

**Use of Empirically-Based Models to
Evaluate the Potential of Energy Efficiency and
Forest Carbon Sequestration for
Mitigating Climate Change**

by

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Abstract

Disagreement over the costs of actions to address climate change is a barrier to implementing effective policies. In this thesis, I focus on two particularly controversial actions: accelerating natural rates of improvement in energy efficiency and increasing carbon sequestration in forests. Analysts using what is known as the conventional bottom-up approach find that each of these actions can achieve substantial mitigation of greenhouse gas emissions at low costs. The prospect of combining low-cost actions with politically feasible policies, such as subsidies and information programs, is particularly enticing for policy-makers. However, actions that appear to be cost-effective based on conventional bottom-up calculations are not necessarily widely adopted – in the energy efficiency literature, this is referred to as the energy efficiency “gap”.

There are two serious problems associated with the conventional bottom-up methodology. First, conventional bottom-up analysis ignores important aspects of human behavior and therefore does not take into account some of the real costs associated with actions. This explains to some degree the “gap” described above. Second, key feedback effects within the economy are not represented in bottom-up models. The energy efficiency “rebound effect” and the analogous phenomenon of “leakage” in forest carbon sequestration each reduce the initial effectiveness of the action in question. As a result of these deficiencies, conventional bottom-up models are likely to underestimate the cost of the actions in question and suggest inappropriate policy responses to rising carbon dioxide concentrations in the atmosphere.

In the three papers comprising my PhD thesis, I develop and apply new models to test the findings of the bottom-up approach. These models incorporate empirically estimated behavioral parameters and have the capability to (where necessary) take into account feedback effects within the economy. My research suggests that neither energy efficiency nor forest carbon sequestration is the “magic bullet” against climate change. Subsidy programs designed to achieve these actions – including subsidies in the form of offsets – would require large public expenditures, especially due to free-rider problems. To successfully meet the challenge of climate change, policy-makers must implement broad-based policies that impose a substantial financial or regulatory constraint on greenhouse gas emissions.

Keywords: bottom-up model; climate policy; energy efficiency; forest carbon sequestration; greenhouse gas; mitigation cost

*To Rhys and the other one on the way, in the
hope that we can preserve the life-support
systems of this planet for future generations.*

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1. Introduction

Deep cuts in greenhouse gas (GHG) emissions from human activity are necessary in order to limit global climate change – carbon dioxide emissions (CO₂) in particular must be addressed. However, after more than twenty years, the international climate change effort and the efforts of most national governments have failed to realise substantial reductions.

There are a number of reasons why it has been difficult to implement effective climate policy (Dessler and Parson, 2010; Hamilton, 2010; Jaccard, 2013; Murphy et al., 2007a; Victor, 2011). First, the impacts of climate change will be felt in the medium- to long-term, whereas costs must be incurred up-front to avert or mitigate the problem. Human beings have difficulty with long-term thinking and our political system reflects this bias towards the short-term. Second, until fairly recently, mitigation costs were balanced against an uncertain link between anthropogenic GHG emissions and climate change.¹ Third, addressing climate change is a global public good, and global public goods are very difficult to provide without a global system of governance when there is a considerable challenge involved. This is evidenced by prolonged debates between the developed and developing countries over their respective roles in reducing GHG emissions. Fourth, powerful groups such as the fossil fuel industry have a vested interest in the status quo, and therefore tend to oppose meaningful climate action. A fifth impediment to meaningful climate policy provides the impetus for my thesis. Experts disagree with respect to the costs of alternative actions to reduce the concentration of CO₂ in the earth's atmosphere. As a result of cost disputes, policy-makers have difficulty identifying the best measure or combination of measures to implement.

¹ Now that a scientific consensus has been achieved with respect to our influence on the climate, this is less of an issue. However, uncertainty remains with respect to the magnitude, timing and location of climate change impacts.

My goal is to provide useful information to policy-makers about the likely cost and effectiveness of different actions and policies for substantially mitigating our impact on the global climate. We have often been distracted from the hard work of crafting an effective response to the difficult problem of climate change by promises that specific actions can achieve major reductions in the atmospheric concentration of CO₂ at low costs, and that these actions can be realized through politically feasible policies. In other words, these are claims that climate change is not a difficult problem after all. My research focuses on two categories of actions that have been touted by their respective advocates as the low-cost solution to the climate change problem: accelerating natural rates of improvement in energy efficiency and increasing carbon sequestration in forests. The prospect of combining these actions with policies that score well in terms of political feasibility, such as subsidies and information programs, is especially enticing.

Analysts who come to the conclusion that substantial emissions abatement or CO₂ removals can be achieved at a low cost tend to use what are referred to as “bottom-up” methodologies. Conventional bottom-up models explore how firms and households ought to behave given information about expected financial costs of alternative technologies and land uses. Future streams of costs and benefits are generally compared to present costs and benefits using a social discount rate. Decisions at the individual level are aggregated to produce a sector- or economy-wide analysis.

Conventional bottom-up models have been criticized on two counts.² First, these models are not behaviorally realistic because they ignore some of the real costs associated with actions. Second, they do not take into account feedback effects that may be associated with the actions in question. In the case of energy efficiency and forest carbon sequestration, the feedback effects that are of concern reduce the initial effectiveness of the actions. As a result of these shortcomings, conventional bottom-up models are likely to underestimate the cost of emissions abatement and suggest inappropriate policy responses to rising CO₂ concentrations in the atmosphere. My thesis involves developing and applying new models to test the findings of the bottom-up approach.

² I use the term “conventional” here because more advanced bottom-up models exist that address some of the criticisms of this approach.

In the following section, I formally define the term “action” and provide an overview of the various actions that are available to mitigate climate change. Section 1.2 defines the term “policy” and discusses policy options that may be implemented to achieve actions. In section 1.3, I review some of the literature on energy efficiency, specifically the energy efficiency gap and energy efficiency rebound. Issues relating to the lack of behavioral realism and feedback effects in conventional bottom-up models are discussed in detail. In section 1.4, I consider forest carbon sequestration and draw parallels with the energy efficiency literature. Finally, in section 1.5, I give an overview of the thesis.

1.1. Actions to mitigate climate change

An action is defined as “a change in the choice of equipment, buildings, infrastructure and land use, or in operating and management practices, or in lifestyles” (Jaccard, 2005, p. 260). There is a vast array of actions available for addressing climate change.³ GHG emissions from the combustion of fossil fuels can be reduced through technological change by improving energy efficiency, changing the mix of energy sources that are consumed, and capturing and storing the CO₂ that is released as a result of fossil fuel combustion. Examples of efficiency actions are improvements in energy supply and distribution; the combined generation of heat and power (cogeneration); the acquisition and use of more efficient vehicles, lighting, appliances and equipment; and improved insulation in homes and other buildings. Emissions can be reduced through changes in the energy mix by switching from fossil fuels with a higher carbon content to fossil fuels with a lower carbon content (e.g. from coal to natural gas), or shifting away from fossil fuels and towards the other primary energy sources, which are renewables (e.g. hydro, wind, biomass, solar, geothermal) and nuclear power. There are also a variety of actions available for reducing process emissions in the industrial sector, and non-combustion GHG emissions in the agricultural and waste sectors.

³ The Summary for Policymakers in the latest Intergovernmental Panel on Climate Change report on mitigation (2007) provides a useful summary by sector (Table SPM.3).

Reducing GHG emissions is not the only way to mitigate climate change. The atmospheric CO₂ concentration can also be lowered through actions that enhance agricultural and forest carbon sinks. Agricultural sinks can be enhanced through improved land management practices, such as conservation tillage, as well as revegetation. The amount of carbon stored in forests can be increased through afforestation, reforestation, improved forest management practices, and reducing emissions from deforestation and degradation (REDD).

1.2. Policies to achieve actions

Actions may be realized through the implementation of policy. A policy is “an effort by public authorities to induce actions by consumers, businesses and perhaps other levels of government” (Jaccard, 2005, p. 260). Policy options include direct regulation, emissions taxes, emissions cap and tradable permits, subsidies and information provision. These policy alternatives are discussed below in terms of the following evaluative criteria: effectiveness (in this case at reducing GHG emissions or enhancing carbon sinks), economic efficiency, political feasibility and administrative feasibility.⁴

Conventional regulations include emissions standards, energy efficiency standards, building code changes, and other requirements with respect to specific technology characteristics. Regulations have the advantage of specifying a particular outcome; however, they must be ambitious enough to stimulate changes beyond what would have happened in the absence of the regulatory intervention in order to be environmentally effective.⁵ Furthermore, the theoretical and economic literature suggests that the incentives for technological innovation are not as strong under regulation as under market-based instruments (Milliman and Prince, 1989; Parry, 2003). Regulations are not economically efficient when they require identical actions from

⁴ Much of this discussion is based on Jaccard (2005), section 8.2 “Policy options for a cleaner energy system.”

⁵ Jaffe et al. (1999) remind us that “although energy taxes, for example, will always have some effect, typical command-and-control approaches [such as state building codes] can actually have little effect if they are set below existing standards of practice” (p. 11).

participants who have different costs of compliance. In terms of political feasibility, a regulatory approach to pollution control may meet with less resistance from industry groups than the emissions taxes and auctioned permits discussed below. This is because, while regulations raise internal operations costs for firms, they do not require transfer payments to government, as these market-based policies do (Milliman and Prince, 1989). Regulations are administratively feasible.

Financial disincentives such as taxes, charges or levies applied to GHG emissions on a per unit basis can improve economic efficiency by universally pricing the negative environmental externality associated with the emissions. These instruments are more flexible than regulations, allowing those with higher costs of abatement to abate less (they will pay more tax), and those with lower costs of abatement to abate more (they will pay less tax). Theoretically, marginal abatement costs are equalized across economic actors under an emissions tax, thereby minimizing the cost of reaching a given level of abatement. The optimal amount of emissions reduction is achieved when the tax is set at the intersection of the marginal cost of emissions damage and marginal cost of emissions abatement curves.⁶ In practice, it is extremely difficult to identify this optimal tax level, since the damage costs are inherently uncertain. There is also uncertainty about the cost of emissions abatement, making it difficult to know in advance how effective a tax will be at reducing emissions. Emissions taxes are administratively feasible because they can be integrated with existing methods of establishing prices and collecting taxes. However, they face challenges in terms of political feasibility, as taxes in general tend to be viewed with suspicion or rejected outright by the general public (Caplan, 2007).

Emissions cap and tradable permits programs can combine the certainty of regulation with the flexibility of a tax. A governing body sets a maximum level for emissions (the emissions cap) and then distributes tradable emissions permits that allow total emissions equal to the level of the cap. Permits may be granted to existing firms or sold in a permit auction. The environmental effectiveness of the policy is known in

⁶ The marginal cost of emissions damage curve represents the incremental social cost of emissions as emissions increase – in the context of CO₂ emissions, the social cost of emissions is sometimes called the “social cost of carbon.”

advance,⁷ while market forces ensure that marginal abatement costs are equalized across participants, thereby achieving the abatement target at the lowest possible cost and promoting economic efficiency. Cap-and-trade programs may be more politically feasible than emissions taxes, but can be administratively complex.

Financial incentives, also known as subsidies, can take the form of rebates, grants, low-interest loans, tax credits, insurance guarantees, publicly funded infrastructure and public R&D. Subsidies are obviously popular with the beneficiaries, and therefore have certain advantages in terms of political feasibility. However, they are associated with a number of serious problems, including what is known as the “free-rider” problem. It is impossible to design a subsidy program to completely exclude free-riders who would have undertaken the desired action anyway.⁸ This means the programs are never as effective as they appear to be based on participation data. Also, as Joskow and Marron (1992) point out, administration expenditures to “attract, monitor, and evaluate” (p. 67) free-riders are essentially wasted, thereby reducing economic efficiency.⁹ Aside from the free-rider problem, subsidy programs can be costly to administer because efforts are necessary to attract participants, ensure that the action being subsidized is actually undertaken, and evaluate program performance. Energy efficiency subsidies do not encourage consumers and firms to reduce their utilization of energy consuming equipment and appliances, as do policies that result in an increase in energy prices (Jaffe et al., 1999).

⁷ The downside to this certainty is that technological progress theoretically does not result in additional emissions abatement, as would be the case under an emissions tax.

⁸ It is helpful here to draw parallels with terminology used more generally in the field of economics. My use of the term “free-riders” is related to, but distinct from, its conventional use in economics to refer to those who consume a public good without paying for it. Furthermore, the concept of free-riding applied in my thesis is related to the concept of adverse selection in economics, in that there is asymmetric information between those administering the subsidy program and those participating in it – the participants know more about whether they would have undertaken the action in the absence of the subsidy than the administrators do.

⁹ Joskow and Marron (1992) explain that the actual subsidies provided to free-riders are simply transfer payments, and as such do not reduce economic efficiency. However, once constituents become aware of a free-rider problem, the political feasibility of providing such payments is obviously greatly reduced, regardless of the economist’s definition of efficiency.

Programs that provide information to consumers and firms so as to encourage voluntary actions have the potential to improve economic efficiency, due to the public good and positive externality qualities of information (as discussed below in the context of energy efficiency). These programs are politically and administratively feasible, and have therefore been used extensively to promote GHG emissions mitigation and energy efficiency improvements.¹⁰

1.3. The energy efficiency gap and energy efficiency rebound

Interest in energy efficiency as a public policy goal began in the wake of the 1970s oil supply crisis. This is when Lovins (1977) published his book *Soft Energy Paths*, proposing efficiency as the first step in any energy policy directed at environmental protection and energy security. According to Lovins, the higher capital costs of the most efficient technologies are more than compensated for by savings in energy expenditures over time, and opportunities for profitable energy efficiency investments exist throughout the economy. More recently, using a conventional bottom-up approach very similar to that of Lovins, the McKinsey consulting firm has produced estimates of energy efficiency profitability that imply substantial reductions of GHG emissions could be realized at little or no cost (McKinsey, 2007; 2009).

Much of the literature on energy efficiency relates to a “gap” or “paradox,” whereby energy efficient technologies that appear to be cost-effective at current prices based on bottom-up calculations are not widely adopted. The efficiency gap can also be restated as a discrepancy between the higher implicit discount rates used in actual purchase decisions and the lower discount rates applied by bottom-up analysts (Jaffe and Stavins, 1994). Proponents of energy efficiency and the bottom-up approach have postulated that a number of market barriers account for the energy efficiency gap (Sutherland, 1991). They argue that these barriers should be addressed through government intervention so as to shrink the size of the gap. Mainstream economists

¹⁰ I explore some of the issues surrounding voluntary programs for environmental protection, in the context of electricity supply decisions, in Murphy and Jaccard (2003).

tend to dispute such calls for widespread government intervention to improve energy efficiency, on the basis that many of the barriers identified are not market failures and their presence does not, therefore, reduce economic efficiency (Jaffe et al., 1999; Jaffe and Stavins, 1994; Sutherland, 1991).¹¹ This perspective implies that reducing GHG emissions is more costly than indicated by the findings of conventional bottom-up analysis (Jaffe et al., 1999).

Market failure explanations for the energy paradox generally relate to a lack of information on energy efficient and low-emission technologies due to the public good qualities of information.¹² Non-market failure explanations, on the other hand, represent real (although intangible) costs to consumers and firms of acquiring energy efficient technologies that are not included in bottom-up models. The purchaser of a new technology that has greater energy efficiency faces uncertainty about future energy prices, the future prices of similar technologies, and the performance of the technology. This uncertainty, combined with the irreversible nature of the investment, means that it may be appropriate to use a relatively high discount rate to calculate the net present value of the energy savings.¹³ Energy efficient technologies may also have qualitative attributes that make them less attractive to users than existing technologies (e.g. some efficient lighting technologies do not provide the same quality of light as the incandescent bulbs they are purported to replace). There are generally costs associated

¹¹ Other economists have recently proposed that systematic behavioral anomalies offer an alternative explanation for the energy efficiency gap, and that behavioral failures as well as market failures provide a rationale for policy intervention. The literature on behavioral anomalies and failures, as well as other explanations for the energy efficiency gap is reviewed by Gillingham and Palmer (2013).

¹² There may be other failures in energy markets, which, while they do not help to explain the energy efficiency gap, are candidates for policy intervention on the basis that economic efficiency could be improved by eliminating them. These include negative environmental externalities associated with energy generation and use (including GHG emissions), low energy prices due to subsidies and pricing at average instead of marginal costs, externalities related to the national security costs that arise from dependence on oil imports from politically unstable regions, and inadequate incentives for the private sector to invest in research and development due to imperfections in the patent system (Jaffe and Stavins, 1994; Sutherland, 1991).

¹³ Investments in energy efficiency by households or small, privately owned firms are irreversible in the sense that they are illiquid. Unlike investments in securities, for example, there is no secondary market where these assets “can be readily liquidated or traded and where market prices adjust to equilibrium very quickly” (Sutherland, 1991, p. 28).

with adopting an energy efficient technology that are not included in conventional bottom-up analysis. These include the information acquisition costs that are not related to the public good qualities of information. Finally, even when an energy efficiency investment is profitable for the average household or firm, there may be individuals in a heterogeneous population for whom this is not the case.

There are a number of specific policy implications that stem from this discussion of the energy efficiency gap and the market failure and non-market failure explanations for it. If the true social costs of energy efficiency investments are higher than anticipated by conventional bottom-up analysis, then regulations, such as appliance standards, designed to close the energy efficiency gap may reduce economic efficiency. On the other hand, because the availability of information can be limited by market failures, there does appear to be a role for mandatory energy-efficiency labelling and other policies that encourage the supply of information (Jaffe et al., 1999; Sutherland, 1991).¹⁴ Subsidies can be quite effective in promoting the adoption of energy efficient technologies. This may be because they reduce the up-front capital costs to which purchasers appear to be particularly sensitive, given the high implicit discount rates that have been observed.¹⁵ However, subsidy programs “can require large public expenditures per unit of effect” because it is difficult to exclude free-riders who would have undertaken the energy efficiency improvement even in the absence of the subsidy payments (Jaffe et al., 1999, p. 11).

Bottom-up analyses of the potential for energy efficiency improvements have been criticized for being unrealistic because they do not take into account the potential economic feedbacks associated with energy efficiency gains, in particular what has become known as the “rebound effect.” Khazzoom (1987) critiques Lovins for completely ignoring the price elasticity of demand for energy services (e.g. lighting, mobility, space heating and cooling). Since advances in energy efficiency reduce the

¹⁴ However, even when a true market failure is identified, the cost-benefit test to determine whether government intervention is appropriate must include the costs of policy implementation (Jaffe et al., 1999; Jaffe and Stavins, 1994).

¹⁵ In contrast, policies that increase energy prices (such as carbon taxes) result in greater energy savings in the future; however, these savings may be heavily discounted in actual purchase decisions (Jaffe et al., 1999).

amount of energy consumed per unit of energy service enjoyed, the price of the energy service in question is reduced (at constant energy prices), and we should expect to see an increase in the demand for this service. Therefore, the energy savings from the initial efficiency improvements may be reduced or neutralized; energy use may even increase as a result of the technological change in energy efficiency. Brookes (1990) adds a macroeconomic dimension to the debate, arguing that the “purchasing power released by lower expenditure on existing uses of fuel finds an outlet somewhere and in modern industrial societies it is almost bound to be in the purchase of goods and services that require energy in their production if not on other uses of fuel itself” (p. 201). Sorrell et al. (2009) review empirical estimates of the direct rebound effect associated with the price elasticity of demand argument of Khazzoom, and conclude that, in the OECD, this effect is generally expected to be below 30% for household energy services.¹⁶

1.4. Parallels with forest carbon sequestration

As forests grow, they remove CO₂ and sequester carbon in trees and other plants, litter and soil. The economics of forest carbon sinks was not a subject of research until anthropogenic climate change was recognized as a problem. The literature dates back to the late 1980s, and is reviewed by Richards and Stokes (2004), Stavins and Richards (2005), and van Kooten and Sohngen (2007). Since that time, studies indicating that forest carbon sequestration has the potential to offset a large portion of anthropogenic CO₂ emissions at surprisingly low costs have captured the attention of environmentalists and policy-makers. The majority of studies on the cost of forest carbon sequestration are bottom-up studies.

