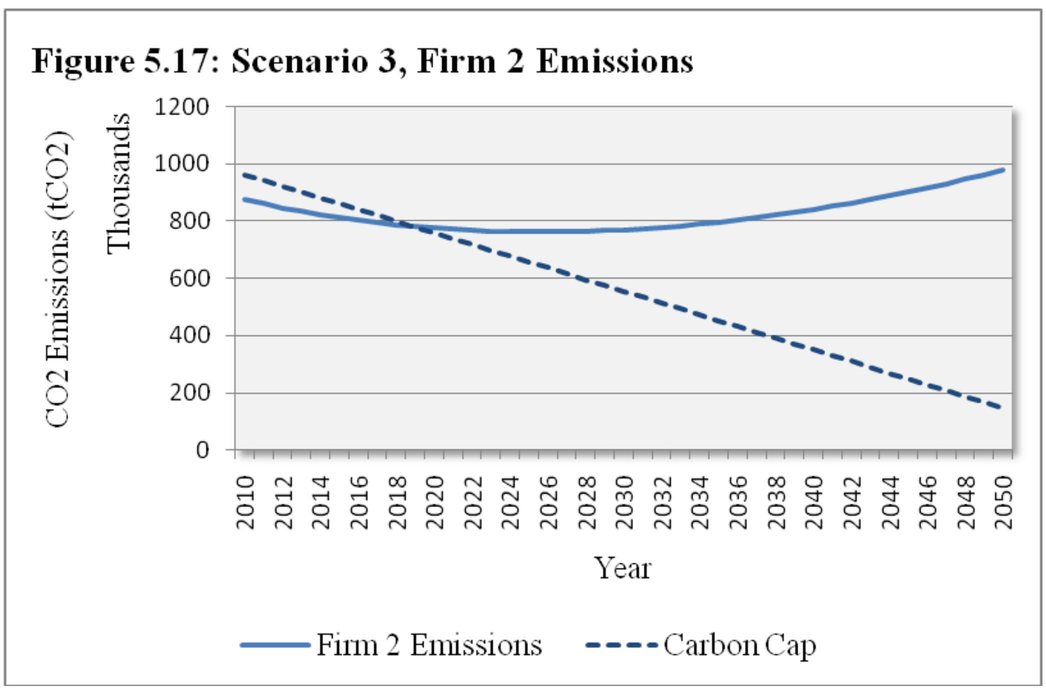


Figure 5.17: Scenario 3, Firm 2 Emissions
CO2 Emissions (tCO2)
Thousands
1200
1000
800
600
400
200
0
2010
2012
2014
2016
2018
2020
2022
2024
2026
2028
2030
2032
2034
2036
2038
2040
2042
2044
2046
2048
2050
Year
Firm 2 Emissions
Carbon Cap

From Figure 5.16, it is clear that Firm 1 never meets its annual carbon reduction goal. Although it does achieve significant reductions between the year 2020 and 2036, Firm 1's emissions never dip below its carbon cap. Thus, for the entirety of this simulation, Firm 1 purchases credits to compensate for exceeding its emissions allowance. Similarly, Firm 2 does not invest in emission abatement after the year 2019 despite exceeding its allowances for the remainder of the simulation. However, there is at least one significant difference between the behavior of the two firms pertaining to the relationship between each firm's WTP and the market carbon price.

Firm 1 makes no investments between 2010 and 2019, the nine years that coincide with the period in which Firm 1 is the carbon price setter. When Firm 2 becomes the price setter, its larger abatement price per emissions sets the market carbon price higher than Firm 1's WTP. Thus Firm 1, no longer willing to pay for carbon credits, begins to invest in emission mitigation. This may indicate that in regional cap and trade systems, local firms that are influential enough to be price setters might simply choose to purchase credits rather than reduce their emissions. Since the market price is exactly what they would be willing to pay to avoid further investments, the price setter does not invest in abatement. This is significant because it implies that the largest electricity producers, and thus the largest emitters, may not make any changes to their fossil fuel electric generation portfolio. Although the credit revenue may be used to invest in carbon sequestration elsewhere, the electric generation system would remain just as carbon intensive. As a corollary, firms that cease to be influential during the simulation find themselves significantly lagging behind the goals of the cap and trade system.

Chapter 6 Reality Check

The system dynamics model developed for this paper generated results that seem reasonable for the scenarios in the simulated a cap and trade program. Though some results may have been unexpected, such as the oscillation present in the behavior of Firm 2 (aside from its market dynamics), a clear explanation of each can be made by observing the causal loop structure of the structure. Through the search for an explanation within simulation results, reasonable causes can be found and used to learn more about the simulated environment that the model is projecting. Alternatively, this process may uncover certain factors within the model structure, such as exogenous input assumptions, variable equations, or decision-making rules, that prove to be crucial in determining simulation results. The identification of these factors can help improve a model by forcing one to reexamine the assumptions on which the model is built, such as how an agent or firm makes decisions during the simulation and the nature of the environment in which the firm is acting.

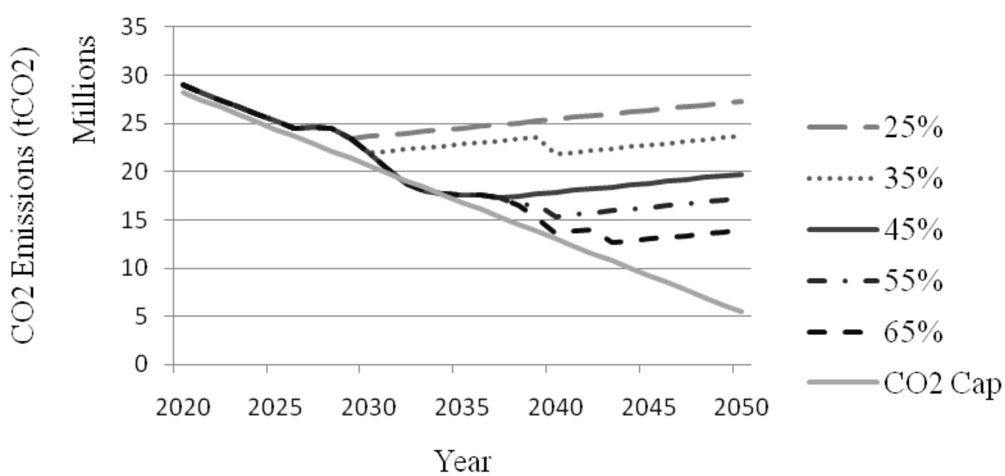
In the flow of information throughout the system dynamics model, these factors can end up acting like gates or valves that have dramatic reverberations throughout the system. Though the values or rules implicit in the model's variables and constants may be realistic, there may also be a range of values that could be used as reasonable inputs. Since a small variation within the realistic range of a key model value can cause large variations in model results, it is important to evaluate an assumption's placement within its reasonable range of values. A sensitivity analysis, where one value is changed to varying degrees to observe the change in output, can aid in this evaluation. This chapter discusses a variety of important factors within the cap and trade model presented in this paper and performs a 'reality check' by taking a closer look at the assumptions implicit in each, including a sensitivity analysis for some inputs.