The literature on forest carbon sequestration (as reviewed by Richards and Stokes, 2004; Stavins and Richards, 2005; van Kooten and Sohngen, 2007) is comprised of numerous studies providing dramatically different cost estimates, even among studies with the same geographic scope. Direct comparison of the results is not

¹⁶ It is convention to express the rebound effect in percentage terms. A rebound effect of 30% means that 30% of the energy savings that should theoretically have resulted from the energy efficiency improvement are not realized in practice (Sorrell et al., 2009).

possible because of the inconsistent use of terminology, wide ranging assumptions with respect to key parameter values, and different methodological approaches. In particular, three methods have been applied to estimating land opportunity costs, which are the most important factor influencing carbon sequestration costs: bottom-up engineering, sectoral optimization and econometric analysis. The majority of studies are bottom-up studies in which analysts typically base their estimates either on observed prices for land rental or land purchase, or on the revenues and costs associated with alternative land uses. Econometric studies, on the other hand, use historical data to characterize relationships between relative returns to alternative land uses and landowner behavior. The resulting carbon sequestration cost estimates implicitly take into account the (revealed) preferences of landowners. The sectoral optimization approach is discussed below in the context of emissions leakage.

There are parallels to the energy efficiency gap in the literature on forest carbon sequestration. In the US, “millions of acres have persistently remained in marginal agriculture, while economic comparisons suggest that these acres should be converted to other uses” (Parks, 1995, pp. 34-35). Stavins (1999) argues that bottom-up analyses of forest carbon sequestration do not portray landowner behavior in a realistic manner. He gives four reasons for this, some of which relate to the explanations for the energy efficiency gap discussed above. First, a change in land use may require an irreversible investment on the part of the landowner, and this investment may be associated with considerable uncertainty (Parks, 1995). Second, a landowner may experience non-monetary (non-market) returns from forests (Plantinga, 1997) or agricultural land. This is analogous to the observation above that alternative energy-consuming technologies have different attributes, which may be more or less desirable to purchasers. Third, there may be a delay in the response of a landowner to economic incentives, due to liquidity constraints or “decision-making inertia.”¹⁷ Fourth, the analyst may be unaware of some of the (private) market costs and benefits to which the landowner is responding. Plantinga et al. (1999) also note that agricultural landowners may not possess the

¹⁷ With respect to market failures in energy efficiency, Jaffe et al. (1999) characterize the role of financing constraints for small-scale investments as “controversial.” Jaffe and Stavins (1994) discuss inertia in the context of the energy efficiency gap, but find that this concept represents an alternative characterization of the gap, rather than offering a credible explanation for it.

knowledge and skills necessary to manage forest land; becoming familiar with forestry practices therefore represents an additional cost of afforestation. The cost of acquiring knowledge and skills is akin to the cost of acquiring information, as discussed above in the context of energy efficiency investments.

There is also an analogue to energy efficiency rebound in the forest carbon sequestration literature – a phenomenon known as “leakage” of CO₂ back to the atmosphere. Here again the concern is that the action in question (afforestation in this case) may result in economic feedbacks at either the micro or macro levels that reduce its initial impact. Van Kooten and Sohngen (2007) define these two types of leakage. At the micro-level, a farmer who conducts afforestation on a portion of their land may find that agricultural output declines, and may compensate through deforestation of another area. At the macro-level, leakage can occur if enough land is converted from farms to forests in aggregate, resulting in lower agricultural output, higher prices and, consequently, the deforestation of land not currently under cultivation. Sectoral optimization models have been developed that represent interactions between the forest products and agricultural markets, and are therefore able to address the problem of leakage associated with forest-based carbon sequestration programs.

Although interest in forest carbon sequestration is relatively recent, governments have been promoting afforestation, reforestation and the maintenance of existing forests for decades through subsidy programs. For example, in the US, a number of federal cost-share programs for private tree planting activities have been implemented over the past century, including the 1936 Agricultural Conservation Program and the 1986 Conservation Reserve Program (Sun, 2007). Costa Rica has awarded contracts for forest protection under its environmental services payments program since 1997 (Robalino et al., 2008).

When it comes to forest carbon sequestration, subsidy payments often take the form of offset credits. The promise of forest carbon sequestration has led policy-makers to explore offset credits as a way of fostering the desired land-use and land management changes. Offsets are relevant in the context of cap-and-trade programs, such as the Kyoto Protocol or the European Union Emission Trading Scheme (EU-ETS). Forest carbon offsets are being considered as part of ongoing negotiations to establish a

post-Kyoto international climate regime. In particular, “[a]n international system that enables countries to earn carbon credits by reducing emissions from deforestation and degradation (REDD) will almost certainly be a prominent feature of whatever post-2012 international climate architecture emerges from ongoing negotiations” (Blackman, 2010, p. 4). Forest carbon offsets are permitted under a number of sub-national cap-and-trade systems that are being developed in the US and Canada, including the Regional Greenhouse Gas Initiative (Northeast and Mid-Atlantic States), the California Cap-and-Trade Program, and the Alberta Offset System.

Cap-and-trade programs regulate emissions from only a portion of the sources that exist within their jurisdictions, due to political and/or administrative constraints. Unregulated entities can be countries (developing countries did not face binding constraints under the Kyoto Protocol), sectors (such as agriculture and forestry) or facilities (small facilities may not be included). These exemptions reduce economic efficiency if the unregulated entities have abatement opportunities with costs that are lower than the marginal cost of abatement by the regulated entities.

To stimulate actions by the unregulated entities to reduce GHG emissions and/or enhance carbon sinks, offsets mechanisms are often put in place; however, this type of policy has a downside. Under an offsets system, unregulated entities can receive credits for their actions, which can then be sold to the regulated entities and used as emissions permits. Offset credits are a form of subsidy and are therefore subject to the free-rider problem described above. The term that refers to this standard problem in the offsets literature is “additionality.” Projects that are awarded offset credits must be additional to what would have occurred in the absence of the incentives created by the offsets mechanism; otherwise the integrity of the cap-and-trade program is threatened.

1.5. Summary of the thesis

In the three papers comprising my PhD thesis, I develop models with empirically estimated behavioral parameters and the capability to (where necessary) take into account feedback effects within the economy. I use these models to examine the potential roles of energy efficiency and forest carbon sequestration in addressing the

climate change problem, and to evaluate the suitability of policies for achieving energy efficiency improvements and increases in the forest land base.

Where possible, the models employed in my thesis have behavioral parameters estimated by applying econometric techniques to quasi-experimental data. In the social sciences (and some areas of the natural sciences) it is generally not possible to achieve the ideal randomized experimental design in which a control group and a treatment group are evaluated before and after the treatment. In the field of biodiversity conservation, Ferraro and Pattanayak (2006) call for the application of quasi-experimental techniques to avoid “depend[ing] on intuition and anecdote” (p. 482). Although a number of quasi-experimental methods exist, my research uses “natural experiments” in which a variable (or variables) of interest happened to change historically and behavioral outcomes were observed, and “hypothetical experiments” in which survey participants are provided with choice sets designed to elicit their preferences.¹⁸ The former generates what is known as revealed preference data, while the latter produces stated preference data. Econometric techniques may be applied to quasi-experimental data to isolate the impact of a variable of interest from other covariates. This allows the analyst to establish a counterfactual scenario describing what would have happened if a given change had not occurred in the variable of interest. Analysis of the counterfactual is fundamental to policy evaluation, particularly when the free-rider problem exists.

The first two papers presented here use the CIMS energy-economy model to assess the potential and cost of energy efficiency in the US. CIMS is one of a number of models that combine the technological explicitness of the bottom-up approach with behavioral realism; the model also includes some economic feedbacks.¹⁹

Three behavioral parameters are included in CIMS: the first represents the weighted average time preference of decision-makers, the second takes into account the intangible costs and benefits that consumers and businesses perceive (in addition to

¹⁸ The terms “quasi-experiment” and “natural experiment” are used somewhat loosely in this interdisciplinary context to establish thematic links between the three papers comprising my thesis.

¹⁹ A more detailed description of CIMS is provided by Jaccard (2009).

expected financial costs), and the third portrays the extent to which costs and perceptions are heterogeneous within the marketplace. Recent efforts at parameterization involve the estimation of discrete choice econometric models, the results of which are used to derive behavioral parameters for CIMS. Rivers and Jaccard (2005) explain that discrete choice models capture the relationships between the attributes of a technology (e.g. capital cost, operation and maintenance cost, fuel cost, etc.) and the probability that it will be selected. They describe the application of this methodology to stated preference data generated by presenting survey respondents with hypothetical choice sets between alternative technologies characterized by varying levels of different attributes. Axsen et al. (2009) estimate discrete choice models using a combination of stated preference data and revealed preference data to inform parameter estimates in CIMS. The revealed preference data describes actual purchase decisions given historical variation in technology attribute levels (as influenced by energy prices, for example). This type of data captures the outcome of “natural experiments” in which attribute levels changed without any intervention from the analyst.

When a policy imposes a significant regulatory constraint or financial penalty on energy consumption or the associated emissions, we can expect feedback effects to occur within the economy. CIMS is an integrated, energy-economy equilibrium model that simulates the interaction of energy supply-demand and the macroeconomic performance of the economy, including trade effects (Bataille et al., 2006).²⁰ These feedback interactions allow the model to capture some of the potential rebound effects of energy efficiency actions.

In the first of three papers comprising my thesis, I use CIMS to simulate end-use energy efficiency standards and an economy-wide carbon tax that increases over time. I consider the impacts on energy consumption and GHG emissions in the buildings and transportation sectors, as well as for the US economy overall. This work was completed as part of EMF-25, a comparative modeling exercise organized by the Energy Modeling Forum at Stanford University. I find that ambitious efficiency standards can achieve sizeable reductions in energy consumption and direct GHG emissions from the end-use

²⁰ CIMS does not represent economic feedbacks to the full extent of a computable general equilibrium model.

sectors. However, to realize the necessary deep reductions in economy-wide GHG emissions, emissions from energy supply must also be reduced, and other actions such as fuel switching and carbon capture and storage must be taken up. Furthermore, my results indicate that the efficiency standards tested are not a cost-effective means of reducing GHG emissions, even within the targeted end-use sectors, primarily because they do not capture low-cost opportunities for fuel switching.

In the second paper, I critically evaluate a highly influential bottom-up study by the McKinsey consulting firm. The McKinsey report presents the case that there is a large potential for profitable energy efficiency in the US, and that substantial GHG emissions reductions can therefore be realized at low costs. At comparable marginal costs, CIMS simulations reveal a more modest potential for GHG emissions reductions, as well as a smaller contribution from energy efficiency relative to fuel switching and carbon capture and storage. Because both models are technologically explicit, I was able to run CIMS in a way that is compatible with the McKinsey bottom-up method. This was done by adjusting the behavioral parameters and turning off some of the economic feedbacks in the model. The results of this modeling experiment are much closer to the McKinsey findings, suggesting that the differences that were initially observed are in large part attributable to behavioral realism.

In my third paper, I address the potential and cost of forest carbon sequestration using a simple econometric model of afforestation on private land in Ontario, Canada. Here, varying levels of support for afforestation from programs administered (primarily) by the Ontario Ministry of Natural Resources (OMNR) between 1990 and 2002 provide a natural experiment that reveals landowner preferences with respect to land use. I estimated the model from quasi-experimental data on the tree planting subsidies and other benefits that were available during the time frame of the study, other relevant covariates, and resulting afforestation activity. I then used it to simulate a hypothetical program that subsidizes afforestation through the provision of offsets. Behavioral realism is embodied in the historical data used to estimate the parameters of the model, and leakage can be simulated exogenously based on the results. Simulation of a base case scenario in which offsets are not awarded for afforestation projects allows me to estimate the additionality of the hypothetical program. Across a range of offset prices (representing marginal costs) and assumptions regarding the rate of carbon

sequestration, I estimate sequestration potential to be much lower than reported by bottom-up studies. So low, in fact, that feedback effects such as leakage would not be triggered. In my simulations, the hypothetical afforestation offsets program is shown to have low levels of additionality (high levels of free-ridership).

The layout of my thesis is somewhat unconventional. The first and second papers described above are presented much as they appeared in *The Energy Journal* and *Energy Policy*, respectively. Because the journal format does not allow for an extended description of the US version of CIMS (CIMS-US), the following chapter (2) has been included to provide this methodological background. In order to present a complete description in one place, there is necessarily some repetition between this chapter and the first two papers, which follow as chapters 3 and 4. Next, I include the third paper in a more extended format (chapter 5), as is traditionally associated with a thesis. Finally, in chapter 6, I discuss differences between the papers in how they address the common goal of evaluating actions and policies to mitigate climate change using models that incorporate empirically estimated behavioral parameters and representations of key economic feedbacks. Some of the key policy prescriptions that emerge from my research are also discussed in this concluding chapter.

2. Methodology: The CIMS-US model

In this thesis, my goal is to provide useful information to policy-makers about the likely cost and effectiveness of different actions and policies for addressing climate change. I do this by developing models with empirically estimated behavioral parameters, and the capability to (where necessary) take into account feedback effects within the economy. These models are in contrast to conventional bottom-up models that lack such qualities. The first two papers presented below (chapters 3 and 4) use the CIMS energy-economy model to assess the potential and cost of energy efficiency in the US. CIMS is one of a number of hybrid models that combine the technological explicitness of the bottom-up approach with behavioral realism; the model also includes some economic feedbacks. In the following section, I review the bottom-up approach to energy-economy modeling, as well as the contrasting top-down approach. In section 2.2, I describe the design of CIMS, including how empirically estimated behavioral parameters are incorporated into the model and how economic feedbacks are represented.²¹ The chapter concludes with a discussion of the reference case for the US version of CIMS used in the analysis for my thesis.

2.1. Conventional approaches to energy-economy modeling

The CIMS model was developed in the context of two competing approaches to modeling energy consumption as a result of human economic activity: bottom-up and top-down. Bottom-up analysis estimates how changes in energy efficiency, fuel,

²¹ As mentioned in the introduction, there is necessarily some overlap between this chapter and the first two (published) papers of my thesis, in which I report results from CIMS. In order to compile the description of the CIMS methodology that appears here, I also used material from two other papers on which I am a co-author: Murphy et al. (2007b) and Jaccard et al. (2004).

emission control equipment, and infrastructure might influence energy use and thus environmental impacts. In conventional bottom-up models, technologies that provide the same energy service are assumed to be perfect substitutes except for differences in their anticipated financial costs and emissions. When their financial costs in different time periods are converted into present value using a social discount rate, many emerging technologies available for abating emissions appear to be profitable or just slightly more expensive relative to existing equipment and buildings. Bottom-up models often show, therefore, that environmental improvement can be profitable or low cost if these low-emission technologies were to achieve market dominance. Traditional bottom-up models are partial-equilibrium models – focusing on optimization of costs within the energy sector or a specific subsector, but omitting linkages between these sectors and the wider economy.

Many economists criticize the conventional bottom-up approach, however, for its assumption that a single, anticipated estimate of financial cost indicates the full social cost of technological change (Jaffe et al., 1999; Jaffe and Stavins, 1994; Sutherland, 1991). New technologies present greater risks, as do the longer paybacks associated with investments such as energy efficiency. Some low-cost, low-emission technologies are not perfect substitutes in the eyes of the businesses or consumers expected to adopt them. In addition, the partial-equilibrium approach can obscure key feedbacks within the economy that would be better captured with a full-equilibrium approach. To the extent that they ignore some of these costs and feedbacks, bottom-up models may inadvertently suggest the wrong technological and policy options for policy makers.

The contrasting top-down approach estimates aggregate relationships between the relative costs and market shares of energy and other inputs to the economy, and links these to sectoral and total economic output in a broader equilibrium framework. Elasticity of substitution (ESUB) parameters represent the degree of substitutability between competing inputs (energy and capital, coal and natural gas, etc.) as their relative prices change. Another key parameter, the autonomous energy efficiency index (AEEI), indicates the rate at which price-independent technological evolution improves energy productivity. At their most basic level, conventional top-down models represent the economy through a series of simultaneous equations linking economic outputs and inputs (especially energy), whose parameters are estimated econometrically from time-

series data. Models that link all of the major macroeconomic feedbacks in a full equilibrium framework are referred to as computable general equilibrium (CGE) models. Because they incorporate to some extent the transitional costs and risks of technological change, top-down cost estimates for achieving GHG reduction targets are almost always higher than bottom-up cost estimates.

A considerable challenge for top-down models is the estimation of statistically significant parameters from real-world experience. Often there is insufficient variability in the historical record for confident parameter estimation, and therefore most CGE modelers set the key ESUB parameters in their models judgmentally (Loschel, 2002). Furthermore, if the critical top-down parameters for portraying technological change – ESUB and the AEEI – are estimated from aggregate, historical data, there is no guarantee that these parameter values will remain valid into a future under substantially different policies, different energy prices, and with different technological options for environmental improvement (DeCanio, 2003; Grubb et al., 2002; Laitner et al., 2003). As conditions change, the estimated cost of GHG abatement may decrease, but conventional top-down models are unable to help policy makers assess this dynamic.

Another difficulty with the top-down approach is that conventional top-down models represent technological change as an abstract, aggregate phenomenon. Because these models do not keep track of individual energy end-uses and the technologies that serve them, the top-down approach only helps policy makers assess economy-wide policy instruments, such as taxes and tradable permits. However, policy makers often prefer, for political acceptability, policies that focus on individual end-uses and technologies in the form of technology- and building-specific tax credits, subsidies, penalties, regulations and information programs. This is especially the case where emissions charges would need to be substantial in order to overcome significant costs of environmental improvement. Therefore, a model could be more useful if it could assess both technology-focused policies and economy-wide, price-based policies.

The past decade has seen significant advances in the development of hybrid modeling approaches that can help resolve disputes about the cost of improving energy efficiency and reducing GHG emissions, and are also capable of performing a more useful range of policy simulations. Ideally, such models combine critical elements of the

conventional bottom-up and top-down approaches in order to satisfy at least three criteria: explicit representation of the potential for technological change, microeconomic realism in accounting for how consumers and businesses will decide among future technology options as policies and other conditions evolve, and macroeconomic feedbacks in reflecting how changes in production costs and preferences will change the structure of the economy and the growth rate of total output. Hybrid energy-economy models have generally been built either by incorporating technological detail into a top-down framework (Bohringer, 1998; Frei et al., 2003; Jacobsen, 1998; Koopmans and teVelde, 2001) or by incorporating behavioural realism and/or macroeconomic feedbacks into an integrated bottom-up framework (Bataille et al., 2006; Jaccard et al., 1996; Morris et al., 2002; Nystrom and Wene, 1999; Sanstad et al., 2001).²²

2.2. Design of the CIMS hybrid model

CIMS is classified as a hybrid model because it fulfils the three criteria outlined in the previous paragraph. CIMS is technologically explicit, keeping track of vintages of capital stocks of different efficiency and other qualities. It also incorporates behavioural parameters estimated from a combination of market research into past technology choices (revealed preferences) and discrete choice surveys of possible future technology choices (stated preferences) (Rivers and Jaccard, 2006). CIMS represents substantial energy supply-demand and macroeconomic feedbacks, although not to the full extent of top-down computable general equilibrium models.

The Canadian version of CIMS has been used extensively by governments, industry organizations and non-government organizations across the country to assess the direct costs to businesses and consumers, as well as some of the macroeconomic impacts, of policies to reduce greenhouse gas emissions and local air pollution. Beginning in 1999, CIMS was one of the four main models employed by the Canadian government in the national consultation process to meet Canada's international

²² Integrated models treat all actions to reduce energy use and/or GHG emissions as happening simultaneously; thereby taking into account the impacts that individual actions can have on each other. In some conventional bottom-up models this is not the case.

greenhouse gas emission reduction commitments (e.g. Energy Research Group / M.K. Jaccard and Associates, 2000; M.K. Jaccard and Associates, 2003; M.K. Jaccard and Associates, 2007).²³ My work with the Energy Modeling Forum (EMF) at Stanford University for this thesis is the first major project using the US version of CIMS.

2.2.1. Model structure and characterization of technologies

The basic structure of the CIMS model is presented in Figure 2.1. Energy supply and energy demand components are each made up of a number of sub-models representing particular sectors or sub-sectors. The version of CIMS that I use in my analysis is a model of the US energy–economy system in which the US is considered as a single region. Energy supply includes sub-models for electricity generation, petroleum refining, petroleum crude extraction, natural gas production, coal mining, ethanol production, and biodiesel production (some energy is also produced from landfill gas). Energy demand includes sub-models for residential buildings, commercial buildings, personal transportation, freight transportation, and industrial production. Of the energy demand components, the industrial component is the most complex because of its heterogeneous processes and technologies. CIMS-US incorporates detailed representations of chemicals, industrial minerals, iron and steel, metal smelting, pulp and paper, other manufacturing, mineral mining, and agriculture.

Each sub-model in CIMS has its own driving variable, usually expressing the total amount of final product or service produced, or the amount of raw input processed (e.g., square meters of commercial floor space, person-kilometers traveled, tonnes of steel, tonnes of mineral ore throughput, cubic meters of refined petroleum products). Initially, the driving variables are set exogenously, often based on official government forecasts, but they can adjust endogenously in response to policy.

²³ I was part of the project team on the first two reports cited, and was project manager and lead author on the third report.

CIMS Macro-Economy Module

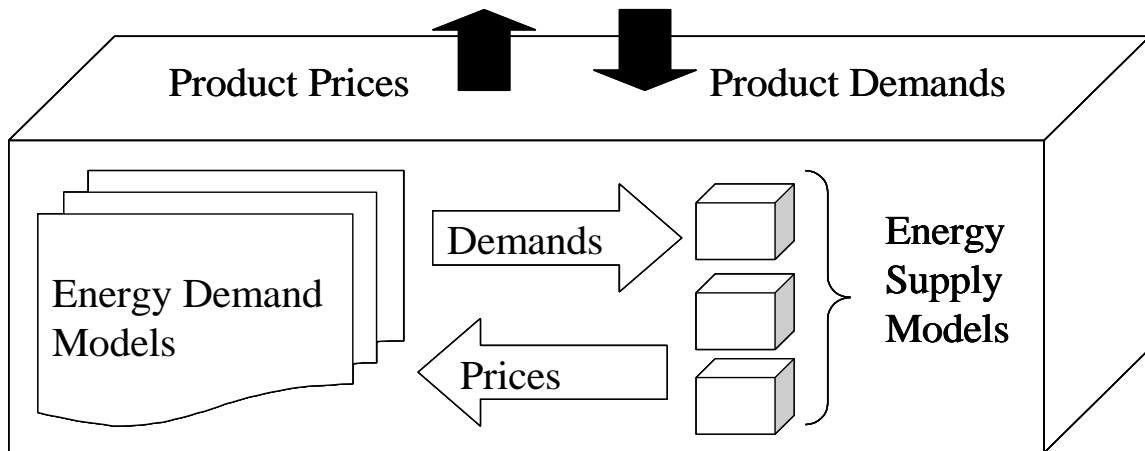


Figure 2.1: Basic structure of the CIMS model

The sequence of activities required to generate the final product of a sector or sub-sector is described in a process flow model, as illustrated in Figure 2.2 for the iron and steel industry. A CIMS flow model is geared towards representing technology evolution and energy consumption rather than economic criteria (as in a top-down model where units are typically in monetary terms). The flow model represents process stages in which energy consumption can be distinctly estimated; hierarchical processes are linked by engineering ratios. Technology competitions take place at the lowest level nodes in the hierarchy, what are referred to as “energy service nodes” in CIMS.

Often, major process technologies have requirements for steam generation or other auxiliary energy services in addition to their direct fuel consumption. Auxiliary systems that supply these services fall into four general categories: steam generation systems (boilers and cogenerators); lighting; heating, ventilating, and air conditioning (HVAC) systems; and electric motor systems (motors and the pumps, fans, compressors, and conveyers driven by them). Generic steam and electric motor systems are described by a separate auxiliary process flow diagram and can be called upon by any of the industrial subsectors. Because the energy demands for lighting and HVAC tend to be relatively small, these services are usually linked directly to the process flow model for a sector or sub-sector through ratios that estimate the amount of energy service required. Additional services that are specific to a particular sector or sub-sector are represented in the flow model, but by nodes that are outside of the main

flow diagram (e.g., the oxygen, reheating, slab roughing, and slab finishing nodes in Figure 2.2).

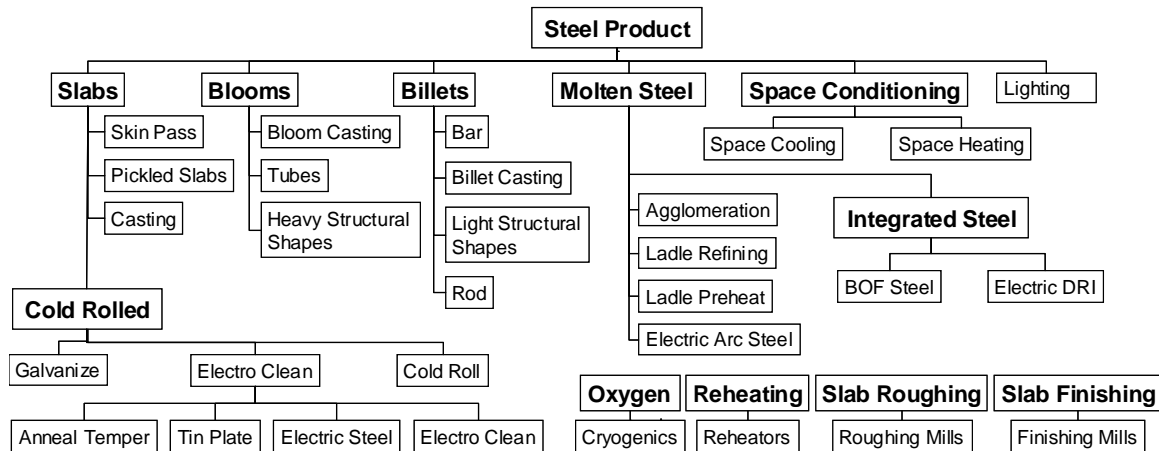


Figure 2.2: Process flow model for the iron and steel products industry

Source: Murphy et al., 2007b.

Representations of key technologies that are able to satisfy a given energy service demand are incorporated into the sub-models of CIMS, including new technologies that may not yet have achieved significant market penetration. For example, referring to Figure 2.2, there are several different configurations of basic oxygen furnace (BOF), which consume different fuel types, have different waste gas recovery rates, different energy efficiencies, and different costs. In terms of technical and financial characteristics, equipment is represented in CIMS in a way that is similar to a bottom-up model. CIMS contains data on the initial market shares of equipment stocks in a base year, which is currently 2000. Individual technologies are described by their capacity, capital cost, unit energy consumption (and output for energy conversion equipment), non-energy operating cost, emissions, average lifespan, and first year of market availability (for new technologies). Process emissions linked to production levels rather than technology type or fuel consumption are also represented.

The original source for data on industrial technologies in CIMS was the Industrial Sector Technology Use Model (ISTUM) developed by the US Department of Energy

(1983).²⁴ These data were significantly updated at Simon Fraser University in the mid to late 1990s to create the Intra-Sectoral Technology Use Model (also called ISTUM) (Nyboer, 1997). There are various additional sources for the current CIMS technology database, including public statistical agencies, energy utilities, literature reviews, industry associations, equipment manufacturers, surveys of sector experts, and a comprehensive review as part of Canada's National Climate Change Process in 1999–2000. Because there are few detailed surveys of the annual energy consumption of the individual capital stocks tracked by the model (especially smaller units), these must be estimated from surveys at different levels of technological detail and by calibrating the model's simulated energy consumption to real-world aggregate data.

2.2.2. *Simulation procedure and technology choice algorithm*

CIMS uses a capital stock vintaging framework, where technologies are retired according to an age-dependent function, and new technologies fill the gap between service demand and existing capital stock in each five-year period of the simulation. Such a formulation is important because long-lived capital stocks (e.g. power plants, pipelines, buildings, roads, industrial equipment) cause significant inertia in energy consumption and GHG emissions. CIMS allows retrofits of unretired stocks if warranted by changing economic conditions, but unlike some technologically detailed models does not allow the life of a technology to be extended through investments in upgrading or maintenance.

Technologies compete for a share of the new capital stock at energy service nodes in CIMS based on a comparison of their costs as illustrated in Eq. (2.1). Instead of basing its simulation of technology choice only on anticipated financial costs and a social discount rate (as in conventional bottom-up analysis), CIMS applies a costing definition that reflects revealed and stated consumer and business preferences with respect to specific technologies and time. The market share competition is also mediated by some technology-specific controls not shown in the equation, such as maximum market share limits in cases where a technology is constrained by physical,

²⁴ Jaccard and Roop (1990) describe the early evolution of ISTUM.

technical, or regulatory factors. CIMS includes a technology obsolescence function (not activated for the exercises reported here) that removes technologies from competition if their market share falls below a threshold value (Peters, 2006).

$$MS_j = \frac{\left[CC_j * \frac{r}{1 - (1+r)^{-n_j}} + MC_j + EC_j + i_j \right]^{-v}}{\sum_{k=1}^K \left\{ \left[CC_k * \frac{r}{1 - (1+r)^{-n_k}} + MC_k + EC_k + i_k \right]^{-v} \right\}} \quad (2.1)$$

MS_j is the market share of technology j , CC_j is its capital cost, n_j is its average lifespan, MC_j is its annual maintenance and operation cost, and EC_j is its annual energy cost, which depends on energy prices and energy consumption per unit of energy service output – producing a tonne of cold rolled steel, heating one square meter of a residence, transporting a person or tonne of cargo one kilometer, etc.

The CIMS market share algorithm takes into account three behavioural parameters, denoted r , i , and v in Eq. (2.1). The r parameter represents the weighted average time preference of decision-makers for a given energy service demand; it is the same for all technologies competing to provide that energy service, but can differ between energy services according to empirical evidence. The r parameter and the technology lifespan (n_j) are used to calculate a capital recovery factor that is multiplied by the up-front capital cost (CC_j) of the technology in order to annualize it. Annual maintenance, operation (MC_j), and energy costs (EC_j) can then be added to the annualized capital cost. In a conventional bottom-up model, with r set at a social discount rate, this summation would represent the life-cycle cost of technology j , and the technology with the lowest cost would capture 100% of the market. In CIMS, the r parameter for most energy service nodes is significantly higher than a social discount rate. For example, throughout most of the industrial sector, the discount rate for technology choice is set at 30% for non-discretionary technologies (major industrial processes) and at 50% for discretionary technologies (auxiliary technologies), retrofits, and any other technologies.

The i parameter represents all intangible costs and benefits that consumers and businesses perceive, additional to the simple financial cost values used in most bottom-

up analyses, for technology j as compared to all other technologies k at a given energy service node. For example, public transit and light-duty vehicles compete to provide the service of personal transportation. Empirical evidence suggests that some consumers impute an intangible, non-financial cost on public transportation to reflect their perceptions of its lower convenience, status, and comfort relative to the personal vehicle.

Finally, the v parameter represents heterogeneity in the market, whereby individual consumers and businesses experience different costs for what is the same technology because of location-specific factors, or because of differences in their preferences or perceptions. The v parameter determines the shape of the inverse power function that allocates market share to technology j . A high value of v means that the technology with the lowest cost captures almost the entire new market share. A low value means that the market shares of new equipment are distributed fairly evenly, even if their costs differ significantly. The v parameter is set at 10 for most technology choices; when v is set at this level a competition between technology A and technology B will result in technology B capturing 85% of the market if technology A is 15% more expensive.

To estimate values for the behavioural parameters of CIMS that reflect the real world, model users have surveyed the literature on empirical research into historical market choices. Studies of this nature provide information on the revealed preferences of consumers. The challenge with this approach is that new and emerging technologies can provide substantially different choices from the past. Also, historical situations may not have the variation in energy prices and other values that enable statistical estimation. Because of these constraints to revealed preference estimation, model users have also conducted many stated preference studies in which businesses and consumers are presented with hypothetical choices between well-known technologies and emerging technologies. The most common approach to provide consumer and business values is through discrete choice surveys and analysis (Axsen et al., 2009; Rivers and Jaccard, 2006).

2.2.3. Energy supply-demand and macroeconomic feedbacks

When a policy imposes a significant regulatory constraint or financial penalty on energy consumption or GHG emissions, we can expect the interaction of energy supply and demand, as well as the overall structure and performance of the economy to be affected. CIMS is an integrated, energy-economy equilibrium model that simulates the interaction of energy supply-demand and the macroeconomic performance of the economy, including trade effects. These linkages are taken into account by evaluating a policy simulation relative to a reference case simulation in which the driving variables and energy prices are set based on exogenous forecasts. The model operates by iteration of two sequential phases in each five-year period, with as many iterations as necessary to arrive at a new policy equilibrium (Bataille et al., 2006).

In the first phase, the policy is applied to the energy demand sectors of the economy. Goods and services producers in the industrial sub-models and consumers in the other energy demand models choose capital stocks based on the technology choice algorithm described above and the initial set of energy prices. Using the estimated technology market shares, the model then calculates demand for electricity, refined petroleum goods, and primary energy commodities. The energy supply models are responsible for meeting these demands. When endogenous pricing is switched on for a particular energy commodity, the cost of production relative to the reference case is estimated and if the change exceeds a threshold amount, the model is considered to be in disequilibrium and re-runs based on prices calculated from the new costs of production. The model iterates automatically until a new equilibrium set of energy prices and demands is reached. An energy trade component, based on Armington price elasticities²⁵ applied to changes in the cost of producing energy commodities, can be included to adjust trade in energy commodities in this first phase. For the simulations reported in the first two papers of my thesis, endogenous pricing is used for electricity generation and refined petroleum production only; energy trade is not activated.

²⁵ Armington elasticity refers to the elasticity of substitution between otherwise similar products that are differentiated based on the country in which they were produced.

Endogenous energy pricing is based on average costs in the version of CIMS that I applied in my thesis. This assumption is particularly relevant for electricity generation, which is being transformed by new technologies such as combined cycle natural gas turbines and wind turbines, whose cost characteristics are different from the existing capital stock (Bataille, 2005). The distinction between average and marginal cost pricing is even more important when simulating a policy constraint on GHG emissions. There is a large potential for reducing emissions from electricity supply by switching to renewables (hydroelectricity, geothermal, municipal waste, biomass, solar and wind) and by implementing carbon capture and storage with fossil fuel-based generation. Because these options tend to have higher costs than the existing capital stock, electricity price increases will be higher under marginal cost pricing than under average cost pricing. CIMS uses average cost pricing based on the assumption that electricity prices are still generally regulated to reflect average generation costs. The validity of this assumption will need to be re-examined in the future based on the extent of electricity market de-regulation (Bataille, 2005). The US Energy Information Administration's (EIA) Annual Energy Outlook for 2010 assumes that the majority of the electricity load (62%) is still priced based on its average cost (L. Aniti, EIA, personal communication, Sept. 13, 2010).

In the second phase of a CIMS simulation, once a new equilibrium set of energy prices and demands under policy has been reached, the model calculates the degree to which the costs of producing traded goods and services have changed. Assuming perfectly competitive markets, these changes translate directly into prices. For internationally traded goods, CIMS adjusts demand using Armington price elasticities that provide a long-run demand response that blends domestic and international demand for these goods. For example, an increase in the cost of production of pulp and paper, caused by paying a GHG tax, purchasing tradable permits for GHG emissions, or investing in GHG abatement, would lead to some reduction in output from that sector if the Armington price elasticity has a positive value. If demand for any good or service has shifted more than a threshold amount, the model is considered to be in disequilibrium and the energy supply and final demand phases are re-run using the last set of prices and demands. The model continues re-iterating until supply and demand for all goods and services come to a new equilibrium and repeats this convergence

procedure in each subsequent five-year period of a complete run, which is user defined and usually extends for 30–50 years.

Although it incorporates substantial feedbacks, the version of CIMS used in the analysis for this thesis does not equilibrate government budgets and the markets for employment and investment as most CGE models do. Also, its representation of the economy’s inputs and outputs is skewed toward energy supply activities, energy-intensive industries, and key energy end uses in the residential, commercial/institutional, and transportation sectors. CIMS has been used to estimate key ESUB values for simulating the technological response to price changes by consumers and firms in a CGE framework (Bataille et al., 2006; Peters et al., 2010).

2.2.4. Endogenous technological change

CIMS includes two functions for simulating endogenous change in the characteristics of technologies that are new to the market: a declining capital cost function and a declining intangible cost function. The declining capital cost function links a technology’s capital cost in future periods to its cumulative production, reflecting economies of scale and economies of learning. In the formulation, shown in Eq. (2.2), $CC(t)$ is the capital cost of a technology at time t , $N(t)$ is the cumulative production of that technology at time t , and PR is the progress ratio, defined as the percentage reduction in cost associated with a doubling of cumulative production.

$$CC(t) = CC(0) \left[\frac{N(t)}{N(0)} \right]^{\log_2(PR)} \quad (2.2)$$

The declining intangible cost function of CIMS links the intangible costs of a technology in a given period with its market share in the previous period, reflecting the ‘neighbor effect’ – improved availability of information and decreased perceptions of risk among consumers and firms as emerging technologies penetrate the market (Mau et al., 2008). Intangible costs for technologies decline according to Eq. (2.3), where $i(t)$ is the intangible cost of a technology at time t , MS_{t-1} is the market share of the technology at time $t - 1$, and A and k are estimated parameters reflecting the rate of decline of the intangible cost in response to increases in the market share of the technology.

$$i(t) = \frac{i(0)}{1 + Ae^{k*MS_{t-1}}} \quad (2.3)$$

2.3. Reference case for CIMS-US

The results reported in the first two papers of this thesis are generated relative to a reference case simulation that embodies a number of assumptions about the future. Some of these assumptions are directly incorporated into CIMS-US. Driving variables and energy prices are set based on exogenous forecasts from the EIA's Annual Energy Outlook for 2009(a) (AEO 2009). Other assumptions are revealed by running the model and identifying trends in the reference case output.

2.3.1. *Exogenous forecasts for driving variables and energy prices*

The driving variables for the energy supply and energy demand sub-models of CIMS-US, as well as energy prices, are set based on the AEO reference case for 2009. AEO 2009 reports historical data for 2006 and 2007, and projections from 2008 to 2030. An updated version of the reference case (EIA, 2009a) is used, which takes into account the energy-related stimulus provisions of the American Recovery and Reinvestment Act of 2009, and also reflects changes in the macroeconomic outlook since the published version. Generally speaking, the CIMS reference case does not explicitly include the numerous examples of federal and state legislation and regulations that affect energy consumption, and which are incorporated into AEO 2009. However, these would be implicit, to some extent at least, in historical data used to calibrate CIMS, as well as the forecasts of energy prices and driving variables informed by the updated AEO 2009. AEO 2009 extends only to the year 2030, whereas some of the CIMS simulations reported in my thesis are to 2050. The forecasts of the driving variables are extended to 2050 using growth rates prior to 2030; whereas energy prices are held at 2030 levels for the duration of the CIMS reference case simulation.

The driving variables used in CIMS-US incorporate basic assumptions about future economic growth. AEO 2009 forecasts slow economic growth in the short-term due to the 2008 downturn in financial markets. As shown in Figure 2.3, real gross

domestic product (GDP) falls between 2008 and 2009, but begins to climb again in 2010. The average annual growth rate of real GDP is 2.4% between 2006 and 2030, and 2.7% between 2009 and 2030. For comparison, in the AEO 2007 reference case (EIA, 2007), growth is projected to average 2.9% per year. Industrial output is forecast to grow at a slower pace than the economy as a whole (1.0% average annual growth in value of shipments). This is consistent with the trend in recent decades, as imports of industrial goods have increased. The historical trend is exacerbated by slower projected growth in exports and investment as a result of the economic downturn. The growth rate for the energy-intensive manufacturing sectors is even lower than for industry as a whole (0.7% average annual growth), due to higher energy prices (see discussion below) and more foreign competition than in the past (EIA, 2009a; 2009b).