Physical Constraints

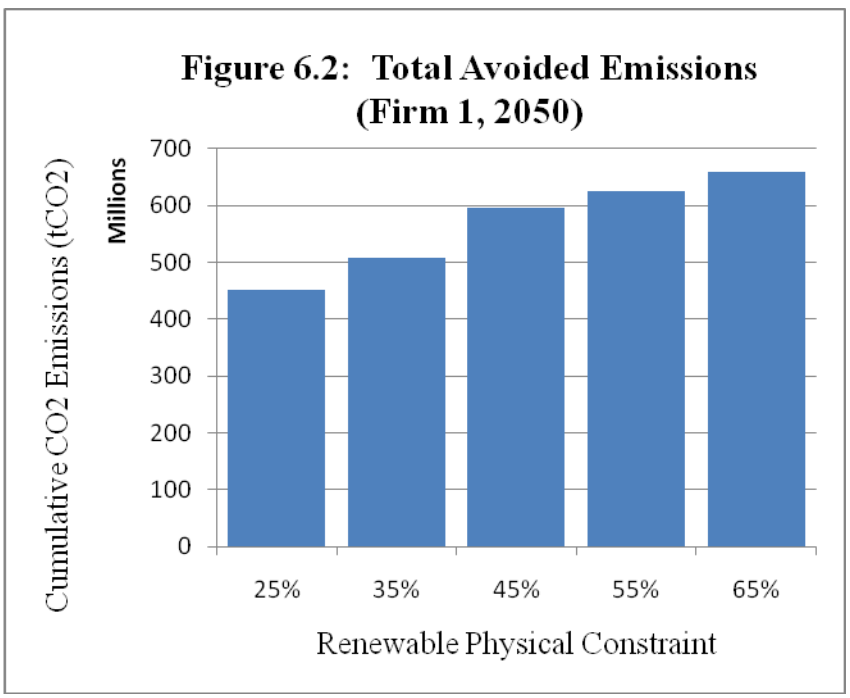
In Scenario 1, Firm 1 followed the annual goals set by the cap and trade emission allowances within a reasonable margin. As discussed in the previous chapter, however, the firm was no longer able to reduce emissions once it hit the assumed physical constraint on energy efficiency and renewable development despite a likely willingness to make further commitments. The values used for the physical constraints on efficiency and renewables are assumptions (outlined in Chapter 4) that provide reasonable estimates for a general situation, but may not specifically apply to each scenario. In Scenario 1, the maximum energy efficiency gain is 35%, while the maximum share of renewable energy for electricity generation is 45%. The results from Scenario 1 make it clear that these constraints are crucial, make-or-break factors for the model simulation. To determine the effect of this assumption on the simulation, a simple sensitivity analysis may be helpful.

The inputs for Scenario 1 were repeated for this analysis to replicate a consistent series of scenario variations where the physical constraint on renewable energy development was systematically modified. Scenario 1 provides an example that is much like the overall electric grid of Minnesota. Because Scenario 2 demonstrated a specific example where the physical constraint was assumed to be much larger, this analysis was only performed for Scenario 1. The baseline value for the constraint is the same as the value used for the original scenario, where renewable energy could only account for 45% of Firm 1's electric generation. A range of evenly spaced values were used between 25% and 65%, at intervals of 10%, to observe the impacts on Firm 1's annual emissions. Theoretically, a lower value for the constraint would further limit the amount that a firm can invest in renewable energy, causing the firm to run out of options sooner in the simulation. The results of this analysis, shown in Figure 6.1, corroborate this expectation.

Figure 6.1: Effect of the Renewable Constraint on Firm 1



In the baseline case, a physical constraint of 45% results in Firm 1 abandoning emission abatement efforts by the year 2035, as seen by the constant upward slope in Figure 6.1. Likewise, the lower, more stringent constraints of 35% and 25% result in the firm abandoning efforts, with some variation, by the year 2030. Higher, more flexible constraints, in contrast, result in later abandonment dates of 2040 and 2043 for 55% and 65%, respectively. Note that in each case, the firm's annual emissions show similar behavior once the firm has abandoned its abatement efforts. Once it has given up on reducing its CO2 emissions, the firm's behavior is influenced primarily by the annual electric demand that it must supply energy to. Here, that demand has projected 1% annual growth when no efficiency investments are being made, thus all five lines in the graph are parallel in the later years of the simulation. Despite retaining a similar slope, however, each case maintains a different scale of annual emissions depending on the implicit abandonment date. This results in cumulative emissions that are significantly different by the year 2050, as depicted in Figure 6.2.



Higher assumed physical constraints result in greater abatement of emissions over the course of the simulation. When compared to the baseline projection, a 45% renewable constraint yielded approximately 600 million *avoided* metric tons of CO_2. In comparison, a constraint of 25% yielded approximately 450 million avoided tCO_2, while a constraint of 65% yielded approximately 650 million avoided tCO_2.

Despite the wide range of values tested in this analysis, every constraint observed here prevents the firm from abiding by its annual emissions allowance during the later years of the simulation. As a result, the 2050 goal is never achieved if a firm is limited by the constraint. In order to achieve the 2050 goal, this model reported, through further simulation not shown here, that a constraint as high as 85% is necessary to allow the firm to meet is annual emissions cap. At this value, the firm abates a total amount of about 694 million CO_2 emissions by 2050.

These figures demonstrate that the assumed renewable energy development constraint has a singular and significant effect on the results of this simulation. While it is obvious that an assumed limitation would affect the model results, it is the *magnitude* of that effect that is important to note. Originating from issues such as geographic distribution, transmission line construction, and the capacity factors implied by technology such as wind turbines, this physical constraint will influence the range of options that are available to firms enrolled in a cap and trade program. Not only is it necessary to consider this when projecting the impacts of a cap and trade program, the maximum capacity that renewable energy can contribute to the electric grid is a very important consideration when designing any energy or climate change policy. The implications of this are discussed in the next chapter.

Demand Growth Rate

All scenarios in this research assumed an annual electricity demand growth rate of 1%. As electricity is consumed at residential, commercial, and industrial sites, a number of factors that influence this rate include, but are not limited to: regional and national economic growth; new building construction; technological change and its impact on the energy consumed by appliances and other machines; and change in consumer behavior over time. Although 1% is a reasonable growth rate given economic conditions at the time of this writing, a wide array of unexpected events or trends could occur during the years of this simulation. Because it is impossible to predict the growth rate with absolute certainty, it is important to consider the impact that the assumed growth rate has on the results projected by this model. To study this, an analysis similar to the one conducted for the renewable energy constraint was performed. A range of assumed growth rates were used to replicate Scenario 1 and the resulting behavior of Firm 1 was observed.

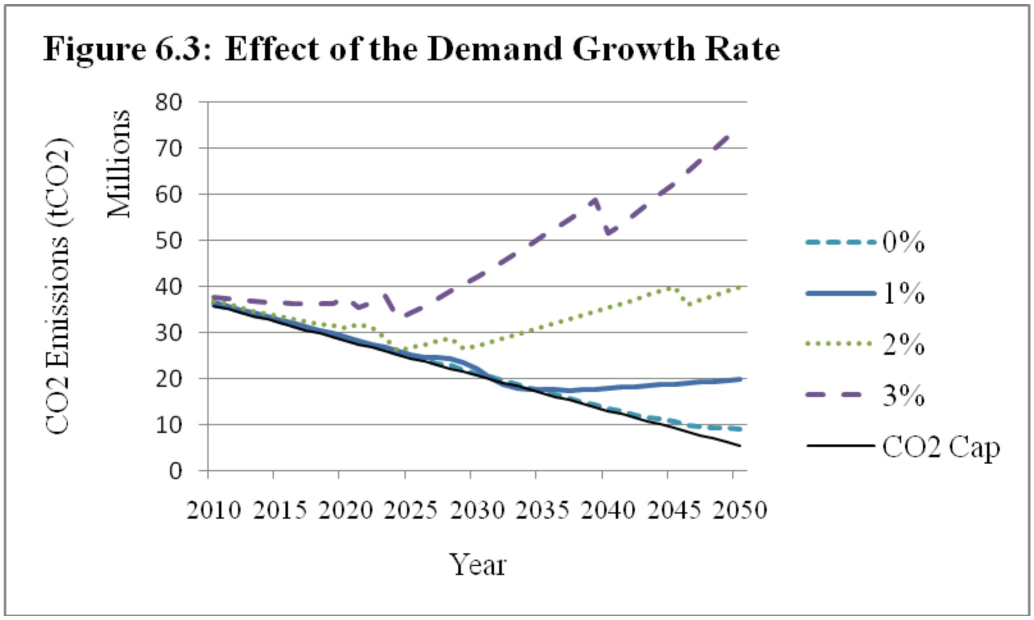


Figure 6.3 presents the results of the growth rate assumption sensitivity analysis. All three scenarios described in Chapter 5 assumed an electric demand growth rate of 1% per year. For reference, the emissions resulting from the 1% growth rate are identical to the results of Scenario 1, as depicted in Figure 5.3 as a solid line. A larger growth in electric demand, such as 2% or 3%, makes it more difficult for the firm to reduce its emissions each year. Because it must compensate for a larger increase in demand, the firm must invest larger amounts into energy efficiency and renewables. However, this causes the firm the run up against the physical constraint on both efficiency in renewables described earlier in this chapter. Thus, at growth rates of 2% and 3%, the firm is no longer able to comply with the cap and trade program by the years 2030 and 2025, respectively. In contrast, a very low assumed demand growth requires the firm to invest less capital into abatement efforts. As a result, the firm obeys the cap and trade program's annual

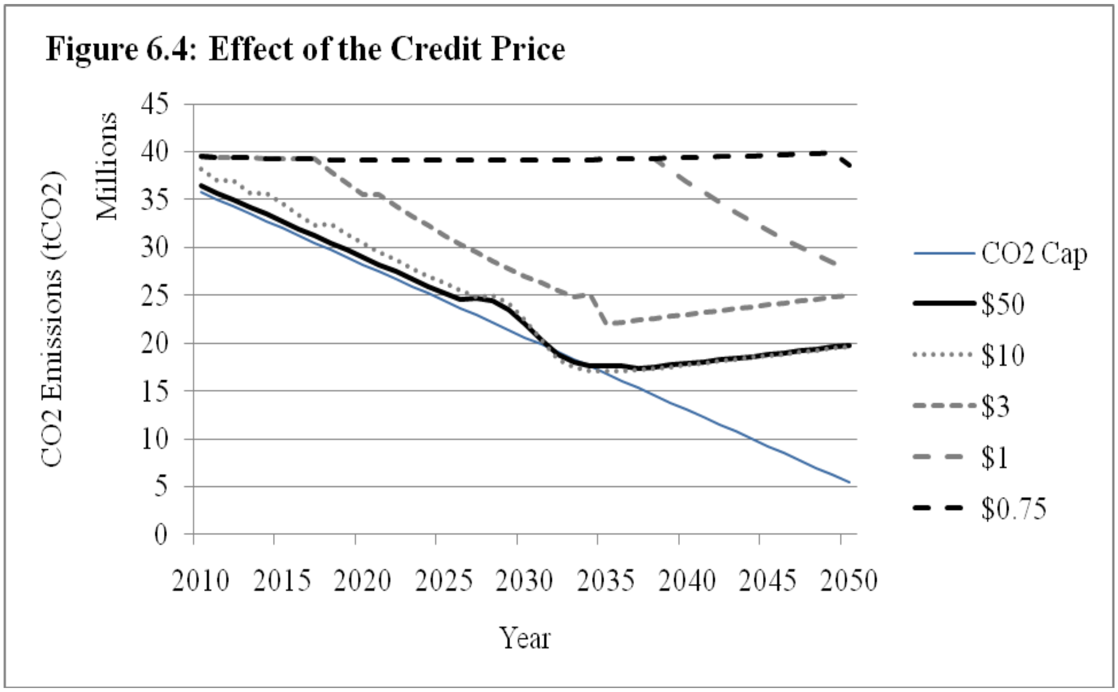
allowances and, within a small margin, meets the 2050 goal without being limited by the two physical constraints.

These findings clearly identify the assumed growth rate of electricity demand as another crucial factor in this model's simulation results. As growth rates increase, it is more difficult for each firm to reduce its annual emissions. Having to compensate for a larger increase in electric generation, the firm must spend more capital in mitigation options like efficiency and renewable energy. In consequence, the maximum levels of energy efficiency and renewable energy will be met sooner. At the time of writing, a 1% growth rate is a reasonable assumption given current economic conditions (EIA 2009). However, values such as 2% or 3% are also within the reasonable range of growth rates. This may be worrisome, because electric demand is very much influenced by economic growth and these results indicate that a healthier economy would lead to a less successful fulfillment of cap and trade emissions goals. The inverse of this implies that economic decline may lead to the successful abatement of enough CO2 emissions to mitigate global climate change. Either way, determining the assumed growth rate becomes an important factor that greatly influences the results of projecting firm behavior under a cap and trade program.

Carbon Price

Aside from Scenario 3, the results discussed in this paper assumed an initial carbon credit price of $50 per metric ton of CO2. This number falls in the middle of the range of reasonable peer valuations of CO_2 emissions (Tol 2003). For the purpose of simulation, any price behavior can be assumed, such as a linearly increase, an oscillation, or a random annual change based on stochastic functions. Projecting the price of CO_2 credits in a cap and trade market can be difficult, however, because CO_2 markets have shown great fluctuation and are often determined by a dynamic system of complex factors (Benz and Truck 2009).

In this model, firms decided to invest in abatement strategies depending on whether it was more expensive to pay for carbon credits. The assumed value of carbon in the cap and trade market, therefore, is likely another factor that has a dramatic impact on simulation results. Similar to the renewable constraint and demand growth analysis explained previously, the simulation was repeated a number of times with varying credit price values to observe its impact on the modeling results. Through test simulations, it was determined that very little variation occurred until the carbon price was lowered to under \$10/tCO_2. Subsequently, this analysis tested carbon price values of \$50, \$10, \$3, \$1 and \$0.75 per ton of CO_2. Figure 6.4 charts the results of these simulations.



The results of this analysis indicate that low values for the carbon credit price result in later start dates for emission abatement activities. A firm will not invest in efficiency or renewables until it believes these investments will be less costly than the total price of mandatory credit purchases. At low carbon prices, firms conduct business as usual until their annual emissions allowance has decreased substantially enough to equal the cost of available abatement investments. As shown in Figure 6.4, lowering the carbon price from $50 to $10 per ton had little effect on the firm's annual emissions. After a very short delay, the firm quickly caught up with the carbon cap until it ran up against the maximum renewable physical constraint, as in the original simulation of Scenario 1. At a price of $3 per ton, however, the firm waits until after the year 2017 to begin investing in emissions abatement. By this time, the firm is so far behind the cap that if fails to meet any goals by the year 2050 and a significantly higher amount of emissions occurs. An even lower price of $1 per ton keeps the firm from investing until the year 2039. Finally, after a number of simulations, it was determined that a firm will never invest in abatement at any carbon price below about $0.75 per ton.