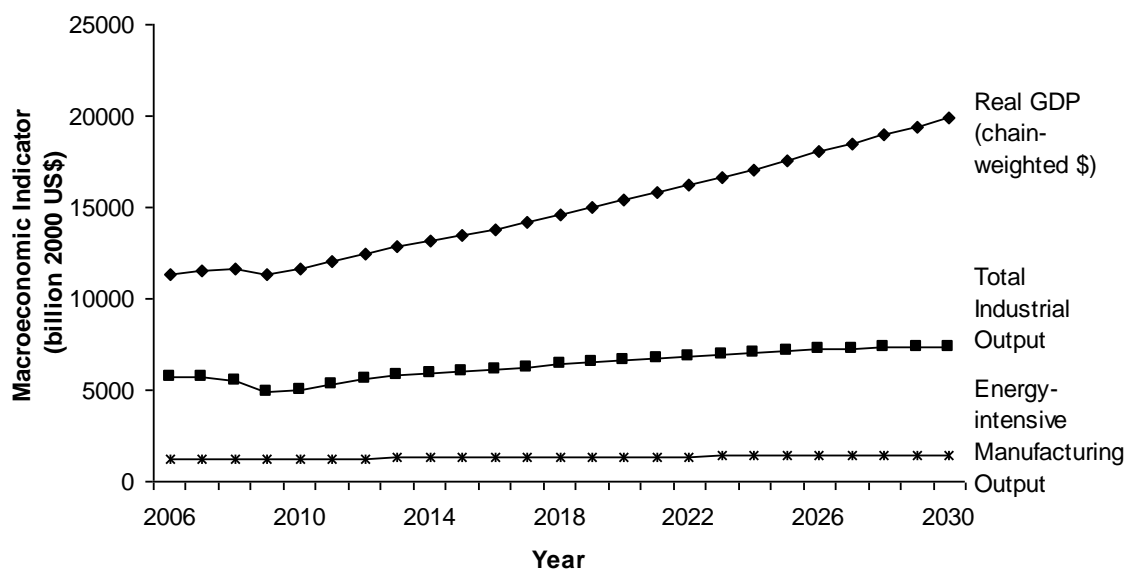


Figure 2.3: Economic growth forecasts from the AEO 2009 update

Note: Industrial output is measured in value of shipments. Source: EIA, 2009a (Table 20: Macroeconomic Indicators).

The recent economic crisis placed downward pressure on oil prices; however, AEO 2009 hypothesizes that this is a short-term trend. Real oil prices are projected to rise over the long-term, leading to higher gasoline prices for consumers (Figure 2.4). The factors behind this trend include an increase in the forecasted demand for energy,

especially in countries such as India and China, as well as the assumption that many countries will take steps to limit access to their oil resources (EIA, 2009b).

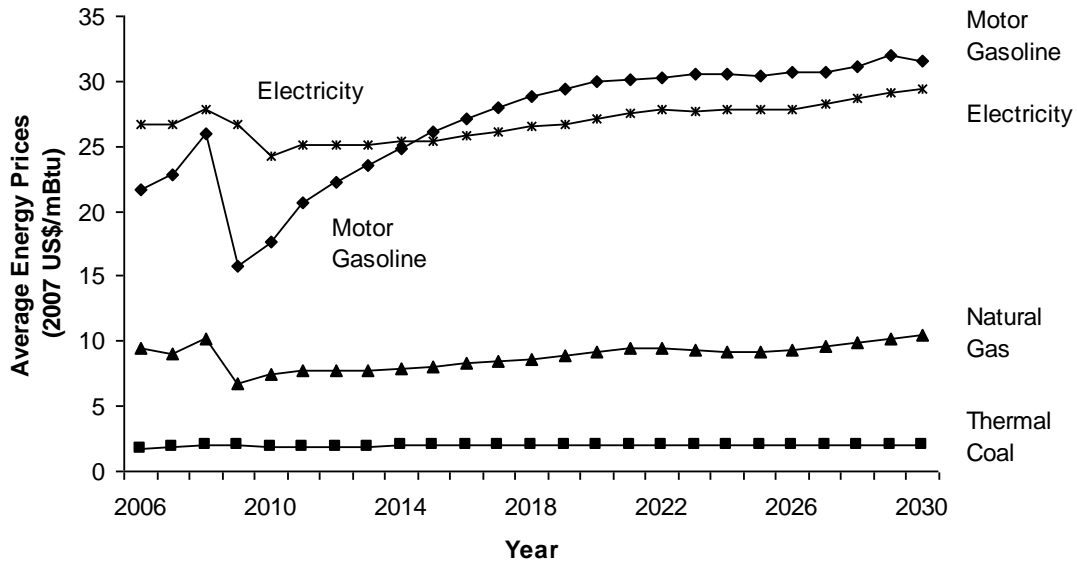


Figure 2.4: Energy price forecasts from the AEO 2009 update

Notes: Energy prices are expressed as the weighted average price to all users, derived from prices in each sector and the corresponding sectoral consumption. For motor gasoline, price is the sales weighted-average price for all grades; it includes Federal, State, and local taxes. Source: EIA, 2009a (Table 3: Energy Prices by Sector and Source).

2.3.2. Trends identified in the reference case output

Three important (and overlapping) trends revealed by running the CIMS-US model and examining the reference case output are: 1) declining consumption of refined petroleum products despite economic growth, 2) a shift in the electricity generation mix from coal and nuclear to natural gas and renewables, and 3) significant reductions in end-use energy intensity.²⁶ Improvements in energy efficiency result in energy consumption growing at a slower rate than the economy overall to 2030, while fuel switching and the shift in the electricity generation mix result in GHG emissions growing at a slower rate than energy consumption. Trends similar to those described above are

²⁶ Energy intensity is calculated as energy use divided by output.

also apparent in AEO 2009, which extends to 2030. After 2030, energy consumption and GHG emissions begin to grow at a faster rate in the CIMS-US projection.

In the CIMS-US reference case simulation, consumption of refined petroleum products decreases by 4% between 2005 and 2050, despite economic growth. This decline is at least in part due to the endogenous response of the model to the rebounding gasoline price discussed above. There is a 38% reduction in energy consumption per mile traveled for light-duty vehicles over the forecast period as a result of efficiency gains within vehicle categories (as opposed to switching from light trucks to cars, for example). Conventional gasoline motors become more efficient and there is a dramatic increase in sales of alternative-fuel and advanced-technology light-duty vehicles. Vehicles with hybrid and plug-in hybrid electric motors capture 60% of new vehicle sales by 2050. Light-duty vehicles consume more ethanol in the reference case projection than they do today, and airplanes, buses, trains, and freight trucks use biodiesel.

The electricity generation mix shifts away from coal and nuclear towards natural gas and renewables in the reference case forecast. Natural gas-fired generation accounts for 14% of domestic electricity production in 2005, but captures 56% of the increase in production between 2005 and 2050. Coal-fired generation, which dominates the supply mix in 2005 at 56%, accounts for only 23% of the increase. Generation from renewable sources (wind in particular) accounts for 8% of total production in 2005, and 20% of new production to 2050. Nuclear generation remains fairly constant throughout the simulation, and therefore loses market share in the face of increasing electricity production overall.

End-use energy intensity is reduced considerably over the forecast period in the reference case. I noted a 38% reduction in the intensity of light-duty vehicle transportation above, and substantial improvements are also apparent in residential buildings and manufacturing industry. For residential buildings, energy consumption per square foot decreases 34% between 2005 and 2050. For manufacturing industry, energy intensity is estimated as energy consumption per dollar of output produced, and the decline is 23%. Energy efficiency improvements occur naturally over time as technology stocks turn over and technological advances enable more efficient options to

become commercially available. In the analysis for this thesis, high-efficiency technologies are more likely to be selected in the reference case due to real energy price increases embodied in the updated AEO 2009 forecast.

As a result of energy efficiency improvements such as those described above, total primary energy consumption is projected to increase by only 0.4% per year on average between 2005 and 2030 in the CIMS-US reference case. This is much slower than the 2.4% average annual growth rate of real GDP from the updated AEO 2009. Fuel switching and the shift in the electricity generation mix reduce growth in energy-related GHG emissions relative to growth in energy consumption; such that GHG emissions do not increase appreciably in the forecast to 2030 (average annual growth is less than 0.1%). Total primary energy consumption and GHG emissions from the reference case simulation are shown in Figure 2.5.

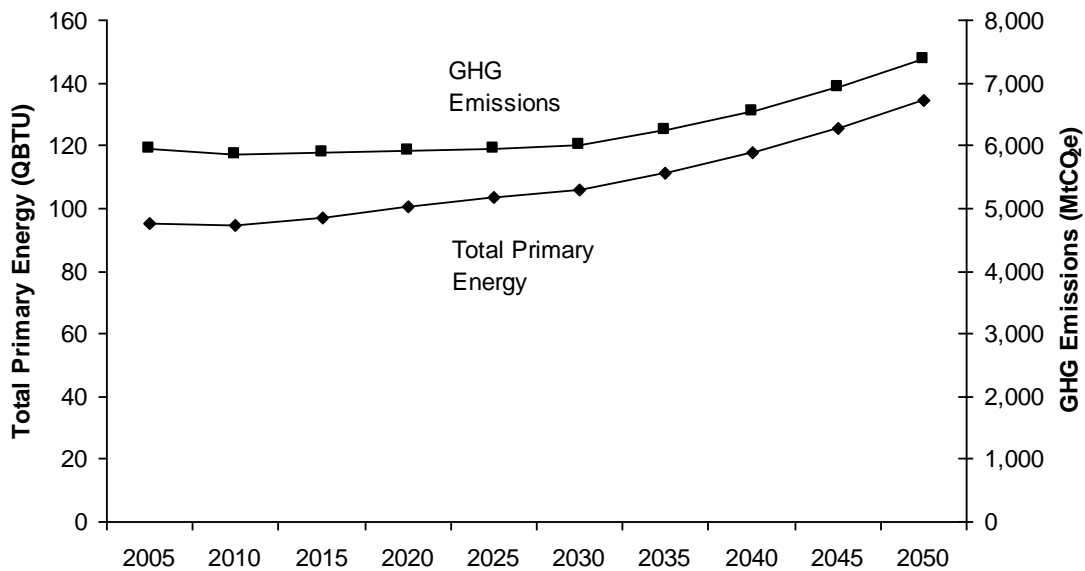


Figure 2.5: CIMS reference case forecasts of energy consumption and GHG emissions for the US economy

From 2030 to 2050, the average annual rates of growth for energy consumption (1.2%) and GHG emissions (1.0%) are higher than prior to 2030 according to the CIMS reference case forecast. This may be because the technological potential of the model is finite, whereas the driving variables are assumed to grow exponentially. CIMS represents energy efficiency and GHG intensity improvements in terms of the real or

anticipated technology options that are available for meeting energy service demands. Over a simulation period that extends as far as 2050 (or beyond) it is not always possible to anticipate future new technology options or process improvements, and technological options can therefore become exhausted before the end of the simulation.²⁷ This is a potential area for future work to improve the model, perhaps through an endogenous representation of invention and innovation (commercialization), including the impact of research and development funding on these processes.²⁸

²⁷ However, there is also the potential for technological change to evolve in the other direction, as a result of the development and marketing of new energy products and services that did not exist before. Thirty years ago, analysts could not have predicted the impact of the personal computer and the sport utility vehicle on energy consumption and GHG emissions today.

²⁸ Jaffe et al. (1999) discuss in detail the steps of technology evolution (invention, innovation, diffusion and product use) in the context of energy efficiency and climate change policy.

3. Modeling efficiency standards and a carbon tax: Simulations for the U.S. using a hybrid approach²⁹

3.1. Abstract

Analysts using a bottom-up approach have argued that a large potential exists for improving energy efficiency profitably or at a low cost, while top-down modelers tend to find that it is more expensive to meet energy conservation and greenhouse gas (GHG) reduction goals. Hybrid energy-economy models have been developed that combine characteristics of these divergent approaches in order to help resolve disputes about costs, and test a range of policy approaches. Ideally, such models are technologically explicit, take into account the behavior of businesses and consumers, and incorporate macroeconomic feedbacks. In this study, we use a hybrid model to simulate the impact of end-use energy efficiency standards and an economy-wide carbon tax on GHG emissions and energy consumption in the US to the year 2050. Our results indicate that policies must target abatement opportunities beyond end-use energy efficiency in order to achieve deep GHG emissions reductions in a cost-effective manner.

3.2. Introduction

For more than three decades, it has been argued that opportunities for profitable energy efficiency exist throughout the economy. In the wake of the first oil price shock, Amory Lovins (1977) published *Soft Energy Paths* in which he proposes energy efficiency as the first step in any energy policy directed at environmental protection and

²⁹ This paper was published as: Murphy, R. and Jaccard, M., 2011. Modeling efficiency standards and a carbon tax: simulations for the U.S. using a hybrid approach. *The Energy Journal*, 32(Strategies for Mitigating Climate Change Through Energy Efficiency: A Multi-Model Perspective):43-60. <http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol32-S11-4>

energy security. He suggests that a 75% reduction in energy use for a given level of services is profitable over about a 30 year timeframe via the full adoption of commercially available technologies (Lovins et al., 1981). In the 1980s, utilities and governments developed ambitious programs to foster energy efficiency, especially but not only in the electricity sector. Interest in energy efficiency declined in the 1990s, but re-emerged over the last decade as this is an appealing option for policy makers to reduce energy-related greenhouse gas (GHG) emissions. Using an approach very similar to that of Lovins, the McKinsey consulting firm has produced estimates of energy efficiency profitability for the US and other countries, estimates which imply that substantial reductions of GHG emissions could be realized at little or no cost (for the US, see McKinsey, 2007; 2009).

The approach pioneered by Lovins and adopted more recently by McKinsey is often referred to as bottom-up analysis. In this type of analysis, technologies that provide the same energy service are generally assumed to be perfect substitutes except for differences in their anticipated financial costs and emissions. When their financial costs in different time periods are converted into present value using a social discount rate, many emerging technologies available for abating emissions appear to be profitable or just slightly more expensive relative to conventional technologies. This is especially the case for energy-efficient substitutes for more conventional technologies, because the higher capital cost of an efficient technology can be offset by lower energy costs over its lifetime. Many economists criticize the bottom-up approach, however, for its assumption that a single, anticipated estimate of financial cost indicates the full social cost of technological change (Sutherland, 1991; Jaffe and Stavins, 1994; Jaffe et al., 1999). New technologies present greater risks, as do the longer paybacks associated with investments such as energy efficiency. Some low-cost, low-emission technologies are not perfect substitutes in the eyes of the businesses or consumers expected to adopt them. To the extent that they ignore some of these costs, bottom-up models may inadvertently suggest the wrong technological and policy options for policy makers.

The fact that some elements of the full social cost are not taken into account by bottom-up models helps explain why investments in energy efficiency that appear profitable according to this approach are not necessarily realized. Proponents of the bottom-up methodology tend to attribute this “energy paradox” to a variety of

institutional, information, and financing barriers, which they argue should be addressed through government intervention. Mainstream economists, on the other hand, recommend government intervention only to address a smaller subset of market failures that reduce economic efficiency. Market failure explanations for the energy paradox generally relate to a lack of information on energy-efficient and low-emission technologies due to the public good and positive externality qualities of information. Where such failures are identified, government intervention may be appropriate, but only if the benefits outweigh the costs to society, including the costs of policy implementation (Jaffe and Stavins, 1994; Jaffe et al., 1999).

The contrasting top-down approach, usually applied by economists, estimates aggregate relationships between the relative costs and market shares of energy and other inputs to the economy, and links these to sectoral and total economic output in a broader equilibrium framework. At their most basic level, conventional top-down models represent the economy through a series of simultaneous equations linking economic outputs and inputs (especially energy), whose parameters are estimated econometrically from time-series data. Models that link all of the major macroeconomic feedbacks in a full equilibrium framework are referred to as computable general equilibrium (CGE) models. Top-down models are used to simulate the economy's response to a financial signal (an emissions tax, an emissions permit price) that increases the relative cost of emissions-intensive technologies and energy forms. The magnitude of the financial signal necessary to achieve a given emissions reduction target indicates its implicit cost. Because they incorporate to some extent the transitional costs and risks of technological change, top-down cost estimates for achieving GHG reduction targets are almost always higher than bottom-up cost estimates.

A considerable challenge for top-down models is the estimation of statistically significant parameters from real-world experience. Often there is insufficient variability in the historical record for confident parameter estimation, and therefore most CGE modelers set the key elasticity of substitution (ESUB) parameters in their models judgmentally (Loschel, 2002). Furthermore, if the critical top-down parameters for portraying technological change – ESUB and the autonomous energy efficiency index (AEEI) – are estimated from aggregate, historical data, there is no guarantee that these parameter values will remain valid into a future under substantially different policies,

different energy prices, and with different technological options for environmental improvement (Grubb et al., 2002; DeCanio, 2003; Laitner et al., 2003). For example, the parameters of a top-down model may incorporate market failures that could be addressed in future to the overall benefit of society. As conditions change, the estimated cost of GHG abatement may decrease, but conventional top-down models are unable to help policy makers assess this dynamic.

Another difficulty with the top-down approach is that policy makers often prefer, for political acceptability, policies that focus on individual technologies in the form of technology- and building-specific tax credits, subsidies, penalties, regulations, and information programs. This is especially the case where emissions charges would need to be high in order to overcome significant costs of environmental improvement. Because conventional top-down models represent technological change as an abstract, aggregate phenomenon, this approach helps policy makers assess only economy-wide policy instruments such as taxes and tradable permits. A model would be more useful if it could assess the combined effect of these economy-wide, price-based policies along with technology-focused policies.

The past decade has seen significant advances in the development of hybrid modeling approaches that can help resolve disputes about the cost of improving energy efficiency and reducing GHG emissions, and are also capable of performing a more useful range of policy simulations. Ideally, such models combine critical elements of the conventional bottom-up and top-down approaches in order to satisfy at least three criteria: explicit representation of the potential for technological change, microeconomic realism in accounting for how businesses and firms will decide among future technology options as policies and other conditions evolve, and macroeconomic feedbacks in reflecting how changes in production costs and preferences will change the structure of the economy and the growth rate of total output.

In this paper, we use a hybrid energy-economy model to simulate two policy options for reducing GHG emissions and energy consumption in the US to the year 2050: energy efficiency standards in the buildings and personal transportation sectors, and an economy-wide carbon price with escalating stringency over time. The former would traditionally have been associated with bottom-up modeling, while the latter would

traditionally have been associated with top-down modeling. Using a hybrid modeling framework, we are able to simulate both policies and compare their impacts on GHG emissions and energy use. Our results shed light on the cost of improving energy efficiency and its appropriate role in mitigating GHG emissions relative to other responses when parameters estimated from behavioral research are taken into account. We also use the hybrid methodological approach to test simultaneous implementation of the efficiency standards and the carbon tax, considering whether the policies might cause the same actions or complement each other by causing different actions.

Our study is one of a number presented in this special issue by modeling teams who participated in EMF-25, a project organized by the Energy Modeling Forum to investigate the potential for energy efficiency policies to mitigate climate change and reduce energy demand. Key assumptions about reference case economic activity and energy prices, as well as the design of the policies tested were established by the EMF and standardized across the different models.

We provide a description of the hybrid model used in this study and how some of its key parameters are estimated in the following section. In section 3.4, we discuss our methodology for representing the policy options. The presentation and analysis of our simulation results begins in section 3.5, which compares the effects of the efficiency standards and the carbon tax on GHG emissions and energy consumption in the buildings and personal transportation sectors. In section 3.6, we disaggregate the estimated emissions reductions by action to improve our understanding of the results from section 3.5. We also include a brief discussion of the impact of reduced equipment costs (subsidies) in this section. The effect on GHG emissions of combining the standards with the carbon tax is examined in section 3.7. Section 3.8 considers GHG emissions and energy consumption not just in the buildings and personal transportation sectors, but across the entire economy, and section 3.9 provides some insights on the cost-effectiveness of the efficiency standards. We conclude in section 3.10 with a summary of the insights gained from this analysis.