These results may indicate that a price of $50 per ton of CO2 is unnecessarily high for the firm being simulated in Scenario 1. While much of this study assumed the carbon price to be exogenous, there is opportunity for market intervention by the cap and trade regulatory agency. Therefore, it is important to consider the market effects of varying levels of the carbon prices. A high carbon price may overburden the firm when a much lower price may have the same effect on emissions. Since the cost of mandatory credit purchases provides enough of a disincentive to emit CO2 until a much lower value, the firm will perform very similarly as it did under $50/ton as it would at a less costly price. Of course, as seen by the analysis of willingness-to-pay levels in the previous chapter, each firm faces different investment costs due to its size, generation portfolio and emission rate. Due to its greater WTP, it is likely that higher carbon prices may be appropriate to give Firm 2 enough incentive to invest in abatement due. The modeling and policy implications of this, and the rest of the results of this research, will be discussed in the following chapter.

Chapter 7: Discussion

In general, the results of this analysis are relatively straightforward. As modeled, this virtual cap and trade policy provided the economic framework for each firm to substantially reduce its CO2 emissions. Under scenarios 1 and 2, the firms avoided a cumulative total of approximately 625 million metric tons of CO2. Only Firm 2, the smaller and more heavily renewable firm, was able to meet the final GHG goal of an 85% reduction from 1990 levels by the year 2050, as put forth by the IPCC (IPCC 1995). In contrast, although it acted faithfully under the cap and trade program by following its emissions cap for the majority of the simulation, Firm 1 was no longer able to invest after the year 2035 because of physical limits on the contribution of energy efficiency and renewable energy to reducing CO2 emissions.

Through a series of sensitivity analyses, a best case scenario where each firm achieves its emissions goals was found by using either a renewable constraint of 85% or a demand growth close to 0%. In contrast, renewable constraints lower than 45% or demand growth greater than 2% resulted a in a worst case scenario where emissions that significantly violated the cap and trade goals. As probabilities and stochastic processes were not used in this analysis, these results might be considered point estimates. However, as these results are merely the projections of theoretical scenarios, they are by no means meant to suggest the actual projected outcomes of existing companies. When analyzing policy systems, system dynamics is best used to examine the relative levels of quantities and the relationships between entities, rather than their specific values.

Therefore, the results of this analysis should be considered relative to an initial baseline or to the goals of the cap and trade system.

The research conducted for this paper explored not only the effects of a theoretical cap and trade program, but also the process and method involved in modeling the cap and trade program by using system dynamics. This chapter discusses the implication of the results of this research first in terms of model development, then also in terms of policy formation.

Model Design

Any modeling process involves a wide array of assumptions not only about how a real world entity phenomenon might work, but also about what the best method of simulating that entity or phenomenon within a model. Chapter 6 demonstrated the significant effect that a few assumptions had on the results of this research. The annual rate of demand growth, the maximum improvement potentially provided by energy efficiency, and the maximum contribution of renewable energy capacity to the electric grid are phenomenon that may be realistically measured. In the case of modeling, it is important to choose the most reliable projection for trends such as demand growth. Likewise, intensive scientific study on the true potential of renewable capacity or energy efficiency should be conducted. Though no projection is absolutely reliable, the use of the best available information will lead to the most realistic model results.

Although no extensive primary research was conducted in these areas for this analysis, the values used to provide the assumptions for this model were realistic estimates based on cited and respected sources (as listed in Chapters 2 and 4). An analysis of some of these assumptions supported the assertion that reasonable values were used. In Chapter 6, variations in the values of the renewable energy physical constraint and the electric demand growth rate lead to variations in the *magnitude* or *delay* in simulated firm behavior, but not in the *type* of firm behavior. This indicates that while the numerical value of this simulation's results may differ from reality, it is likely that the trends and behaviors observed in this paper are realistic.

While models are built upon data that can be altered to provide more reasonable assumptions, they are also built upon a series of assumptions on the manner in which reality is simulated. In particular, this model attempts to simulate the decision-making process of individual firms that are regulated under a cap and trade program. A primary assumption implied by this model is that firms act on a cost avoidance or least cost decision framework. While this may be a reasonable assumption, there are a number of limitations that come out of this model's specific decision making process.

First, while calculating a firm's willingness-to-pay, this model assumes that each firm has access to investment capital sufficient enough to avoid the amount of CO2 emissions that are necessary under the cap and trade program. It may not be realistic, however, to believe that Firm 2 has access to the same amount of capital as Firm 1, when Firm 2 it is only about a quarter the size of Firm 1. Furthermore, the WTP calculation used in Scenario 3 was based on an intensity of price per emissions ($/tCO2) that each firm faced when making its investments. This disregards the magnitude of the total cost of each firm's investments. If each firm had access to the same amount of capital, this may not be an issue. But due to the significantly larger amount of credits that it must purchase each year, Firm 1 is actually investing a much larger amount of capital than Firm 2. Specifically, Firm 1 paid a total of $833 million in investments and $6.28 billion in emissions fees, while Firm 2 paid only a total of $41 million investments and $55.6 million in fees (not discounted or adjusted for inflation). Despite this, Scenario 3 saw Firm 2 becoming the price setter for the majority of the simulation. If the size of each firm were to lead one to believe that the two did *not* have access to the same amount of capital, then the assumption used for calculating the market WTP would likely be incorrect. Future cap and trade modeling processes should therefore explore accounting for a firm's access to capital and the total amount a firm would pay in fees, rather than on a per ton basis.

Second, the investment in abatement options to avoid future emission credit costs implies a certain amount of forward-looking decision-making. In this model, firms use the amount of excess emissions each year to determine if it would be less costly to invest now in order to avoid the same amount of emissions in the next year. This is a very short-run analysis, because while the firm may indeed avoid having to pay for a lot of credits the following year, it does not prepare it for the reduction in emission allowances that occurs in further years. This is likely the cause of the oscillatory behavior seen in Scenario 2. Although oscillatory behavior is often seen in SD models economic markets, there may be a different dynamic at play here. In market models, the delay between consumption and production causes an oscillation of supply (Sterman 2000). Here, the oscillation is caused by an overshoot of investment due to the simulated firm's short-sightedness. When Firm 2 has invested enough to avoid paying fees in the present year, it chooses not to invest. As a result, its emissions begin to grow with demand until it once again exceeds the cap. If the investment decision was made on a long-run basis, it is possible that Firm 2 would invest enough to avoid this oscillation. By taking more future years into account, a firm may also begin to exhibit credit banking behavior to generate profits in the future. These issues imply a financial analysis that is more complex than the simple "cheaper solution" comparison that is used here. Therefore, future models should consider taking a closer look at formulating a more complicated decision making process.

Lastly, the input assumptions, WTP calculation and firm decision-making methodology used in this model imply a level of certainty and stability in the market. In reality, markets can involve risk, probability and game-playing in investment decisions. An even more complex system of financial and market analysis might have firms making investment decisions based on their comparative advantage, financial outlook, risk aversion and some level of game theory (Haurie and Viguier 2003). Researchers that aim to simulate decision-making as accurately as possible may wish to research topics such as these to determine how the particular firms being modeled may make investment decisions.

Policy Design

In addition to providing an illustration of the modeling process by demonstrating which factors should be taken into careful consideration when programming a cap and trade model, the components discussed in this chapter also provide insight into crafting more effective or equitable climate change policy. Models like the one developed here can aid in the policymaking process by dissecting each step involved in a policy's implementation and showing the which cause and effect relationships may have the most impact in the real world. Through the results of routine scenario simulations like the ones discussed in this paper, the regional cap and trade model presented a number of considerations that local policymakers should keep in mind. These considerations include basing the emission cap on absolute emissions or emission intensity, the implementation of carbon price controls, and the examination of the physical constraint on energy efficiency and renewable energy.

Scenario 1 and 2 provided unique looks at how two firms might behave differently under the same cap and trade policy. Under the policy, each firm faced an annually reducing carbon cap based on its initial CO2 emission baseline. This is a free allocation system where firms are not required to purchase their initial allotment of credits (CBO 2001). The amount that the cap shrinks each year is based on relative levels of the absolute emissions of each firm and is calculated so that each firm reaches an 85% reduction of its 1990 emissions by the year 2050. As shown in Scenario 1's results, the reductions achieved under this cap might result in a firm investing heavily into energy efficiency. In this scenario, Firm 1 did not choose to invest in renewable energy until it had completely depleted its energy efficiency potential. Under an absolute emissions cap, both efficiency and renewable energy have equal potential to reduce emissions. The generally less expensive cost of efficiency improvement, however, makes it a more attractive choice than renewable energy. Under this policy formation, there is no incentive to reduce the *intensity* of emissions until energy efficiency has reached its maximum potential.

To increase the incentive to invest in renewable energy, the carbon cap could also be based on the emission intensity of each firm. Emission intensity is defined as the amount of emissions generated for each unit of energy produced. A firm whose generation portfolio is based heavily on fossil fuels (like Firm 1) would have a very large emission intensity, while a firm focused primarily on renewables (like Firm 2) would have a very low emission intensity. The only way to achieve emission intensity reductions under such a policy would be to increase the proportion of renewable capacity in the generation portfolio. Investing in energy efficiency would decrease overall emissions, but the intensity of electric generation would remain just as emissive. Therefore, configuring the cap and trade program to use emission intensity caps would favor the development of renewable energy over an investment in energy efficiency.

In addition to altering the type of investment incentive, an emission intensity cap could affect firms uniquely depending on whether it is based on an absolute, market-wide emission rate or a relative, firm-based emission rate. A market-wide rate would impose a single emission intensity goal for every firm in the cap and trade system. While this achieves a uniform goal for the region, it might not be the most equitable policy due to each firm's unique generation portfolio. Alternatively, a relative, firm-based rate would impose a unique intensity cap based on each firm's baseline emission intensity. While each firm would have to achieve the same percentage of emission reduction each year, the actual amount would vary. For instance, Firm 1 began the model with an emission intensity of about 963 tCO2/GWh, while Firm 2 had an intensity of about 104 tCO2/GWh. Because Firm 1's emissions are more than nine times larger than Firm 2's, its annual reduction would also need to be nine times larger. Clearly, this policy configuration puts increased burden on the more carbon intensive firm.

Each configuration of the carbon cap presents a different set of equity and burden depending on a firm's size and emission intensity. An absolute emission cap would fine firms based on their amount of emissions without taking their renewable energy capacity into account. This means that large firms will likely pay more in credit fees than small firms disregarding their commitment to renewable energy. An absolute emission intensity cap would fine each firm based on the intensity of its emissions without regarding the actual amount of CO2 that each firm emits. This would put burden on fossil fuel dependent firms without considering the total size of each firm. Finally, a size-relative emission intensity cap would impose the same percentage amount of reduction on each firm, but would still be more burdensome for fossil fuel dependent firms. Table 7.1 summarizes the equitability of each policy configuration.

Table 7.1: Effect of cap configuration on firm size and portfolio

Cap type	Size	Portfolio
Absolute Emissions	Abatement commitment is relative to firm size	Treats fossil fuel- vs renewable-dependent firms equally
Emission Intensity		
Market-wide	All firms must achieve same reduction magnitude	Favors renewable-dependent firms
Relative	Actual reduction based on firm's size	Favors renewable-dependent firms

Another important policy consideration involves price control on the price of carbon credits in the cap and trade market. The results of Scenario 1 and 2 assumed a stable price of \$50/tCO2 for carbon credits throughout the entire 40 year simulation. Due to changing costs, market conditions and investment decisions, this is likely unrealistic. The results of Scenario 3 demonstrated the behavior of the credit price when local firms are influential enough to become price setters in the regional market. In this instance, the price changed dramatically over time by increasing for the first 30 years of the simulation, then decreasing in the last 10. Price fluctuation may be normal in most markets, but the fluctuation in carbon markets may impact the effectiveness of cap and trade as an emission abatement policy (Benz and Truck 2009). As demonstrated in Chapter 6, there will be no incentive for firms to invest in emission abatement if the carbon price is too low (in this case, around \$3/tCO2 and below for Firm 1). To achieve the maximum potential of CO_2 emission abatement, policymakers should closely monitor the price of carbon credits and consider implementing a price floor to prevent the loss of abatement incentives.

Additionally, because cap and trade programs create brand new markets, the credit price may initially be set by the policymakers (EPA 2003). In this paper, the credit price was set at a reasonable, mid-range value determined by a set of typical, peer-reviewed economic valuations of CO_2 emissions. The reality check in Chapter 6, however, indicated that this price may be unreasonably high because Firm 1 invested in abatement options even at prices as low as \$10/tCO_2. If the credit price is too high, unnecessary costs may be incurred on firms. To prevent the firms from passing unnecessary costs onto consumers, policymakers should pay close attention to market responses to determine the best initial carbon price.

Finally, the results of this research present a very important issue that may extend beyond the scope of regional cap and trade policy. In Scenario 1, Firm 1 behaved faithfully in following its annual carbon cap reductions. In the midst of the simulation, however, the firm was unable to make further investments to curb its emissions due to the physical constraint on both energy efficiency and renewable energy. Despite being willing to abide by the program, the firm was unable to make further emission reductions due to a limited set of abatement options. By utilizing only energy efficiency and renewable energy, Firm 1 was not able to achieve the 2050 goals as set by the IPCC. Clearly, efficiency and renewables alone are not enough to avoid contributing to global warming. Although the revenue generated from its credit purchasing may be used to abate and sequester carbon elsewhere in the system, Firm 1 did not reduce its actual emissions and was thus still contributing to global climate change by the end of this simulation.

Firm 1's size and electric generation portfolio are very close to the total electric grid in the state of Minnesota. The results of this research indicate that if Minnesota hopes to reduce its contribution to global warming, it must look beyond energy efficiency and renewable energy. These options provide only a portion of the emission reductions that must be made. Therefore, a wide range of emission options must be considered or developed. A menu of options is needed that includes not only efficiency and renewables, but also techniques such as biomass co-firing, transitional fossil fuel technology such as integrated gasification combined cycle coal plants, and carbon sequestration, among others. Given enough options, cap and trade has the potential to utilize a carbon market to adequately curb emissions to eliminate the region's contribution to global climate change (CBO 2001). In order for policymakers to help it achieve its full potential, however, the range of options in Minnesota must expand beyond wind power and energy efficiency.

Chapter 8: Conclusion

This study aimed to develop a system dynamics model that simulated the decision-making process of a firm enrolled in a theoretical regional cap and trade program. Through a series of simulation scenarios, the results of this research presented a number of conclusions and issues to take into consideration when developing both policies and mathematical models of policy systems. This chapter lists the conclusions and recommendations that arose from the observations and results of this study's modeling process. These are divided into three groups: modeling results, modeling considerations, and policy considerations.