3.3. The CIMS hybrid energy-economy model

The hybrid model used for this study, called CIMS, is an integrated, energy-economy equilibrium model that simulates the interaction of energy supply-demand and the macroeconomic performance of key sectors of the economy, including trade effects. It is technologically explicit and incorporates microeconomic behavior in portraying the selection of technologies by businesses and consumers. Although it incorporates substantial feedbacks, the version of CIMS used in this analysis does not equilibrate government budgets and the markets for employment and investment as most CGE models do. Also, its representation of the economy's inputs and outputs is skewed toward energy supply activities, energy-intensive industries, and key energy end uses in the residential, commercial/institutional, and transportation sectors.

CIMS simulates the evolution of capital stocks over time through retirements, retrofits, and new purchases, in which consumers and businesses make sequential acquisitions with limited foresight. The model calculates energy costs (and emissions) at each energy service demand node in the economy, such as heated commercial floor space or person-kilometers traveled. In each time period, capital stocks are retired according to an age-dependent function (although retrofit of unretired stocks is possible if warranted by changing economic conditions), and demand for new stocks grows or declines depending on the initial exogenous forecast of economic output, and then the subsequent interplay of energy supply-demand with the macroeconomic module. A model simulation iterates between energy supply-demand and the macroeconomic module until energy price changes fall below a threshold value, and repeats this convergence procedure in each subsequent five-year period of a complete run, which usually extends for 30-50 years but could continue indefinitely.

Technologies compete for market share at energy service nodes based on a comparison of their life-cycle costs (LCCs) mediated by some technology-specific controls, such as a maximum market share limit in the cases where a technology is constrained by physical, technical, or regulatory means from capturing all of a market. Instead of basing its simulation of technology choices only on anticipated financial costs and a social discount rate, CIMS applies a formula for LCC that allows for divergence from that of conventional bottom-up analysis by including behavioral parameters that

reflect revealed and stated consumer and business preferences with respect to specific technologies and time. Eq. (3.1) presents how CIMS simulates technology market shares for new capital stocks

$$MS_j = \frac{\left[CC_j * \frac{r}{1 - (1+r)^{-n_j}} + MC_j + EC_j + i_j \right]^{-v}}{\sum_{k=1}^K \left\{ \left[CC_k * \frac{r}{1 - (1+r)^{-n_k}} + MC_k + EC_k + i_k \right]^{-v} \right\}} \quad (3.1)$$

where MS_j is the market share of technology j , CC_j is its capital cost, MC_j is its maintenance and operation cost, n_j is the average lifespan of the technology, and EC_j is its energy cost, which depends on energy prices and energy consumption per unit of energy service output – producing a tonne of steel, heating one square meter of a residence, transporting a person or tonne of cargo one kilometer. Equipment manufacturers, trade journals, marketers, government ministries, and international agencies provide information on the capital costs and operating characteristics of many energy-using and energy-producing technologies.

The r parameter represents the weighted average time preference of decision makers for a given energy service demand; it is the same for all technologies competing to provide a given energy service, but can differ between different energy services according to empirical evidence. The i parameter represents all intangible costs and benefits that consumers and businesses perceive, additional to the simple financial cost values used in most bottom-up analyses, for technology j as compared to all other technologies k at a given energy service node. For example, public transit and light-duty vehicles compete to provide the service of personal transportation. Empirical evidence suggests that some consumers implicitly put an intangible, non-financial cost on public transportation to reflect their perceptions of its lower convenience, status, and comfort relative to the personal vehicle. Theoretically, the r parameter represents risk relating to

long payback periods, while the i parameter represents risk relating to the newness of a technology.³⁰

The v parameter represents the heterogeneity in the market, whereby individual consumers and businesses experience different LCCs, perhaps as a result of divergent preferences, perhaps as a result of differences in real financial costs. It determines the shape of the inverse power function that allocates market share to technology j . A high value for v means that the technology with the lowest LCC captures almost the entire new market share. A low value for v means that the market shares of new equipment are distributed fairly evenly, even if their LCCs differ significantly.

In previous applications of CIMS, the three key behavioral parameters in Eq. (3.1) (i , r , and v) were estimated through a combination of literature review, judgment, and meta-analysis. However, the available literature usually provides only separate estimates for the three parameters, often using the discount rate to account for several factors, such as time preference and risk aversion to new technologies. This creates problems for predicting the costs and effects of policies that attempt to influence only one of these factors. More recent efforts to estimate these three behavioral parameters involve the use of discrete choice methods for estimating models whose parameters can be transposed into the i , r , and v parameters in CIMS (Jaccard, 2009). The data for a discrete choice model can be acquired from the revealed preferences in actual market transactions or from the stated preferences in a discrete choice survey.³¹

CIMS includes two functions for simulating endogenous change in the characteristics of the new and emerging technologies that are represented in the model: a declining capital cost function and a declining intangible cost function. The declining capital cost function links a technology's cost in future periods to its cumulative

³⁰ Whether it is actually possible to distinguish between these two aspects of risk depends on the method of parameter estimation (see discussion below).

³¹ The behavioral parameters of CIMS may capture some legitimate market failures. This is more likely in cases where the parameter values are estimated using revealed preference data, because stated preference surveys often provide information to participants – the lack of which, in the real world, could result in a market failure. Where a model user believes that market failures exist, they may adjust the behavioral parameters in CIMS accordingly when conducting simulations.

production, reflecting economies of scale and economies of learning. The declining intangible cost function links the intangible costs of a technology in a given period with its market share in the previous period, reflecting the ‘neighbor effect’ – improved availability of information and decreased perceptions of risk as new technologies penetrate the market.

3.4. Modeling the carbon tax and efficiency standards

For this study, the US version of CIMS was standardized to the Energy Information Administration’s Annual Energy Outlook (AEO) for 2009(a). We used the updated version of the AEO 2009 reference case, which takes into account the energy-related stimulus provisions of the American Recovery and Reinvestment Act (ARRA) of 2009, and also reflects changes in the macroeconomic outlook since the published version. We standardized to the updated AEO 2009 by revising the exogenous forecasts of energy prices and sectoral and sub-sectoral driving variables in CIMS (these can be subsequently adjusted, however, by energy supply-demand and macroeconomic feedbacks during a model simulation). We did not explicitly include in our reference case the numerous examples of federal and state legislation and regulations that affect energy consumption, and which are incorporated into AEO 2009. However, these would be implicit, to some extent at least, in historical data used to calibrate CIMS, as well as the forecasts of energy prices and driving variables informed by AEO 2009.

3.4.1. *Economy-wide carbon tax*

The carbon tax rates that were applied in this analysis are shown in Table 3.1. The tax is established in 2010 at \$30/tonne CO₂ equivalent (CO₂e), and grows by 5% per year to the end of the simulation period in 2050. The revenue recycling function in CIMS returns carbon tax revenues collected from each sector of the economy to the sector on a lump sum basis, rather than returning all of the revenues to households.

Table 3.1: *Economy-wide carbon tax rates (\$2007 US/tonne CO₂e)*

2010	2015	2020	2025	2030	2035	2040	2045	2050
30	38	49	62	80	102	130	165	211

3.4.2. End-use energy efficiency standards

We based our efficiency standards on the EMF-25 policy design documentation (EMF, 2010), which includes energy efficiency standards on end-use equipment in the residential and commercial sectors, building codes in these sectors, and light-duty vehicle fuel economy standards. All of the standards were implemented by 2020 and remain the same after that. In some cases, we chose not to incorporate the level of technological detail that would have been required to model particular standards on residential and commercial products as described by the EMF, because additional detail comes at a price in terms of increasing model complexity. To simulate the building codes proposed by the EMF, we identified the shell technologies in the residential and commercial sector models of the current version of CIMS that come closest to achieving 30% and 50% reductions in heating, ventilation, and air conditioning requirements (HVAC) relative to the existing standards in those models. The shell technologies with a 30% reduction were designated as the new standard from 2011 on, and the technologies with a 50% reduction were the standard from 2016 on. The light-duty vehicle fuel economy standards described by the EMF were approximated by standards on vehicle size and engine efficiency in the CIMS personal transportation model.³²

3.5. Impacts on the targeted end-use sectors

The energy efficiency standards described in the previous sub-section are forecast to reduce annual GHG emissions from the buildings and personal transportation sectors by 25% from reference case levels in 2030 and by 30% in 2050 (Figure 3.1). Emissions are also reduced from 2005 levels, with the maximum percentage reduction occurring in 2030 at about 30%. The GHG emissions trajectory for the carbon tax is initially much higher than the trajectory for the standards, with only about a 10% reduction from the reference case in 2030. From this point on, however, emissions under the carbon tax stabilize and then begin to decline, while emissions under the efficiency standards begin to increase, and by 2050 emissions are slightly lower under

³² Our approximation resulted in somewhat more aggressive vehicle standards than those specified by the EMF.

the carbon tax. The simulation results suggest that the efficiency standards would need to increase in stringency over time – as the carbon tax does – in order to maintain greater emissions reductions.³³

The GHG emissions trajectories described above (the solid lines in Figure 3.1) represent emissions at the point of end-use. Adjusting these direct emissions for the efficiency standards and the carbon tax policies to account for the increase or decrease in emissions associated with changes in the output of the electricity generation sector (for each policy simulation relative to the reference case) produces the dashed lines shown in Figure 3.1. The efficiency standards reduce electricity consumption from the buildings and personal transportation sectors, resulting in indirect emissions abatement due to reduced output from the electricity sector. Conversely, under the carbon tax, much of the emissions reductions at the point of end-use are due to fuel switching from fossil fuels to electricity. Accounting for the increase in emissions from greater electricity generation partially offsets direct GHG abatement in the case of the carbon tax (the adjustment would have been larger if the emissions intensity of electricity generation were not significantly reduced over time in this simulation).

The efficiency standards reduce annual energy consumption by about 20% from the reference case in each simulation year from 2030 on, and it is 2045 before energy consumption surpasses 2005 levels. The carbon tax has less of an effect, reducing energy consumption by only 5% from the reference case in 2030, rising to about 10% by 2050. The performance of the carbon tax relative to the standards is much lower in terms of delivered energy consumption than for GHG emissions because fuel switching under the carbon tax can reduce emissions without reducing energy consumption.

³³ While we expect that increasingly stringent energy efficiency standards would reduce energy consumption and GHG emissions further, greater demands for energy services could also result from the efficiency improvements, leading to rebound effects on energy consumption. CIMS accounts for some but not all of the potential rebound effects in the economy.

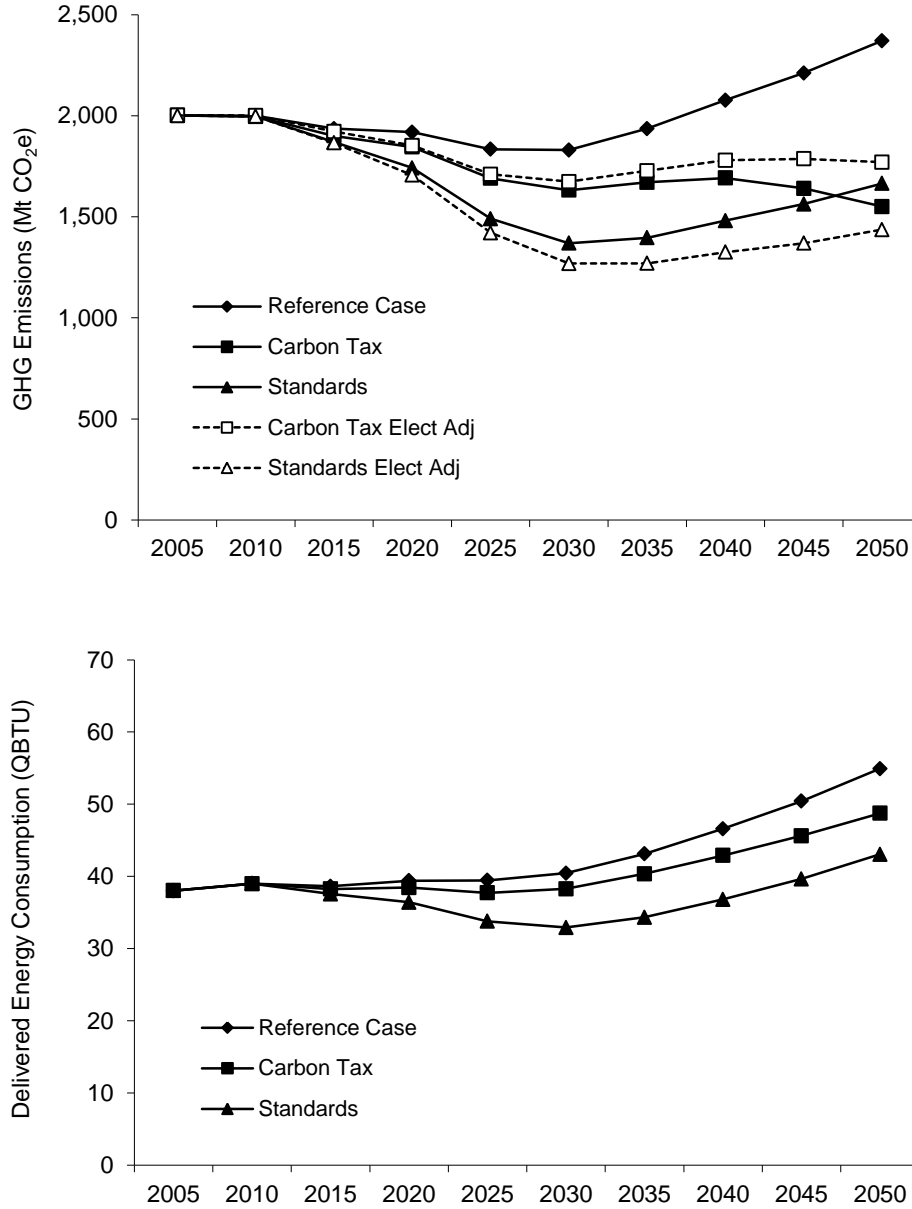


Figure 3.1: *Direct GHG emissions and energy consumption summed over the residential, commercial, and personal transportation sectors*

3.6. Emissions reductions by action

In order to explain the relative effect on direct GHG emissions of the efficiency standards and the carbon tax, we disaggregated the estimated emissions reductions

described in the previous section across a number of different actions. This analysis also helps to illustrate the role of energy efficiency relative to other responses under the carbon tax. Figure 3.2 shows the results for key actions in the year 2030, when the standards reduce more than twice as many emissions as the carbon tax from the targeted end-use sectors. Under the carbon tax, emissions reductions from energy efficiency are similar in magnitude to emissions reductions from fuel switching based on the actions included in the figure.

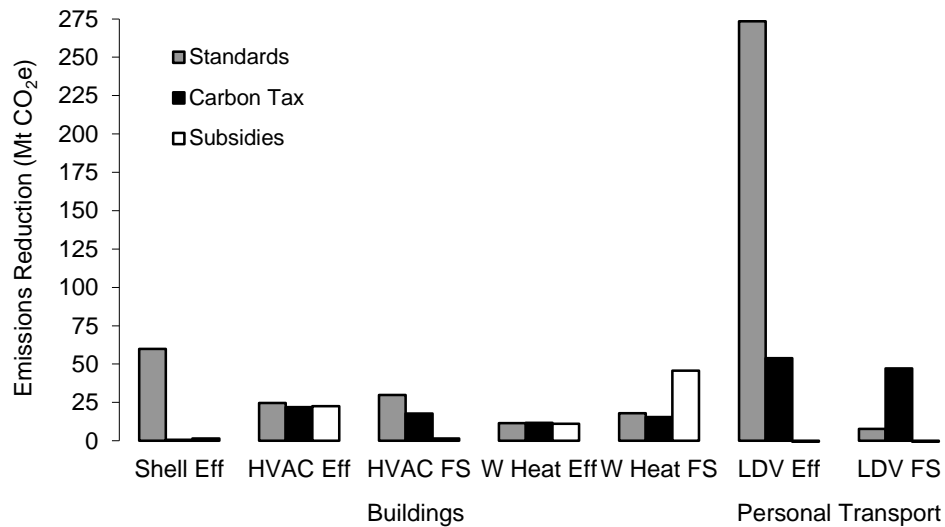


Figure 3.2: Direct GHG emissions reductions by action under the carbon tax, standards, and subsidies policies in 2030

Note: Shell Eff = Building Shell Efficiency; HVAC Eff = Heating, Ventilation, and Air Conditioning Efficiency; HVAC FS = HVAC Fuel Switch; W Heat Eff = Water Heating Efficiency; W Heat FS = Water Heating Fuel Switch; LDV Eff = Light-Duty Vehicle Efficiency; LDV FS = LDV Fuel Switch.

In our simulations, improved light-duty vehicle (LDV) fuel efficiency under the standards has a much larger impact than any other action (although LDV efficiency improvements do occur under the carbon tax as well). The reduction in emissions from fuel switching in LDVs, on the other hand, is much larger under the carbon tax. Based on our behavioral parameter estimates, when larger vehicles and lower efficiency engines (which may be higher performance) are no longer available under the standards, consumers continue to prefer vehicles that use conventional fuels over

alternatives with lower emissions. A price on carbon is necessary to make fuel switching attractive in this case.

A significant reduction in emissions is achieved through improvements in building shell technology under the standards, but this action is not taken up under the carbon tax. Building shell efficiency improvements are costly relative to other methods of reducing emissions when evaluated using a discount rate that reflects revealed and stated preferences. Also, in our modeling, decisions regarding heating, ventilation, and air conditioning (HVAC) technologies occur prior to decisions regarding shell technologies. Because emissions reductions occur due to efficiency improvements and fuel switching in HVAC equipment under the carbon tax (see discussion below), the incentive for building shell improvements is not as strong.

Under both the standards and the carbon tax policies, moderate emissions reductions are associated with improvements in energy efficiency for HVAC and water heating services, as well as fuel switching for these services. Fuel switching to electricity occurs under the standards for HVAC because the efficiency standards are applied to space heating that uses fossil fuels, but not to electric space heating. There is also fuel switching from oil to natural gas for space heating. For water heating, electric heat pumps gain market share from natural gas applications, resulting in emissions reductions through both improved energy efficiency and fuel switching.

According to our simulations, by 2050 the carbon tax surpasses the standards in terms of reducing direct GHG emissions from buildings and personal transportation. The most important action contributing to this shift is a dramatic increase in fuel switching for LDVs, as the escalating carbon price stimulates demand for plug-in hybrid and ethanol vehicles.³⁴ Other changes that reduce the gap between the two policies include increases in emissions reductions from LDV efficiency, HVAC efficiency, and HVAC fuel switching under the carbon tax relative to the standards.

³⁴ In our simulation of the carbon tax, plug-in hybrid and ethanol vehicles are key to achieving significant reductions in GHG emissions. While there is great uncertainty about future technological change, especially as the time horizon extends to 2050, these technologies can be considered as a proxy for a wide array of low- and zero-emission vehicles including full electric and hydrogen fuel cell vehicles.

We also simulated reduced equipment costs (subsidies) corresponding to the energy efficiency standards for the residential and commercial sectors, as described in the EMF-25 policy design documentation (subsidies were not implemented in the transportation sector). In our forecasts, the subsidies are found to have less of an impact relative to the standards on direct GHG emissions and energy consumption in the buildings sectors. As illustrated in Figure 3.2, the overall discrepancy in terms of GHG emissions is in large part due to the fact that there are virtually no emissions reductions from building shell efficiency improvements under the subsidies. The same factors that limit the penetration of this action under the carbon tax are at play here.

3.7. Combined effect of the policies

When the efficiency standards and the carbon tax are run simultaneously, as shown in Figure 3.3, annual direct emissions from the buildings and personal transportation sectors are reduced by about 35% from reference case levels in 2030 and by about 55% in 2050. These emissions reductions are substantially greater than those achieved under the efficiency standards, which in turn reduce emissions by more than the carbon tax (in all years except 2050). To assist in analyzing these results, we constructed an additive emissions trajectory by summing the emissions reductions from when each policy was simulated by itself. The GHG emissions trajectory for the run where the policies are implemented simultaneously is closer to this additive trajectory than to the trajectory for the efficiency standards, suggesting that the standards and the carbon tax tend to complement each other by causing different actions. This finding could be expected given our observations about emissions reductions from key actions under the two policies in the previous section. The policies may complement each other somewhat less over time as more energy efficiency actions are encouraged by the increasing carbon tax.