Modeling results

1. Cap and trade is effective in achieving emission reductions goals (to a certain degree)
2. Large, fossil fuel dependent firms will pay more, on an absolute basis
3. SD Modeling can simulate the fluctuation in carbon credit price as the available abatement options change

Modeling considerations

4. Assumed physical constraints on renewables significantly affect model results
5. Emissions will depend greatly on the annual growth of electric demand
6. Carbon price will influence firm decision making

Policy considerations

7. Different types of emission caps will impact unique firms differently

8. Carbon price control may be necessary

9. Given the limitations of energy efficiency and renewable energy, climate change mitigation will depend on a wide variety of abatement options

Modeling results

1. Cap and trade is effective in achieving emission reductions goals (to a certain degree)

Both Scenario 1 and 2 demonstrated unique firms achieving considerable reductions in CO_2 emissions by the year 2050. In Scenario 1, the large and fossil-fuel dependent Firm 1 achieved a cumulative total reduction of about 616 million metric tons of CO_2. The moderately sized, renewable dependent Firm 2 achieved a cumulative total reduction of about 9.83 million metric tons of CO_2 in Scenario 2. In both cases, the firms acted faithfully under the cap and trade program restrictions by purchasing credits and investing in abatement options. In Scenario 1, however, Firm 1 was not able to achieve its ultimate goals due to a realistic physical constraint that limited the amount of investments it could make in efficiency and renewables.

2. Large, fossil fuel dependent firms will pay more, on an absolute basis

Table 5.5 compared the costs incurred by Firm 1 and Firm 2 in the first two scenarios of Chapter 5. At a moderate discount rate of 3%, a total cost of about $2.85 billion was imposed on Firm 1. In contrast, the renewable-dependent Firm 2 generated about $2.15 million in revenue from selling credits to the market.

Figures 5.11 and 5.12 contrast the distribution of costs for Firm 1 and Firm 2, respectively. In the case of the larger firm, the majority of costs originated from the mandatory purchasing of credits. Investment into renewables and energy efficiency accounted for only about 11.7% of Firm 1's total costs. On the other hand, Firm 2's costs were about evenly split between mandatory credit purchases (52.2% of total cost) and renewable investment (47.8%).

3. SD Modeling can simulate the fluctuation in carbon credit price as the available abatement options change

Scenario 3 demonstrated a carbon market where Firms 1 and 2 were influential enough to set the price of carbon credits. Firms who become price setters choose to purchase credits rather than invest in abatement options. As a result, firms that cease to be influential during the simulation find themselves significantly lagging behind the goals of the cap and trade system.

Modeling considerations

4. Assumed physical constraints on renewables significantly affect model results

This study assumed that renewable energy could contribute no more than 45% of the region's total electric generation. Originating from issues such as geographic distribution, transmission line construction, and the capacity factors implied by technology such as wind turbines, this physical constraint will influence the range of options that are available to firms enrolled in a cap and trade program. Figure 6.3 presents the results of a sensitivity analysis conducted for Scenario 1 (which approximates the MN electric grid) to determine the assumed physical constraint's effects on simulation results. A lower and tighter assumed physical constraint, such as 25%, would dramatically increase the amount of emissions projected by this model. At tighter constraints, firms face stricter limits on the amount of investments they can make into abatement options. These figures demonstrate that the assumed renewable energy development constraint has a singular and significant effect on the results of this simulation.

5. Emissions will depend greatly on the annual growth of electric demand

All scenarios in this research assumed an annual electricity demand growth rate of 1%. Although 1% is a reasonable growth rate given economic conditions at the time of this writing, a wide array of unexpected events or trends could occur during the years of this simulation. Figure 5.3 presents alternative CO2 emission results for a number of assumed demand growth rates. Even at rates of 2% or 3%, Firm 1 ceased emission abatement early in the simulation, causing CO2 emissions to rise dramatically. These findings clearly identify the assumed growth rate of electricity demand as another crucial factor in this model's simulation results. As growth rates increase, it is more difficult for each firm to reduce its annual emissions. Determining the assumed growth rate becomes an important factor that greatly influences the results of projecting firm behavior under a cap and trade program.

6. Carbon price will influence firm decision making

While Scenario 3 demonstrated that price setting firms will choose credit purchasing over abatement investment, the sensitivity analysis conducted in Chapter 6 demonstrated that the assumed carbon price in Scenarios 1 and 2 may be too high. The analysis observed very similar firm behavior for credit values between $10 and $50 per metric ton of CO_2. However, credit values below $3/t$CO_2$ resulted in no abatement investments and thus increased CO_2 emission from Firm 1. Clearly, the decision on how to model the carbon price, whether exogenously or endogenously, has a dramatic impact on the simulation results.

Policy considerations

7. Different types of emission caps will impact unique firm differently

Chapter 7 discussed the impact of choosing between an absolute emission cap or an emission intensity cap. An absolute emission cap would set a cap on actual emissions for each firm. An emission intensity cap could set a market-wide cap on intensity, or a firm-based relative intensity cap. A cap based on emission intensity would divide the total amount of desired emissions by the amount of energy expected to be produced. All firms could then be held to this one number, or each firm could have an individual intensity calculated based on their share of energy production. Table 8.1 presents the equitability of each option.

Table 8.1: Effect of cap configuration on firm size and portfolio

Cap type	Size	Portfolio
Absolute Emissions	Abatement commitment is relative to firm size	Treats fossil fuel- vs renewable-dependent firms equally
Emission Intensity		
Market-wide	All firms must achieve same reduction magnitude	Favors renewable-dependent firms
Relative	Actual reduction based on firm's size	Favors renewable-dependent firms

As shown in the table, the type of carbon cap will determine which types firms are favored or burdened. Policymakers should therefore take this into consideration when crafting cap and trade programs.

8. Carbon price control may be necessary

As demonstrated in Chapter 6, there will be no incentive for some firms to invest in emission abatement if the carbon price is too low (in the case of scenario, around \$3/tCO2 and below for Firm 1, for example). To achieve the maximum potential of CO2 emission abatement, policymakers should closely monitor the price of carbon credits and consider implementing a price floor to prevent the loss of abatement incentives. Additionally, because cap and trade programs create brand new markets, the credit price may initially be set by the policymakers (EPA 2003). If the credit price is too high, unnecessary costs may be incurred on firms. To prevent the firms from passing unnecessary costs onto consumers, policymakers should pay close attention to market responses to determine the best initial carbon price.

9. Given the limitations of energy efficiency and wind energy, climate change mitigation will depend on a wide variety of abatement options

The results of this research indicate that if Minnesota hopes to reduce its contribution to global warming, it must look beyond energy efficiency and renewable wind energy. These options provide only a portion of the emission reductions that must be made, no matter the particular climate change policy. Therefore, a wide range of emission options must be considered or developed. A menu of options is needed that includes not only efficiency and wind, but also techniques such as biomass co-firing, transitional fossil fuel technology such as integrated gasification combined cycle coal plants, nuclear energy, and carbon sequestration, among others. Given enough options, cap and trade has the potential to utilize a carbon market to adequately curb emissions to eliminate the region's contribution to global climate change (CBO 2001). In order for policymakers to help it achieve its full potential, however, the range of options in Minnesota must expand beyond wind power and energy efficiency.

Appendix 1 Model Variable Definitions

Allowance Slope: The slope of the annual reduction of each firm's carbon cap allowance.

Allowance Slope[Firm] = 758898, 20400, 1.02002e+006
Units: tCO2/year

Annual Allowance Reduction: The annual reduction of a firm's carbon cap allowance.

Annual Allowance Reduction[Firm] = Allowance Slope[Firm]
Units: tCO2/year

Annual New Construction: The growth rate of new building construction (1%).

Annual New Construction[Firm] = 0.01*Built Environment[Firm]
Units: SqFt/year

Average Annual Electricity Use Per Unit: The average energy consumption per square foot of *existing* built environment.

Average Annual Electricity Use Per Unit[Firm] = Total Annual Electricity Use of Built Environment[Firm]/Built Environment[Firm]
Units: GWh/SqFt

Average Annual Energy Use Per Unit in Construction: The average energy consumption per square foot of new built environment under construction.

Average Annual Energy Use Per Unit in Construction[Firm] = Total Annual Potential Electricity Use of New Construction[Firm]/Built Environment Under Construction[Firm]
Units: GWh/SqFt

Average Unit Life: The average lifespan of a building.
Average Unit Life = 85
Units: year

Built Environment: The total amount of energy consuming buildings
Built Environment[Firm] = INTEG (Construction Completion[Firm]-Demolition[Firm], Initial Built Environment[Firm])
Units: SqFt

Built Environment Under Construction: The amount of new building construction as determined by a 1% growth rate.

Built Environment Under Construction[Firm] = INTEG (Annual New Construction[Firm]-Construction Completion[Firm],Initial Built Environment[Firm]*0.01)
Units: SqFt

Build Time: The average construction period for a building.
Build Time = 2
Units: year

Buydown Price: The marginal cost of emissions abatement face by a firm. Used for determining WTA and WTP.

Buydown Price[Firm] = IF THEN ELSE(
Total Demand Reduction[Firm]<Initial Production[Firm]*0.35,
IF THEN ELSE(
Equivalent Buydown[Firm]<Demand[Firm]*0.02,
Efficiency Investment Price[Firm],
(((Efficiency Investment Price[Firm]*Demand[Firm]*0.02)+(Renewable Investment Price[Firm]*Equivalent Renewable Purchase[Firm]-(Demand[Firm]*0.02))))/(Equivalent Renewable Purchase[Firm]+(Demand[Firm]*0.02))),
Renewable Investment Price[Firm])
Units: $/GWh

Carbon Price: The price of a carbon credit when regulated by the cap and trade program.
Units: $/tCO2

Construction Completion: The rate of flow between a building being under construction and being completed

Construction Completion [Firm] = Built Environment Under Construction[Firm]/Build Time
Units: SqFt/year

Credits: The number of credits sold annually by each firm.
Credits Sold[Firm] = IF THEN ELSE(Credits Available or Needed[Firm] < 0, Credits Available or Needed[Firm]*(-1), 0)
Units: tCO2

Credit Allowance: The annual CO2 credit allowance or cap for each firm
Credit Allowance[Firm] = INTEG (-Annual Allowance Reduction[Firm],Initial Allowance[Firm])
Units: tCO2

Credits Available or Needed: The amount of credits a firm must sell or purchase.
Credits Available or Needed[Firm] = (Emissions[Firm]*Per Annum Factor)-Credit Allowance[Firm]
Units: tCO2

Credit Cost: The total cost incurred by a credit purchasing firm.
Credit Cost[Firm] = Carbon Price*Credits Available or Needed[Firm]
Units: $

Credit Cost Incurred: The total annual amount of cost incurred from purchasing credits
Credit Cost Incurred[Firm] = Credit Cost[Firm]/Per Annum Factor
Units: $/year

Credit Price: The price of a carbon credit when determined by the market's highest WTP
Credit Price = IF THEN ELSE(Max WTP>Min WTA, Max WTP, 50)
Units: $/tCO2

Cumulative Credit Cost: The total cumulative cost of purchasing credits for each firm over the entire model simulation.
Cumulative Credit Cost[Firm]= INTEG (Credit Cost Incurred[Firm], 0)
Units: $

Cumulative Efficiency Investment: The total cumulative investment into energy efficiency improvements by each firm.
Cumulative Efficiency Investment[Firm]= INTEG (Efficiency Investment Cost[Firm], 0)
Units: $

Cumulative Emissions: The total cumulative amount of CO2 emissions by each firm over the entire model simulation.
Cumulative Emissions[Firm]= INTEG (Emissions[Firm],0)
Units: tCO2

Decision: The decision making rule in which each firm chooses the least expensive of three options: do nothing/buy credits, invest in renewable energy, or invest in energy efficiency.
Decision[Firm]= IF THEN ELSE(
(Credit Cost[Firm]<Equivalent Renewable Investment[Firm]) :AND: (Credit Cost[Firm]<Equivalent Efficiency Investment[Firm]),
0 ,
IF THEN ELSE((Equivalent Efficiency Investment[Firm]<Equivalent Renewable Investment[Firm]) :AND: (Total Demand Reduction[Firm] < Initial Production[Firm]*0.35),
1,
2))
Units: None

Demand: Total annual electricity demand.
Demand[Firm] = Total Annual Electricity Use of Built Environment[Firm]
Units: GWh

Demolition: The demolition of old buildings as determined by an 85 year lifespan.
Demolition[Firm] = Built Environment[Firm]/Average Unit Life
Units: SqFt/year

Efficiency Investment: The dollar amount of investment into energy efficiency, as determined by the **Decision** variable
Efficiency Investment[Firm] = IF THEN ELSE(Decision[Firm]=1, Equivalent Efficiency Investment[Firm] , 0)
Units: $

Efficiency Investment Cost: The total cost of a firm's efficiency investment
Efficiency Investment Cost[Firm] = Efficiency Investment[Firm]/Per Annum Factor
Units: $/year

Efficiency Investment Price: The cost of energy efficiency improvements
Efficiency Investment Price[Firm] = 20000,20000,20000
Units: $/GWh

Electricity Use Decay from Demolition: The change of average rate of electricity use from building retirement and renovation.
Electricity Use Decay from Demolition[Firm] = Average Annual Electricity Use Per Unit[Firm]*Demolition[Firm]
Units: GWh/year

Emissions: The annual amount of CO_2 emissions for each firm.
Emissions[Firm] = Emission Rate[Firm]*Energy Production[Firm]/Per Annum Factor
Units: tCO_2/year

Emission Rate: A firm's total electric generation CO_2 emission rate.
Emission Rate[Firm] = Fossil Fuel Emission Rate[Firm]*(Fossil Fuel Generation[Firm]/(Utilized Renewable Capacity[Firm]+Fossil Fuel Generation[Firm]))
Units: tCO_2/GWh

Energy Production: The amount of electric energy produced to meet demand.
Energy Production[Firm] = Demand[Firm]

Units: GWh

Equivalent Buydown: The equivalent amount of demand reduction necessary to avoid purchasing the same amount of credits in the next year.

Equivalent Buydown[Firm] = IF THEN ELSE(Credits Available or Needed[Firm]>0 , Credits Available or Needed[Firm]/Emission Rate[Firm], 0)

Units: GWh

Equivalent Efficiency Investment: The equivalent amount of dollar investment into energy efficiency necessary to avoid purchasing the same amount of carbon credits in the following year.

Equivalent Efficiency Investment[Firm] = MIN(Demand[Firm]*0.03*Efficiency Investment Price[Firm], Equivalent Buydown[Firm]*Efficiency Investment Price[Firm])

Units: $

Equivalent Renewable Investment: The equivalent cost of investing in renewable energy to avoid having to purchase the same amount of credits in the following year.