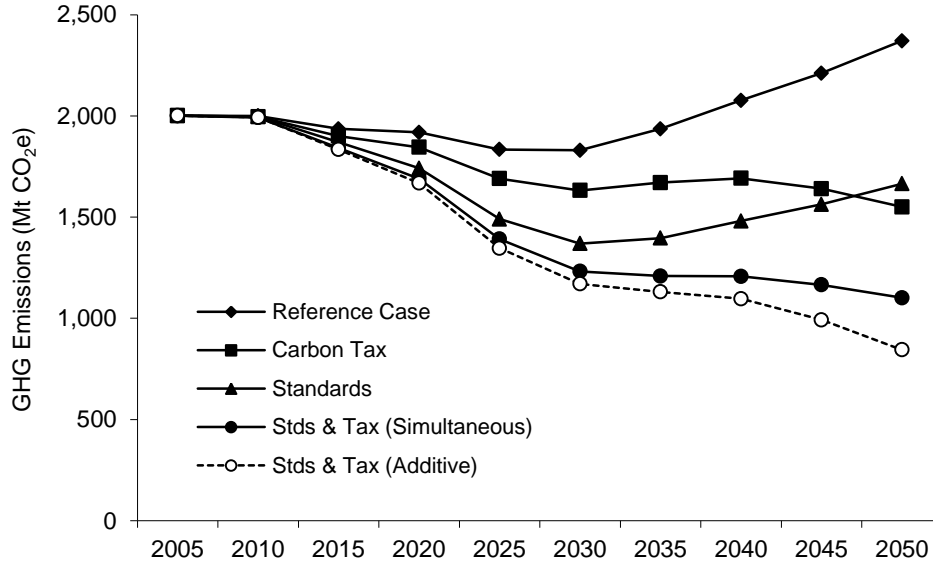


Figure 3.3: Combined effect of the efficiency standards and the carbon tax on direct GHG emissions

3.8. Impacts across the entire economy

According to our simulations, when GHG emissions reductions across the entire economy are taken into account, the carbon tax has much more of an effect than the efficiency-based standards (Figure 3.4).³⁵ Indirect emissions are associated with an increase in electricity generation due to fuel switching under the carbon tax; however, the increase in output is accompanied by a dramatic reduction in the emissions intensity of generation. Carbon capture and storage (implemented in both coal- and natural-gas fired baseload generation plants), a shift to renewable energy sources, fuel switching from coal to natural gas, and energy efficiency improvements contribute to this reduction. Carbon pricing also stimulates emissions reductions from freight

³⁵ Our simulations include GHG emissions from the combustion of fossil fuels, as well as process emissions linked to production levels (e.g. the carbon dioxide released when limestone is calcined in cement and lime production, or the methane released through venting, flaring, and fugitive emissions in natural gas fields, processing plants, and pipelines). However, we have removed process emissions from our results for this paper in order to be more consistent with the Annual Energy Outlook.

transportation, other energy supply (partly from reduced demand for fossil fuels), and the industrial sub-sectors. Under the standards, on the other hand, emissions reductions outside the targeted end-use sectors are limited to the energy supply sectors whose output is diminished as a result of the improvements in energy efficiency. This economy-wide comparison underscores the importance of policy comprehensiveness, across sectors and categories of abatement action, in the design of standards for GHG abatement.

When the efficiency standards and the carbon tax are run simultaneously and the results examined across the entire economy, it appears that the policies complement each other in terms of GHG emissions reductions, as was the case in the previous section (where only the results from the buildings and personal transportation sectors were considered). However, there may be more overlap between actions at the economy-wide level because both policies cause emissions abatement through a reduction in the demand for fossil fuels.

As discussed previously, the efficiency standards have more of an effect than the carbon tax on energy consumption from the buildings and personal transportation sectors in our forecasts. The gap between the two policies grows larger when comparing total primary energy consumption, as in Figure 3.4.³⁶ The reduction in energy demand from the targeted end-use sectors under the standards reduces the output of the energy supply sectors, leading to lower energy consumption by these sectors as well. Under the carbon tax, reductions in energy consumption from efficiency actions outside the buildings and personal transportation sectors are more than offset by higher electricity related losses (losses converting primary forms of energy to electricity, as well as transmission and distribution losses) as the demand for electricity increases.

³⁶ We used a partial substitution method to calculate the primary energy equivalent of electricity generated from solar, hydro, and wind in this analysis. The coefficients used to calculate the primary energy equivalent for these sources are therefore related to the amount of energy required to generate electricity in conventional thermal power plants. If we had instead used a physical energy content method and assumed 100% efficiency for solar, hydro, and wind, we would have observed a smaller gap between the carbon tax and the efficiency standards, as switching to renewables under the carbon tax would have reduced electricity related losses. We used the partial substitution method so that an increase in the share of electricity generation from renewables would come across as a fuel switching action rather than as an energy efficiency action.

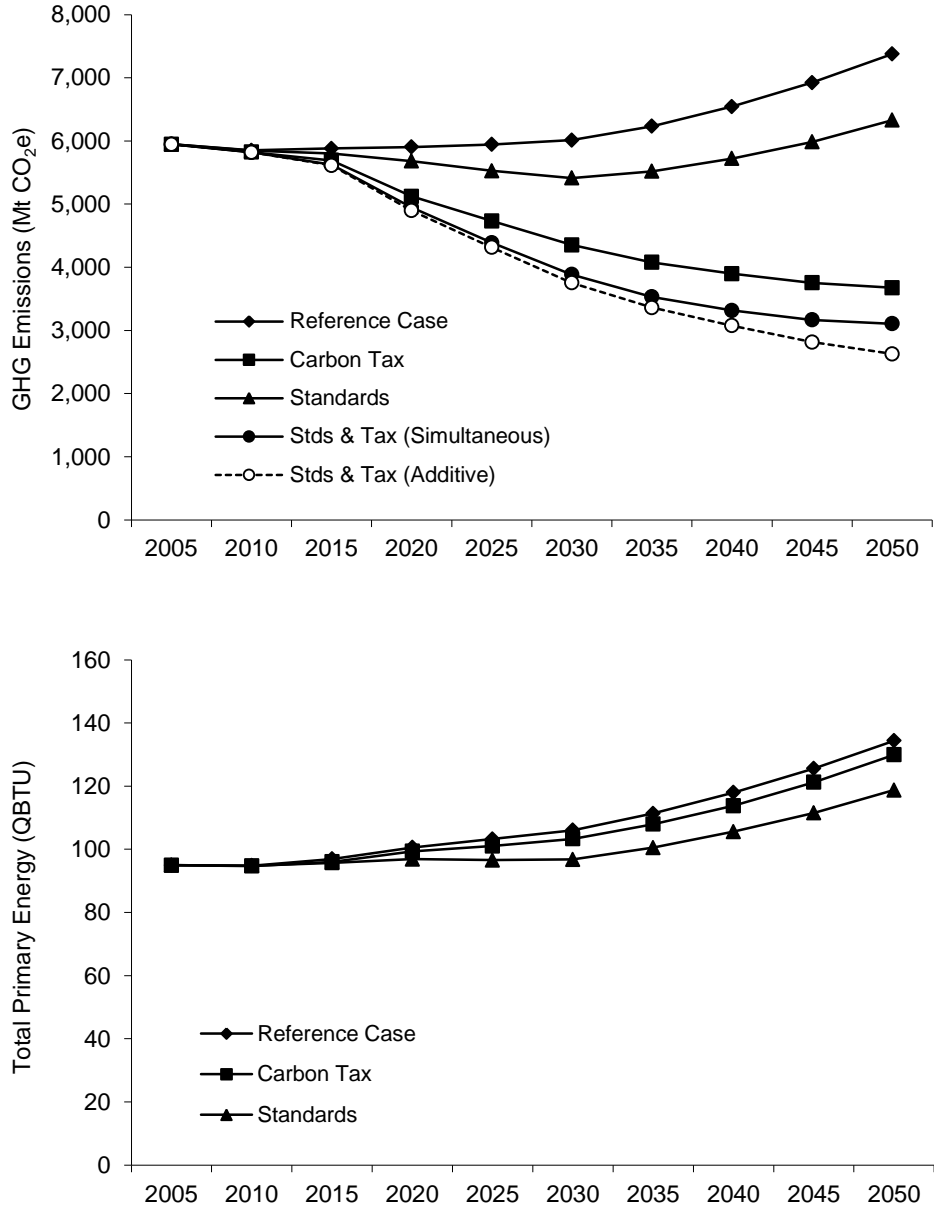


Figure 3.4: Economy-wide GHG emissions (combustion only) and energy consumption

3.9. Observations on cost-effectiveness

The CIMS model that is the basis for our policy simulations can be used to estimate detailed microeconomic costs ranging from anticipated financial costs

evaluated at a social discount rate to costs that take into account market heterogeneity and the revealed and stated preferences of decision makers. Although the model does not incorporate feedbacks to the full extent of a CGE model, a methodology has been developed to estimate impacts on gross domestic product based on its partial equilibrium representation. CIMS has also been used to estimate key elasticity of substitution values for simulating the technological response to price changes by consumers and firms in a CGE framework (Bataille et al., 2006). Such exercises were not undertaken for this particular study; however, it is possible to make some general observations regarding the cost-effectiveness of the energy efficiency standards based on the extent to which marginal costs are equalized across sectors and actions in our simulation.

If we consider a single policy objective of addressing the environmental externality associated with GHG emissions, economic theory indicates that, in the absence of other market failures, cost-effectiveness will be maximized when marginal abatement costs are made equal across actions, economic agents, and sectors. This can be accomplished through an economy-wide carbon tax or tradable permit program. We simulated a series of constant, economy-wide GHG prices at increments of \$25/tonne CO₂e to allow us to investigate the distribution of marginal abatement costs under the energy efficiency standards tested for this study.

As a means to achieve GHG emissions reductions across the entire economy, the standards would have an unnecessarily high cost per unit of emissions reduction because they apply only to the buildings and personal transportation sectors, and would therefore fail to take advantage of low-cost opportunities to reduce emissions outside these sectors. Assuming the efficiency standards would be implemented along with policies to address other economic sectors, however, we can move on to consider the cost-effectiveness of the allocation of emissions reductions within the targeted end-use sectors.

In our simulations, to achieve the same overall reduction in emissions from the end-use sectors in question as under the efficiency standards in 2030, a constant, economy-wide GHG price approximately mid-way between \$125 and \$150/tonne CO₂e is required. To match the emissions reductions from the residential, commercial, and

personal transportation sectors separately, GHG prices of \$175, \$100-125, and \$125-150/tonne CO₂e respectively are necessary. Based on these results, the standards appear to induce greater emissions reductions from the residential sector and less emissions reductions from the commercial sector than would be cost-effective, although the allocation of emissions reductions across the end-use sectors is not far from the cost-effective solution.

For most of the end-use categories targeted by the standards, energy efficiency improvements are much greater in 2030 than under a constant GHG price of \$125-150/tonne CO₂e (the price that achieves the same overall emissions reduction as the standards from the buildings and personal transportation sectors), indicating that the allocation of emissions reductions across actions is not cost-effective according to our simulations, due to the lack of fuel switching actions. Exceptions are space heating and water heating end-uses in the buildings sectors, where efficiency levels are matched at a GHG price of approximately \$100/tonne CO₂.

3.10. Conclusion

Policy makers are understandably interested in the potential for energy efficiency to mitigate climate change and reduce energy demand. For more than three decades, bottom-up analyses conducted by researchers such as Lovins and (more recently) the McKinsey consulting firm have indicated that abundant opportunities exist for improving energy efficiency profitably or at a low cost. Top-down modelers criticize these findings for taking into account neither the risks of new technologies and long payback investments in energy efficiency, nor the intangible preferences of consumers and businesses. However, the top-down approach has its own methodological challenges. In particular, because conventional top-down models do not represent technologies explicitly, they cannot assess policies that focus on individual technologies, such as energy efficiency standards.

As part of an effort organized by the EMF (EMF-25), we simulated two policy options for reducing GHG emissions and energy consumption in the US to the year 2050: energy efficiency standards in the buildings and personal transportation sectors,

and an economy-wide carbon price with escalating stringency over time. We used a hybrid energy-economy model that combines critical elements of the conventional bottom-up and top-down approaches. This allowed us to simulate both the technology-specific efficiency standards and the economy-wide carbon tax.

In our forecasts, the efficiency standards initially perform much better than the escalating carbon tax at reducing direct GHG emissions from the targeted end-use sectors. However, the gap between the emissions trajectories for the two policies becomes smaller during the latter part of the simulation period, and by 2050 the carbon tax achieves greater reductions. This result suggests that the efficiency standards would need to be updated over time. Our policy simulations indicate that the efficiency standards produce greater reductions in energy consumption than the carbon tax for the end-use sectors in question. The hybrid modeling framework we used for this analysis includes parameters estimated from behavioral research, making it less likely than a bottom-up approach to show significant penetration of energy efficiency as a result of pricing GHG emissions. Fuel switching occurs under the carbon tax in our modeling, which reduces GHG emissions but not necessarily energy use.

We disaggregated the estimated emissions reductions from our simulations across a number of different actions. In 2030, the roles of energy efficiency and fuel switching are roughly equal under the carbon tax for the buildings and personal transportation sectors. As expected, energy efficiency dominates under the standards. The major differences we observed between the two policies in terms of the contribution of key actions are also reflected in our assessment of the combined effect of the efficiency standards and the carbon tax, which found that these policies tend to complement each other by causing different actions.

According to our simulations, when the analysis is extended from the buildings and personal transportation sectors to the entire economy, the carbon tax reduces GHG emissions by much more than the efficiency-based standards. Results at the economy-wide level emphasize the need for standards to be designed in a comprehensive way in order to capture abatement opportunities across different sectors, particularly electricity generation, and categories of abatement action – i.e. fuel switching and carbon capture and storage in addition to energy efficiency – if the goal is to reduce GHG emissions.

We simulated constant, economy-wide GHG prices to provide some insight regarding the cost-effectiveness of the standards, and found that the cost per unit of emissions reduction would be unnecessarily high because only energy efficiency actions in the buildings and personal transportation sectors are targeted. This is consistent with our earlier observations that a carbon tax harnesses substantial abatement opportunities in other sectors and from other actions. However, there are still reasons why policy makers might want to implement energy efficiency standards.

Where market failures are identified that limit the adoption of technologies that appear profitable, government intervention in the form of efficiency standards and/or subsidies may be appropriate if the benefits outweigh the costs to society, including the costs of policy implementation. More research is needed to rigorously evaluate potential market failures and the policies designed to address them. Another reason why policy makers might want to consider energy efficiency standards is if a price on GHG emissions is not sufficient to address other environmental, social, and security externalities associated with energy consumption. Our simulation results suggest that if efficiency standards were used to supplement a carbon tax in order to address additional externalities or market failures that limit the penetration of energy-efficient technologies, the policies would tend to complement each other.

3.11. Acknowledgements

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4. Energy efficiency and the cost of GHG abatement: A comparison of bottom-up and hybrid models for the US³⁷

4.1. Abstract

A highly influential report by the McKinsey consulting firm suggests that a large potential for profitable energy efficiency exists in the US, and that substantial greenhouse gas emissions reductions can therefore be achieved at a low cost. This result is consistent with other studies conducted using a bottom-up methodology that dates back to the work of Lovins beginning in the 1970s. Research over the past two decades, however, has identified shortcomings with the conventional bottom-up approach, and this has led to the development of new analytical frameworks that are referred to as hybrid energy-economy models. Using the CIMS hybrid model, we conducted simulations for comparison with the McKinsey results. These exercises suggest a more modest potential to reduce greenhouse gas emissions at a given marginal cost, as well as a smaller contribution from energy efficiency relative to other abatement opportunities such as fuel switching and carbon capture and storage. Hybrid models incorporate parameters reflecting risk and quality into their estimates of technology costs, and our analysis suggests that these play a significant role in explaining differences in the results.

³⁷ This paper was published as: Murphy, R. and Jaccard, M., 2011. Energy efficiency and the cost of GHG abatement: a comparison of bottom-up and hybrid models for the US. *Energy Policy*, 39:7146-7155. <http://dx.doi.org/10.1016/j.enpol.2011.08.033>

4.2. Introduction

The McKinsey consulting company has produced a number of country-specific studies of energy efficiency potential and greenhouse gas (GHG) abatement potential that have been highly influential in policy discussions in both the US and other jurisdictions. Generally speaking, these reports conclude that significant emissions reductions can be achieved at a low cost to society, and that profitable energy efficiency improvements are the reason. For the US, McKinsey estimates that GHG emissions in the year 2030 could be reduced by 30% at marginal costs below \$50/tonne (McKinsey, 2007), and that end-use energy consumption in the year 2020 could be reduced by 23% with savings exceeding costs (McKinsey, 2009). Results such as these suggest that energy efficiency measures should be emphasized as a response to climate change, and that GHG emissions can be reduced substantially without implementing strong regulatory or emissions pricing policies.

The methodology applied in the McKinsey reports is sometimes referred to as bottom-up analysis in that it gathers information about individual energy services and associated technologies, and then combines this into an economy-wide assessment. In the case of GHG abatement, non-energy actions such as afforestation may be considered as well. The approach dates back to the 1970s when, in the wake of the oil supply crisis, analysts drew attention to that fact that more efficient technologies can provide the same level of service (lighting, heating) using much less energy than conventional technologies. In his book *Soft Energy Paths*, Lovins (1977) proposed energy efficiency as the first step in any energy policy directed at environmental protection and energy security. According to Lovins, the most efficient technologies might have higher capital costs, but this would be more than offset by the money saved from lower energy bills. He found that opportunities for such investments exist throughout the economy, suggesting that a 75% reduction in energy use for a given level of services is profitable over about a 30-year timeframe via the full adoption of commercially available technologies (Fickett et al., 1990; Lovins et al., 1981; von Weizsäcker et al., 1997).

In the 1980s an investment crisis in the US electricity industry spurred interest by utility regulators and management in the pursuit of energy efficiency as a less risky

strategy than building new supply. US utilities began to conduct comprehensive bottom-up analyses of the economic potential for energy efficiency, especially electricity efficiency. Life-cycle cost calculations were carried out that involved comparing the future energy savings of more efficient devices to their higher up-front capital costs using the same low discount rate that the utility used to assess its electricity supply options. The information was then used to produce least-cost energy efficiency curves as in Figure 4.1 – upward sloping curves showing the amount of energy savings that is profitable at each energy price level based on the life-cycle cost calculations.

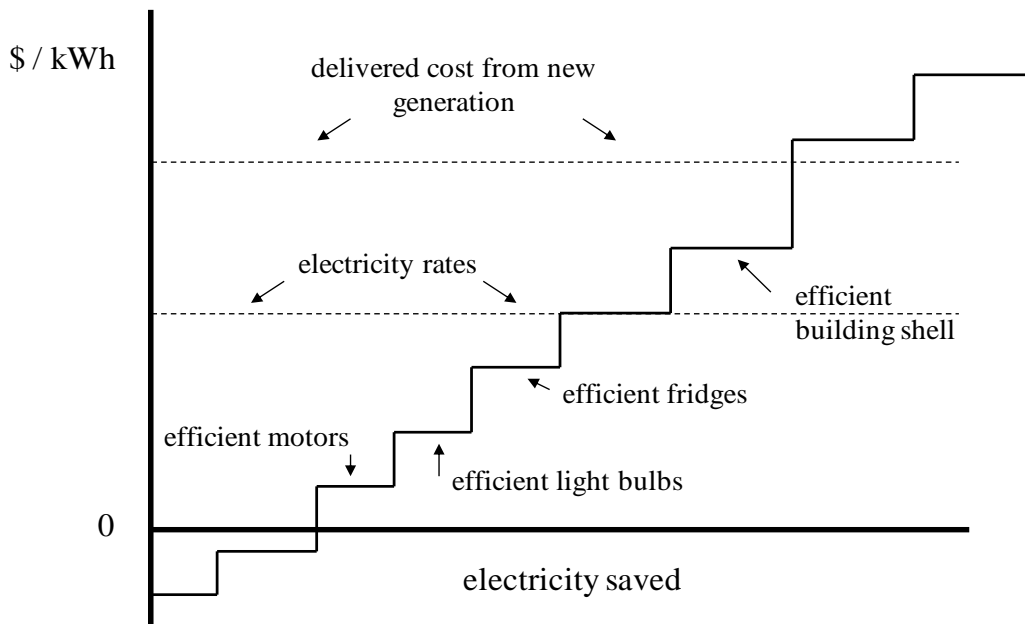


Figure 4.1: Example of a least-cost energy efficiency curve

Utilities and their regulators used bottom-up, least-cost curves to devise energy efficiency programs called demand-side management (DSM). Since utilities could neither raise prices to encourage reduced electricity use (regulation requires them to price electricity at its cost), nor could they implement energy efficiency regulations (an authority of government), their DSM efforts focused on information programs (education, advertising, awards, labeling) and subsidies (grants, low-interest loans) to encourage acquisition of the most efficient technologies.

As early as 1990, empirical research began to suggest there might be problems with the bottom-up approach to assessing the cost of energy efficiency and the expected effectiveness of DSM programs. Nadel (1990) reported that some efficiency programs

are more costly than expected, with an average cost for US industrial and commercial programs of 2 ¢/kWh, which at the time exceeded the cost estimates generated by most utilities conducting DSM. Joskow and Marron (1992) found that when the utility costs of running a DSM program are included, the costs are at least double this amount. Detailed studies have found that the anticipated energy efficiency gains of DSM programs tend to exceed the savings revealed by hindsight analysis (Arimura et al., 2009; Hirst, 1986; Loughran and Kulick, 2004; Metcalf and Hassett, 1999; Sebold and Fox, 1985).

Over the last two decades, a number of specific critiques of the conventional bottom-up methodology have been raised in the literature. Three of the key issues are discussed in the following section and include: 1) a lack of consideration of the impacts that the individual actions being considered can have on each other, 2) the assumption that market conditions are homogenous across different consumers and firms, and 3) the reliance on life-cycle cost calculations that take into account only anticipated financial costs evaluated at a social discount rate, thereby ignoring risk and quality differences between technologies. The first point has been addressed through the development of integrated energy-economy models in which actions occur simultaneously. Further refinements allow for the simulation of broader energy supply-demand and macroeconomic feedback effects. The last two points may be summarized as a lack of behavioral realism. Together, these methodological shortcomings are likely to result in an underestimation of the cost of energy conservation and GHG emissions abatement, as well as an overemphasis on energy efficiency as a response to climate change.

Shortcomings have likewise been identified with the application of a contrasting approach to estimating the cost of emissions reduction, sometimes referred to as top-down. The top-down methodology estimates aggregate relationships between the relative costs and market shares of energy and other inputs to the economy, and links these to sectoral and total economic output in a broader equilibrium framework. The most sophisticated form of top-down model is a computable general equilibrium model – the most prevalent form of top-down model today. When their parameters are estimated from historical data, top-down models offer improved behavioral realism over conventional bottom-up models. On the other hand, conventional top-down models do

not contain explicit representations of technologies, including those that can potentially improve energy efficiency or reduce GHG emissions. As such, this approach may overestimate the cost of achieving policy objectives, and cannot be used to test technology-specific policy options.

Debates over the advantages and disadvantages of these two competing paradigms have led to the development of hybrid energy-economy models, usually through either the incorporation of technological detail into a top-down framework (Bohringer, 1998; Frei et al., 2003; Jacobsen, 1998; Koopmans and te Velde, 2001) or the incorporation of behavioral realism and/or macroeconomic feedbacks into an integrated bottom-up framework (Bataille et al., 2006; Jaccard et al., 1996; Morris et al., 2002; Nystrom and Wene, 1999; Sanstad et al., 2001). However, despite the progression of ideas in the literature over the past twenty years, the McKinsey reports continue to rely on what is essentially a conventional bottom-up methodology. In this paper, therefore, we critically assess the results of the McKinsey consulting company report for the US by presenting comparable simulations using a hybrid analysis and modeling approach. We estimate the cost of GHG emissions abatement and the contribution of energy efficiency in the US over the coming decades, and offer an explanation for divergences between the findings of our hybrid approach and the McKinsey bottom-up approach.

In the next section, we describe the McKinsey methodology according to the firm's 2007 report on GHG abatement potential in the US. We note concerns that have been raised about the conventional bottom-up approach and discuss to what extent each critique applies to the McKinsey analysis. In section 4.4, we explain how hybrid energy-economy models have been developed to address these issues and describe the CIMS hybrid model used in this study. In section 4.5, we present a GHG abatement cost curve generated for the US in 2030 using CIMS and compare this to results from the McKinsey study. We also examine the contribution of energy efficiency relative to fuel switching and carbon capture and storage in each analysis. In section 4.6, we revisit the comparisons made in section 4.5, this time with results from a version of CIMS that has been modified to be more consistent with the conventional bottom-up approach. This allows us to assess the influence of fundamental differences in methodology, in

particular the way in which costs are defined. We summarize and consider the implications of our results in the conclusion.

4.3. The McKinsey analysis and critiques of the conventional bottom-up approach

In its 2007 report on the potential for and cost of reducing GHG emissions in the US economy, the McKinsey consulting firm assesses abatement costs and abatement amounts for more than 250 options to reduce or prevent emissions, including energy efficiency improvements, switches to lower-carbon energy sources, and expanded use of carbon sinks. They do not attempt to model major technological breakthroughs, but focus on opportunities that have either been proven at the commercial scale or are likely to be commercially available by 2030. Actions to reduce GHG emissions are not linked to specific policy instruments. Abatement cost estimates take into account conventional, risk-free capital, operating, and maintenance costs, which are reduced by any savings from lower energy consumption. Costs and savings are annualized by applying a 7% discount rate over the lifetime of the abatement option. Per-tonne abatement costs are calculated by dividing the net discounted cost by the total emissions reduction, with both the numerator and the denominator evaluated over the lifetime of the option. Results of the study are summarized by arranging actions from lowest to highest cost to create a least-cost GHG abatement curve.

The McKinsey team estimates that annual emissions in 2030 could be reduced by 3.0 gigatonnes carbon dioxide equivalent (CO₂e) at marginal costs below \$50/tonne. This result is based on mid-range assumptions (results for low- and high-range cases are also provided), and represents 30% of the reference case emissions forecast for the US in 2030. Because almost 40% of the reductions are found to be achievable at negative marginal costs (savings greater than costs), the average cost per tonne is much lower than the \$50 threshold used in the analysis. Emissions reductions from energy efficiency actions dominate the profitable abatement potential.

The findings of the McKinsey report are typical of studies that apply a conventional bottom-up methodology. Over the last two decades, researchers have

noted a number of shortcomings associated with the least-cost curves for GHG emissions reduction and energy efficiency generated using this approach. We outline three of the key issues below and discuss to what extent each critique applies to the McKinsey study in particular.

First, the conventional bottom-up approach represents a form of extreme “partial equilibrium analysis” in that each action representing a step on the least-cost curve is evaluated separately from all the other actions being considered. In reality, however, many actions are interdependent. For example, improving building shell efficiency reduces the potential energy savings from installing more efficient heating, ventilation, and air conditioning technologies, and vice versa. Interactions also occur between actions in energy supply and actions in the energy demand sectors. For example, a reduction in the emissions intensity of electricity generation reduces the indirect emissions saved by switching to end-use devices that consume less electricity. Integrated energy-economy models that treat all actions as happening simultaneously have been developed to address this problem. These models can also be designed to incorporate broader energy supply-demand and macroeconomic feedback effects. The McKinsey analysis does not use an integrated model, and although the report describes efforts to account exogenously for sequencing and the interactive effects of abatement options, this is not a substitute for integration.

A related issue is that integrated models simulate both a reference case and any alternative scenarios using the same framework, whereas a conventional bottom-up approach subtracts the energy savings or GHG abatement calculated for each action from an exogenous reference case forecast. An integrated model may use an exogenous forecast to calibrate the reference case, but any assumptions required for calibration are carried over when a policy or other external change is simulated (except of course when the change in question specifically impacts one or more of these assumptions). The reference case for the McKinsey analysis is constructed from government forecasts. While we expect that abatement potentials for the various actions are evaluated in the context of a detailed assessment of this reference case, the methodology used to estimate the costs of the actions is not necessarily consistent with either the underlying government forecasts, or even reasonable business-as-usual

expectations with respect to the risks and preferences that affect technology acquisition (see the third issue below).

Second, bottom-up analysis tends to assume that market conditions are homogeneous across individual consumers and firms. In reality, different decision-makers experience different life-cycle costs for technologies, including equipment that is more efficient or has lower GHG emissions. This market heterogeneity may be the result of divergent preferences or perceptions, or location-specific differences in real financial costs. As a result, actions would be taken up progressively along a smooth curve as energy or carbon costs increase, rather than being implemented all at once as a step on a least-cost curve. While a typical least-cost GHG abatement curve assumes 100% market penetration once the average cost calculated for an abatement option is reached, it is our understanding that the McKinsey study evaluates the penetration of each option individually, and that market penetration is generally not set at 100%. Some aspect of market heterogeneity is therefore incorporated into the McKinsey analysis, although each abatement opportunity is still represented as a single step on the cost curve.

Third, conventional bottom-up analysis assumes that technologies which provide the same energy service are perfect substitutes except for differences in anticipated financial costs and emissions. When their financial costs in different time periods are converted into present value using a social discount rate, many emerging technologies available for abating emissions appear to be profitable or just slightly more expensive relative to existing equipment and buildings. This is especially the case for energy-efficient technologies in comparison to their more conventional substitutes. Many economists criticize the bottom-up approach for its assumption that a single, anticipated estimate of financial cost indicates the full social cost of technological change (Jaffe et al., 1999; Jaffe and Stavins, 1994; Pindyck, 1991; Sutherland, 1991). Technologies that are new to the market present greater risks, as do the longer paybacks associated with investments such as energy efficiency. Some high-efficiency and/or low-emissions technologies are not perfect substitutes in the eyes of the businesses or consumers expected to adopt them (e.g. efficient lighting technologies do not provide the same quality of light as incandescent bulbs). These factors mean that the steps of a least-cost curve are likely to under-represent the full cost of energy efficiency or GHG abatement.

The McKinsey analysis is vulnerable to this critique because it uses a social discount rate of 7% to annualize the costs and savings associated with abatement opportunities. When estimating costs, it does not take into account the higher failure rates of newly introduced technologies, the risks of long payback investments, or consumer preferences for specific technologies and technology attributes.

The third issue described above in particular helps explain why investments in energy efficiency that appear profitable at current prices are not necessarily realized. Proponents of the conventional bottom-up methodology tend to attribute this “energy paradox” to a variety of institutional, information, and financing barriers, which they argue should be addressed through government or utility intervention. Mainstream economists, on the other hand, recommend such intervention only to address a smaller subset of market failures that reduce economic efficiency. Market failure explanations for the energy paradox generally relate to a lack of information on energy-efficient and low-emissions technologies due to the public good and positive externality qualities of information. Where such failures are identified, government intervention may be appropriate, but only if the benefits outweigh the costs to society, including the costs of policy implementation (Jaffe et al., 1999; Jaffe and Stavins, 1994).

4.4. Design of the CIMS hybrid energy-economy model

Since the 1990s, energy-economy modelers have been developing and applying innovations to overcome the shortcomings of the conventional bottom-up approach. The resulting “hybrid” models are integrated, and increasingly combine characteristics of the bottom-up approach with characteristics of the top-down approach usually applied by economists. The ideal hybrid model is technologically explicit, behaviorally realistic, and includes macroeconomic feedback effects (Hourcade et al., 2006). The NEMS model of the Energy Information Administration (2009c) in the US is an example of a hybrid energy-economy model.

A hybrid model can be used to produce a cost curve for GHG emissions abatement that is comparable yet different from that produced using the bottom-up approach. This is done by plotting the amount of GHG emissions reduction that occurs

in a given year as ever higher prices are applied to emissions in a series of model simulations. This marginal abatement cost curve is distinct from a least-cost abatement curve because at each point on the curve, simultaneous actions are occurring, both within energy demand and between energy supply and demand, as in the real world. Also, a given action occurs to some degree all the way along the curve, instead of at a single step, to reflect market heterogeneity. Thus, there is some percentage market penetration of a given high efficiency fridge at lower GHG prices, and that same fridge penetrates the market further at higher prices – reflecting the fact that consumers and market conditions are heterogeneous. Finally, the curve takes into account additional costs related to differences between technologies in terms of risk and quality, so it is likely to be higher than a least-cost abatement curve.

For this study, we used the CIMS hybrid energy-economy model to generate alternative results for comparison with the McKinsey analysis (for a more detailed description of CIMS, see Jaccard, 2009). The CIMS model is technologically explicit, keeping track of vintages of capital stocks of different efficiency and other qualities. It also incorporates behavioral parameters estimated from a combination of market research into past technology choices (revealed preferences) and discrete choice surveys of possible future technology choices (stated preferences) (Rivers and Jaccard, 2006). CIMS represents substantial energy supply-demand and macroeconomic feedbacks; although not to the full extent of top-down computable general equilibrium models (Bataille et al., 2006).³⁸ These feedback interactions allow CIMS to capture to some degree the increase in demand for energy that can result from energy efficiency gains – a phenomenon sometimes referred to as the rebound effect.

The basic structure of the CIMS model is presented in Figure 4.2. Energy supply and energy demand components are each made up of a number of sub-models representing particular sectors or sub-sectors. The version of CIMS used in this analysis is a model of the US energy-economy system in which the US is considered as a single region. Energy supply includes sub-models for electricity generation, petroleum refining,

³⁸ CIMS has been used to estimate key elasticity of substitution values for simulating the technological response to price changes by consumers and firms in a computable general equilibrium framework (Bataille et al., 2006; Peters et al., 2010).

petroleum crude extraction, natural gas production, coal mining, ethanol production, and biodiesel production (some energy is also produced from landfill gas). Energy demand includes sub-models for residential buildings, commercial buildings, personal transportation, freight transportation, and industrial production (further broken down into chemicals, industrial minerals, iron and steel, metal smelting, pulp and paper, other manufacturing, mineral mining, and agriculture).

CIMS Macro-Economy Module

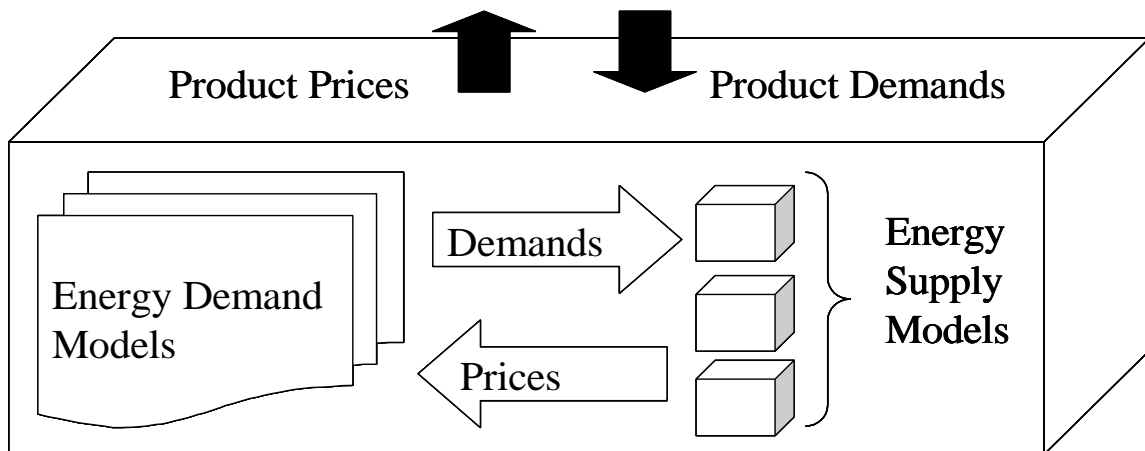


Figure 4.2: Basic structure of the CIMS model

CIMS simulates the evolution of capital stocks over time through retirements, retrofits, and new purchases, in which consumers and businesses make sequential acquisitions with limited foresight. The model calculates energy costs (and emissions) at each energy service demand node in the economy, such as heated commercial floor space or person-kilometers traveled. In each time period, capital stocks are retired according to an age-dependent function, although retrofit of unretired stocks is possible if warranted by changing economic conditions. Demand for new stocks grows or declines depending on an initial exogenous forecast of economic output, and then the subsequent interplay of energy supply-demand with the macroeconomic module. A model simulation iterates between energy supply-demand and the macroeconomic module until energy price changes fall below a threshold value, and repeats this convergence procedure in each subsequent five-year period of a complete run, which is user defined and usually extends for 30-50 years.

Technologies compete for a share of the new capital stock at energy service nodes in CIMS based on a comparison of their costs as illustrated in Eq. (4.1). Instead of basing its simulation of technology choice only on anticipated financial costs and a social discount rate (as in conventional bottom-up analysis), CIMS applies a costing definition that reflects revealed and stated consumer and business preferences with respect to specific technologies and time. The market share competition is also mediated by some technology-specific controls not shown in the equation, such as maximum market share limits in cases where a technology is constrained by physical, technical, or regulatory factors.

$$MS_j = \frac{\left[CC_j * \frac{r}{1 - (1+r)^{-n_j}} + MC_j + EC_j + i_j \right]^{-v}}{\sum_{k=1}^K \left\{ \left[CC_k * \frac{r}{1 - (1+r)^{-n_k}} + MC_k + EC_k + i_k \right]^{-v} \right\}} \quad (4.1)$$

MS_j is the market share of technology j , CC_j is its capital cost, n_j is its average lifespan, MC_j is its annual maintenance and operation cost, and EC_j is its annual energy cost, which depends on energy prices and energy consumption per unit of energy service output – producing a tonne of steel, heating one square meter of a residence, transporting a person or tonne of cargo one kilometer, etc.

The CIMS market share algorithm takes into account three behavioral parameters, denoted r , i , and v in Eq. (4.1). The r parameter represents the weighted average time preference of decision-makers for a given energy service demand; it is the same for all technologies competing to provide that energy service, but can differ between energy services according to empirical evidence. The r parameter and the technology lifespan (n_j) are used to calculate a capital recovery factor that is multiplied by the up-front capital cost (CC_j) of the technology in order to annualize it. Annual maintenance, operation (MC_j), and energy costs (EC_j) can then be added to the annualized capital cost. In a conventional bottom-up model, with r set at a social discount rate, this summation would represent the life-cycle cost of technology j , and the technology with the lowest cost would capture 100% of the market. In CIMS, the r parameter for most energy service nodes is significantly higher than a social discount

rate. As described below, an i parameter is also included in the cost calculation, and a v parameter influences the allocation of market shares.

The i parameter represents all intangible costs and benefits that consumers and businesses perceive, additional to the simple financial cost values used in most bottom-up analyses, for technology j as compared to all other technologies k at a given energy service node. For example, public transit and light-duty vehicles compete to provide the service of personal transportation. Empirical evidence suggests that some consumers impute an intangible, non-financial cost on public transportation to reflect their perceptions of its lower convenience, status, and comfort relative to the personal vehicle.

Finally, the v parameter represents heterogeneity in the market, whereby individual consumers and businesses experience different costs for what is the same technology because of location-specific factors, or because of differences in their preferences or perceptions. The v parameter determines the shape of the inverse power function that allocates market share to technology j . A high value of v means that the technology with the lowest cost captures almost the entire new market share. A low value means that the market shares of new equipment are distributed fairly evenly, even if their costs differ significantly. For the CIMS model in general, the industry and electricity generation sectors have lower discount rates (r parameter values), lower and in some cases zero intangible costs (i parameter values), and less market heterogeneity (higher v parameter values) compared to household energy consumption, personal transportation, and some commercial energy uses.

To estimate values for the behavioral parameters of CIMS that reflect the real world, model users have surveyed the literature on empirical research into historical market choices. Studies of this nature provide information on the revealed preferences of consumers. The challenge with this approach is that new and emerging technologies can provide substantially different choices from the past. Also, historical situations may not have the variation in energy prices and other values that enable statistical estimation.

Because of these constraints to revealed preference estimation, model users have also conducted many stated preference studies in which businesses and

consumers are presented with hypothetical choices between well-known technologies and emerging technologies. The most common approach to provide consumer and business values is through discrete choice surveys and analysis (Axsen et al., 2009; Rivers and Jaccard, 2006).