Equivalent Renewable Investment[Firm] =Equivalent Renewable Purchase[Firm] *Renewable Investment Price[Firm]

Units: $

Equivalent Renewable Purchase: The equivalent amount of electricity generation capacity in order to avoid having to purchase the same amount of credits in the following year.

Equivalent Renewable Purchase[Firm] = IF THEN ELSE(Credits Available or Needed[Firm]>0 ,Credits Available or Needed[Firm]/Fossil Fuel Emission Rate[Firm], 0)

Units: GWh

Firm: The subscript that tracks variables for each firm

Firm: Firm 1, Firm 2, Firm 3

Units: None

Fossil Fuel Generation: The amount of electricity demand met by fossil fuel generation.

Fossil Fuel Generation[Firm] = Energy Production[Firm]-Utilized Renewable Capacity[Firm]

Units: GWh

Initial Allowance: The initial CO_2 credit allowance for each firm.

Initial Allowance[Firm] = 4.03608e+007, 1.08497e+006, 5.42483e+007

Units: tCO_2

Initial Built Environment: The initial total amount of electricity consuming buildings.
Initial Built Environment[Firm] = 5.58733e+008, 1.39683e+008, 6.98417e+008
Units: SqFt

Initial Demand: The initial annual electricity demand faced by each firm.
Initial Demand[Firm] = 41905, 10476, 52381
Units: GWh

Initial Production: The initial amount of electric production for each firm (stock).
Initial Production[Firm] = INTEG (Initial Value[Firm], 0)
Units: GWh

Initial Renewable Capacity: The initial renewable energy capacity of each firm.
Initial Renewable Capacity[Firm] = 2933, 9429, 52381
Units: GWh

Initial Value: The initial amount of electric production for each firm (flow).
Initial Value[Firm] = IF THEN ELSE(Time=1,Energy Production[Firm]/Per Annum Factor,0)
Units: GWh/year

Max WTP: The maximum or highest WTP in the market.
Max WTP = MAX(Willingness to Pay[Firm 1], Willingness to Pay[Firm 2])
Units: $/tCO2

Min WTA: The minimum or lowest WTA in the market.
Min WTA = MIN(Willingness to Accept[Firm 1], Willingness to Accept[Firm 2])
Units: $/tCO2

New Construction Potential Electricity Use: The total use of electricity from potential new buildings under construction.
New Construction Potential Electricity Use[Firm] = Annual New Construction[Firm]*Present Electricity Use Per Unit
Units: GWh/year

New Energy Use Activation: The rate of flow into total annual electricity use determined by the completion of new building construction.
New Energy Use Activation[Firm] = Average Annual Energy Use Per Unit in Construction[Firm]*Construction Completion[Firm]
Units: GWh/year

Per Annum Factor: Factor necessary for some annual calculations.
Units: year

Potential Renewable Fraction: The total percentage amount of renewable capacity including capacity currently under construction.

Potential Renewable Fraction[Firm] = (Renewable Capacity[Firm]+Renewable Construction[Firm])/Demand[Firm]
Units: Fraction

Present Electricity Use Per Unit: The current rate of electric consumption in new buildings

Present Electricity Use Per Unit = 7.5e-005+7.5e-007*Time
Units: GWh/SqFt

Reduction from Efficiency Investment: The amount of annual energy demand reduced by a firm's investments in energy efficiency.

Efficiency Investment Reduction[Firm] = Efficiency Investment[Firm]/(Efficiency Investment Price[Firm]*Per Annum Factor)
Units: GWh/year

Renewable Activation: The rate of flow for renewable energy capacity construction, as determined by a two year construction period.

Renewable Activation[Firm] = IF THEN ELSE(Renewable Construction[Firm]>0 :AND: Potential Renewable Fraction[Firm]<Renewable Fraction Limit[Firm], Renewable Construction[Firm]/2,0)
Units: GWh/year

Renewable Capacity: The current electric generation capacity of each firm's renewable energy.

Renewable Capacity[Firm] = INTEG (Renewable Activation[Firm],Initial Renewable Capacity[Firm])
Units: GWh

Renewable Construction: Total amount of renewable construction.

Renewable Construction[Firm] = INTEG (Renewable Investment Construction[Firm]-Renewable Activation[Firm], 0)
Units: GWh

Renewable Fraction: The fraction of total generation met by renewable capacity.

Renewable Fraction[Firm] = Renewable Capacity[Firm]/Demand[Firm]
Units: Fraction

Renewable Fraction Limit: The physical constraint on renewable energy development.

Renewable Fraction Limit[Firm] = 0.45,1,1
Units:

Renewable Investment: The annual amount of investment into renewables as determined by the decision rule in the **Decision** variable.

Renewable Investment[Firm] = MAX(0, IF THEN ELSE(Potential Renewable Fraction[Firm]<Renewable Fraction Limit[Firm], IF THEN ELSE(Decision[Firm]=2, Equivalent Renewable Investment[Firm], IF THEN ELSE(Decision[Firm]=1,MAX(Equivalent Buydown[Firm] - Equivalent Efficiency Investment[Firm], 0),0)), 0))

Units: $

Renewable Investment Construction: Annual new renewable construction caused by renewable investment.

Renewable Investment Construction[Firm] =Renewable Investment[Firm]/(Renewable Investment Price[Firm]*Per Annum Factor)

Units: GWh/year

Renewable Investment Cost: The annual cost incurred by a firm's renewable energy investments.

Renewable Investment Cost[Firm] = Renewable Investment[Firm]/Per Annum Factor

Units: $/year

Retirement: The rate of retirement for renewable capacity based on a 25 year lifespan.

Retirement[Firm]= Renewable Capacity[Firm]/25

Units: tCO2/year

Total Annual Electricity Use of Built Environment: The total amount of electricity consumed by the built environment.

Total Annual Electricity Use of Built Environment[Firm] = INTEG (New Energy Use Activation[Firm]-Efficiency Investment Reduction[Firm]-Electricity Use Decay from Demolition[Firm], Initial Demand[Firm])

Units: GWh

Total Annual Potential Electricity Use of New Construction: The potential total electric demand of buildings currently under construction.

Total Annual Potential Electricity Use of New Construction[Firm] = INTEG (New Construction Potential Electricity Use[Firm]-New Energy Use Activation[Firm], Present Electricity Use Per Unit*Built Environment Under Construction[Firm])

Units: GWh

Total Demand Reduction: The cumulative total of demand reduced by efficiency investment.

Total Demand Reduction[Firm] = INTEG (Efficiency Investment Reduction[Firm], 0)
Units: GWh

Utilized Renewable Capacity: The total amount of renewable capacity utilized to meet demand.
Utilized Renewable Capacity[Firm] = MIN(Energy Production[Firm],Renewable Capacity[Firm])
Units:

Willingness to Accept: The WTA of a credit selling firm (calculated by the **Buydown Price**)
Willingness to Accept[Firm] = IF THEN ELSE(Credits Available or Needed[Firm]<0, XIDZ(Buydown Price[Firm],Emission Rate[Firm],1e-006), 1e+020)
Units: $/tCO2

Willingness to Pay: The WTP of each firm as determined by its marginal cost, the buydown price.
Willingness to Pay[Firm] = IF THEN ELSE(Credits Available or Needed[Firm]>0, ZIDZ(Buydown Price[Firm], Emission Rate[Firm], 1e-007), 0)
Units: $/tCO2

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