This methodology also has its drawbacks, however. Stated preference data can be biased because when answering a survey, consumers do not face real-world budgetary or information constraints. Also, biases may arise if consumers do not understand the survey properly or if they answer strategically. Consumers, for example, often demonstrate a higher affinity for energy-efficient technologies, such as fuel-efficient vehicles, on stated preference surveys than they do in reality.

CIMS includes two functions for simulating endogenous change in the characteristics of technologies that are new to the market: a declining capital cost function and a declining intangible cost function. The declining capital cost function links a technology's capital cost in future periods to its cumulative production, reflecting economies of scale and economies of learning. The declining intangible cost function links the intangible costs of a technology in a given period with its market share in the previous period, reflecting the 'neighbor effect' – improved availability of information and decreased perceptions of risk among consumers and firms as emerging technologies penetrate the market (Mau et al., 2008).

4.5. Comparison of CIMS and McKinsey

We generated a marginal GHG abatement cost curve for 2030 for the US economy using the CIMS hybrid model. To do this we simulated a series of constant, economy-wide carbon prices at increments of \$25/tonne CO₂e and plotted the corresponding GHG emissions reductions in the year 2030 from the model. In CIMS, a carbon price is applied as an adder to fuel prices based on their carbon content. The carbon price is also applied directly to process emissions associated with production levels rather than the combustion of fossil fuels (e.g. the carbon dioxide released when limestone is calcined in cement and lime production, or the methane released through venting, flaring, and fugitive emissions in natural gas fields, processing plants, and

pipelines). The results of the simulation are representative of the response to either a carbon tax, or an emissions cap-and-trade system in which permits trade at the carbon price (and aggregate emissions are capped at the levels reached during the run).

Electricity has no emissions at the point of end-use; however, electricity prices are affected under a carbon price in CIMS due to the interplay of energy supply and demand. There are three mechanisms through which a carbon price can influence electricity prices in the model: 1) the application of the carbon price makes electricity generation from fossil fuels more expensive, 2) actions are taken to reduce emissions within the electricity supply sector, the costs of which are passed on as higher electricity prices, and 3) changes in the demand for electricity under the carbon price influence the amount of electricity supplied, and therefore its price.

The CIMS marginal GHG abatement cost curve is shown in Figure 4.3 alongside a least-cost abatement curve based on the mid-range case of the McKinsey (2007) report. Instead of using carbon prices as inputs to a series of model simulations, the McKinsey analysis calculates per-tonne abatement costs as outputs according to the methodology described in section 4.3. The initial energy price and output forecasts in CIMS are standardized to the Energy Information Administration's Annual Energy Outlook (AEO) for 2009(a).³⁹ The updated version of the AEO 2009 reference case was used, which takes into account the energy-related stimulus provisions of the American Recovery and Reinvestment Act (ARRA) of 2009, and also reflects changes in the macroeconomic outlook since the published version. The McKinsey analysis uses AEO 2007 (Energy Information Administration, 2007) as the foundation for its reference case, and is therefore based on a different set of assumptions regarding energy prices and economic output.

Growth in annual CO₂e emissions from energy use between 2006 and 2030 is much higher in the AEO 2007 reference case (1.2% per year, 34% overall) than in the updated AEO 2009 (0.2% per year, 5% overall). The CIMS reference case likely incorporates a greater decline in energy intensity, reducing the availability of additional

³⁹ Output may be measured in physical or monetary units in CIMS, depending on the sub-model.

energy-efficient technology options under carbon pricing (as discussed further below). To address this discrepancy, we express GHG emissions abatement as the percent reduction from the corresponding 2030 reference case level. This adjustment assumes that abatement potential in absolute terms is roughly proportional to reference case emissions. If abatement potential as a percentage of reference case emissions decreases with higher reference case emissions, our correction over-estimates the abatement potential in CIMS relative to McKinsey, and vice versa. We also adjusted the McKinsey cost curve to remove the impact of changes in the management of terrestrial carbon sinks (forest and agricultural land), since these are not accounted for in the version of CIMS used in this study.

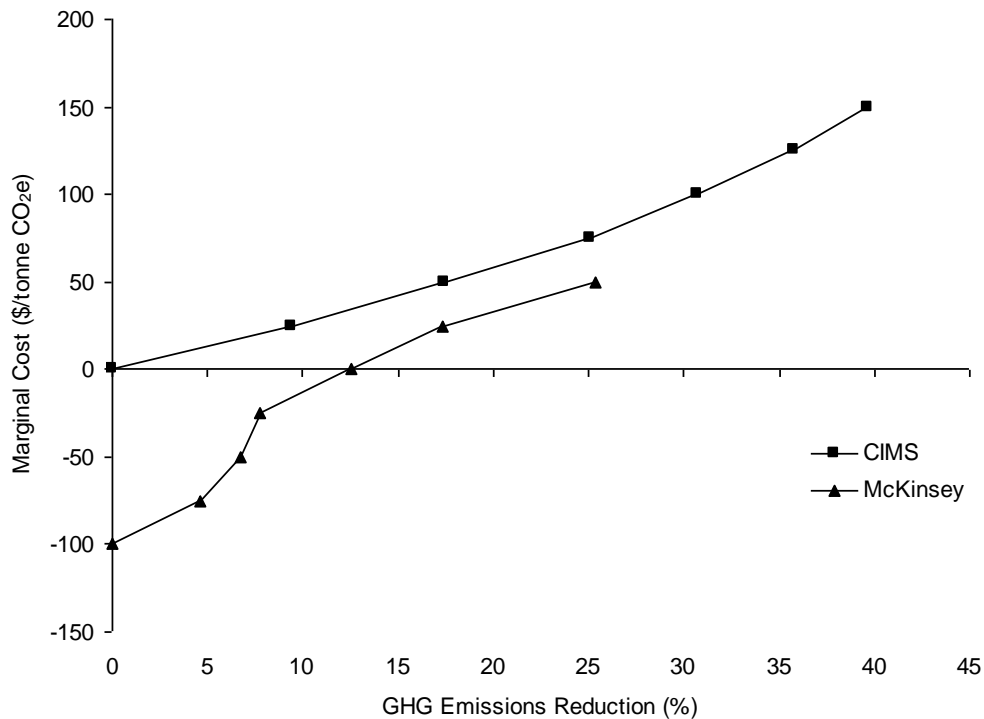


Figure 4.3: GHG abatement cost curves for the US in 2030

The CIMS marginal abatement cost curve is higher than the McKinsey least-cost abatement curve. The adjusted McKinsey curve indicates an emissions reduction potential of 25% at a cost of \$50/tonne CO₂e, whereas the CIMS curve indicates a

reduction of 17%. To achieve a similar GHG abatement to McKinsey, the carbon price must be \$75/tonne in CIMS.⁴⁰

As discussed earlier, we expect the CIMS curve to be higher because the hybrid modeling framework takes into account additional costs associated with energy efficiency and GHG abatement, related to technology and investment risk and to consumer and firm intangible preferences (perhaps reflecting quality differences in technologies and products). Our simulation methodology implicitly assumes that these additional costs cannot be mitigated by addressing market failures. More research is needed; however, the balance of evidence suggests that the potential for profitable energy efficiency is smaller than assumed by conventional bottom-up modelers (Jaffe et al., 1999). Also, because CIMS is an integrated model that deals endogenously with interactive effects, the impacts of particular actions (to reduce energy use or GHG abatement) may be reduced in comparison to the isolated estimation of these actions by McKinsey. The endogenous treatment of market heterogeneity in CIMS could have influenced the comparison with McKinsey as well, although the direction is ambiguous.

Another factor that could have contributed to differences between the CIMS and McKinsey results is possible differences in the abatement options available within the two modeling frameworks, as well as the financial costs and engineering data (energy consumption, GHG emissions, other operating characteristics, date of commercial availability, constraints to market penetration, etc.) used to describe them. The specific input assumptions that characterize abatement opportunities in the McKinsey (2007) analysis are not publicly available, and therefore were not used to inform the CIMS analysis. These assumptions may, however, be quite similar to those used in CIMS, NEMS, and other models informed by high-quality data such as that which is publicly available from the US Energy Information Administration.

To compare the contributions of different types of actions or abatement opportunities between the CIMS hybrid model and McKinsey bottom-up analyses, we disaggregated annual emissions reductions in 2030 at a marginal cost of \$50/tonne

⁴⁰ The CIMS analysis reported in this paper represents price/cost in \$2007 US, whereas the McKinsey analysis uses \$2005 US. Inflation between 2005 and 2007 in the US was not high enough to warrant recalibrating the CIMS model to \$2005 US.

CO₂e into four categories according to whether the reductions are associated with energy efficiency, fuel switching, carbon capture and storage, or other process emissions abatement. Emissions reductions due to a shift to nuclear power generation were not accounted for separately in our disaggregation, as this is not an important action in either analysis. For the CIMS simulations, we assumed that nuclear power does not experience a second major expansion in the US prior to the year 2050.⁴¹ In the McKinsey analysis, emissions reductions from nuclear power generation account for only about 2% of the total abatement potential in the mid-range case (we allocated this portion of abatement to fuel switching).

Because CIMS is an integrated model, a decomposition analysis was performed to disaggregate emissions reductions by category (for a description of the methodology, see the Appendix). In the CIMS decomposition analysis, and throughout this paper, we use energy intensity measures to approximate energy efficiency. Because energy intensity is calculated as energy use divided by output, it is influenced by structural changes as well as by changes in energy efficiency. When energy intensity is calculated based on the monetary value of output, changes in the value per unit of output can also contribute to changes in intensity. For the McKinsey analysis, the disaggregation process simply involved allocating specific actions and their estimated abatement amounts for the mid-range case to the different categories based on information presented in the report. The McKinsey results were again adjusted to remove abatement from changes in the management of terrestrial carbon sinks.

Results are presented in Figure 4.4 as the percentage share of overall abatement associated with each of the categories described above (the shares for all of the categories may not sum exactly to 100% due to rounding). Energy efficiency and process emissions abatement are much more important in the McKinsey analysis than in the CIMS simulation, while the opposite is true for fuel switching and carbon capture and storage. This outcome reflects the fact that the bottom-up methodology for estimating the cost of GHG abatement actions, as exemplified here by the McKinsey study, results in higher profitability for energy efficiency and therefore a larger estimated contribution

⁴¹ CIMS has also been used to test alternative scenarios with a greater role for nuclear power and a lesser role for fossil fuels with carbon capture and storage.

from this action under GHG pricing.⁴² We test this interpretation of the results in the next section. Here, we discuss two other factors that influence the smaller contribution of energy efficiency relative to fuel switching and carbon capture and storage in CIMS: a reduction in energy intensity over the course of the reference case forecast, and moderate electricity price increases.

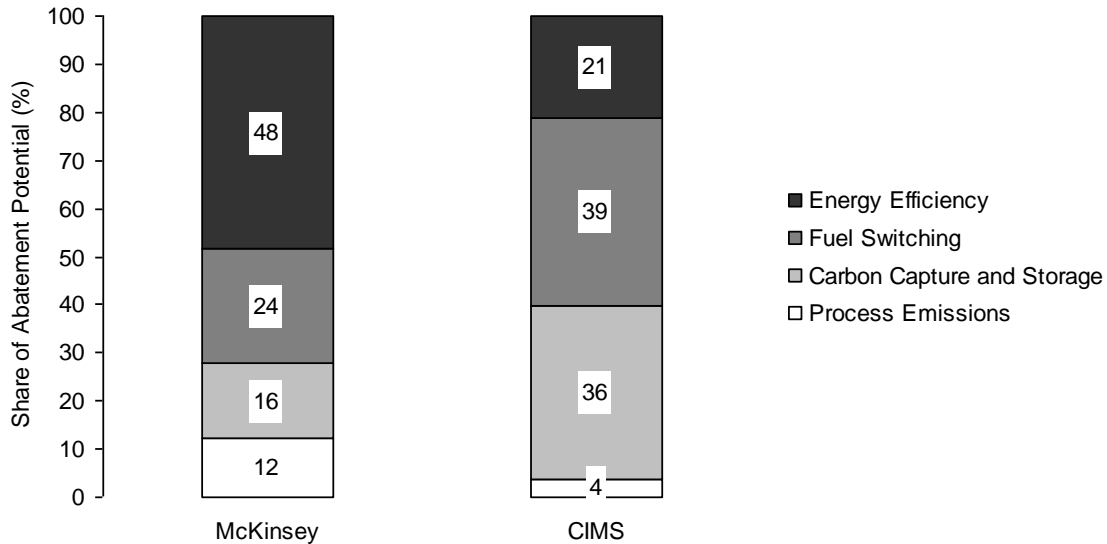


Figure 4.4: Contributions to GHG emissions abatement in 2030 at \$50/tonne CO₂e

In the CIMS reference case simulation, energy intensity is reduced considerably over the forecast period. An examination of end-use intensity trends (Figure 4.5) reveals substantial reductions for residential buildings, manufacturing industry, and light-duty vehicle transportation.⁴³ Energy efficiency improvements occur naturally over time as technology stocks turn over and technological advances enable more efficient options to become commercially available. In our analysis, high-efficiency technologies are more likely to be selected due to energy price increases (in real terms) embodied in the

⁴² The discrepancy in the importance of process emissions reductions is the result of differences in the coverage of these emissions, as well as differences in modeling assumptions, between the two analyses.

⁴³ Energy intensity is measured in terms of energy consumption per square foot for buildings, and on-road energy consumption per mile traveled for light-duty vehicle transportation. For manufacturing industry, energy intensity is estimated as energy consumption per dollar of output produced.

updated AEO 2009 forecast to which we standardized our reference case. The adoption of efficient alternatives in the reference case reduces the abatement potential from energy efficiency under the \$50 carbon price run.⁴⁴ As shown in Figure 4.5, for residential buildings, manufacturing industry, and light-duty vehicle transportation, additional reductions in energy intensity resulting from the carbon price tested are small relative to those that occur in the reference case simulation. The commercial buildings sector does not follow this pattern, mainly because the heat pump, a key technology for improving efficiency, does not gain much market share until the carbon price is implemented. In contrast to energy efficiency, carbon capture and storage and fuel switching to renewable energy sources are actions that are not strongly implemented in the CIMS reference case.

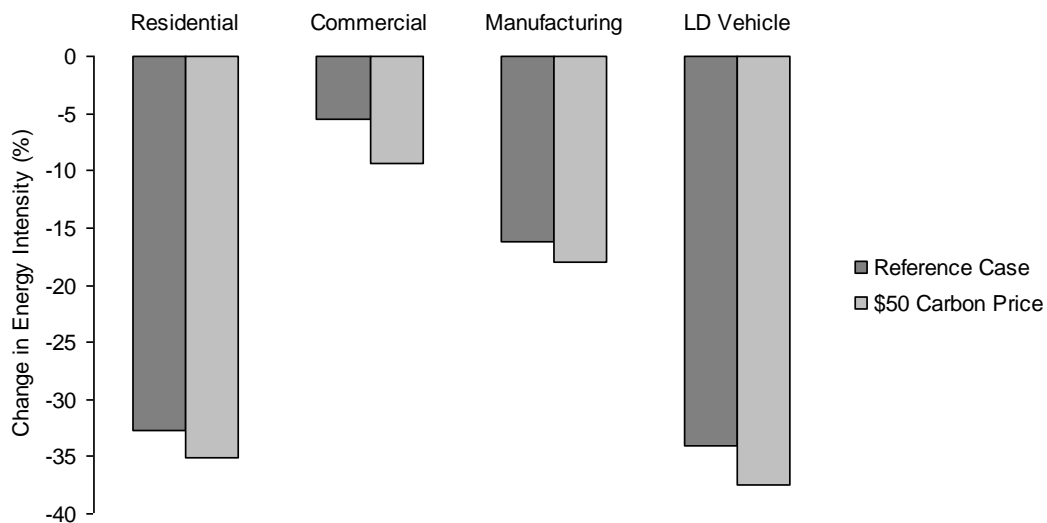


Figure 4.5: Reduction in energy intensity between 2005 and 2030

Another key explanation for the relatively small contribution from energy efficiency in the CIMS \$50 carbon price simulation is that electricity prices do not increase dramatically above reference case levels, and therefore do not act as a critical

⁴⁴ This issue is discussed in detail in the second and third assessment reports of the Intergovernmental Panel on Climate Change (1995; 2001). The reports conclude that uncertainty with respect to rates of energy efficiency improvement in the baseline forecast can have a significant effect on estimates of the cost-effective and/or achievable efficiency potential.

driver for efficiency improvements. In fact, fuel switching to electricity is forecast to occur, since electricity prices are projected to increase by a smaller percentage than the prices of combustion fuels at the point of end-use. Electricity price increases are moderate because we assumed mostly average cost pricing in this analysis. Also, based on the parameter values used for this exercise, emissions per unit of output from electricity generation can be reduced substantially at moderate costs compared to alternative actions – through carbon capture and storage, a shift to renewables, fuel switching from coal to natural gas, and efficiency improvements.⁴⁵ The impact on electricity prices was further reduced by the activation of a revenue recycling function in CIMS that assumes the carbon price is the result of either a carbon tax or a cap-and-trade system with auctioned permits, in which revenues collected from each sector of the economy are returned to that sector on a lump sum basis.

4.6. Implications of fundamental aspects of model design

For the most part, we attribute differences in the results presented for the CIMS hybrid and McKinsey (2007) bottom-up analyses to methodological innovations that were incorporated into CIMS and other hybrid energy-economy models to address problems with the conventional bottom-up approach. In particular, we have emphasized that CIMS accounts for preferences related to risk and quality in its technology cost calculation. To test our assumptions, we made a series of changes to CIMS to attempt to “undo” these innovations to the extent possible. An additional CIMS cost curve, labeled “McKinsey compare” in Figure 4.6, was generated with modifications to CIMS as described below.

1. The McKinsey analysis applies a number of constraints to prevent “material changes in consumer utility or lifestyle preferences.” These

⁴⁵ The incremental cost assumed in CIMS for a new coal-fired plant with carbon capture and storage relative to a new conventional coal-fired plant ranges from \$60 to \$105/tonne CO₂e avoided, depending on the utilization rate. The Interagency Task Force on Carbon Capture and Storage provides a similar range for the incremental costs of new coal-fired plants with carbon capture and storage of between \$60 and \$95/tonne CO₂ avoided in their 2010 report to President Obama. The McKinsey (2007) report cites an average cost of GHG abatement for carbon capture and storage in coal-fired electricity generation (rebuilt and new builds) of \$44/tonne CO₂e.

include the following: “no change in thermostat settings or appliance use; no downsizing of vehicles, homes, or commercial space; [and] traveling the same mileage annually relative to levels assumed in the government reference case” (p. 2). We applied similar constraints in CIMS to maintain consumer utility according to the definition employed by McKinsey and thus prevent the demand responses that would normally occur in an integrated, hybrid model.

2. We changed the time preference or discount rate (r parameter) at each energy service node in CIMS from its original value (based on revealed and stated preference research) to a 7% social discount rate. This was done for the carbon price simulations, but not for the reference case simulation (relative to which GHG abatement was calculated). Likewise, the reference case presented in the McKinsey report is based on government forecasts rather than an integrated model simulation using the same 7% discount rate applied when costing abatement options.
3. We removed the i parameter values representing intangible costs and benefits of specific technologies. Again, we did not alter the reference case simulation.
4. Because the McKinsey analysis does not take into account the impact of a carbon price on the economy, we turned off the macroeconomic feedbacks in CIMS. We also partially disabled the energy supply-demand feedbacks so as to better approximate the “non-integrated” McKinsey methodology. We continued to allow energy production to adjust to changes in energy demand. Energy prices were not determined endogenously in our modified runs, however, except in the case of electricity.

The second and third modifications described above cause market share decisions in CIMS to be based on anticipated financial costs evaluated at the social discount rate. The first modification was necessary to moderate this change in a way that is compatible with the McKinsey study design. Because CIMS is an integrated model, it is not possible to make actions independent from each other; however, we turned off some of the more advanced integration features as described in the fourth modification above. It is possible to run CIMS under the assumption that market conditions are homogenous, but we did not implement this change because the McKinsey analysis claims to incorporate market heterogeneity to some extent.

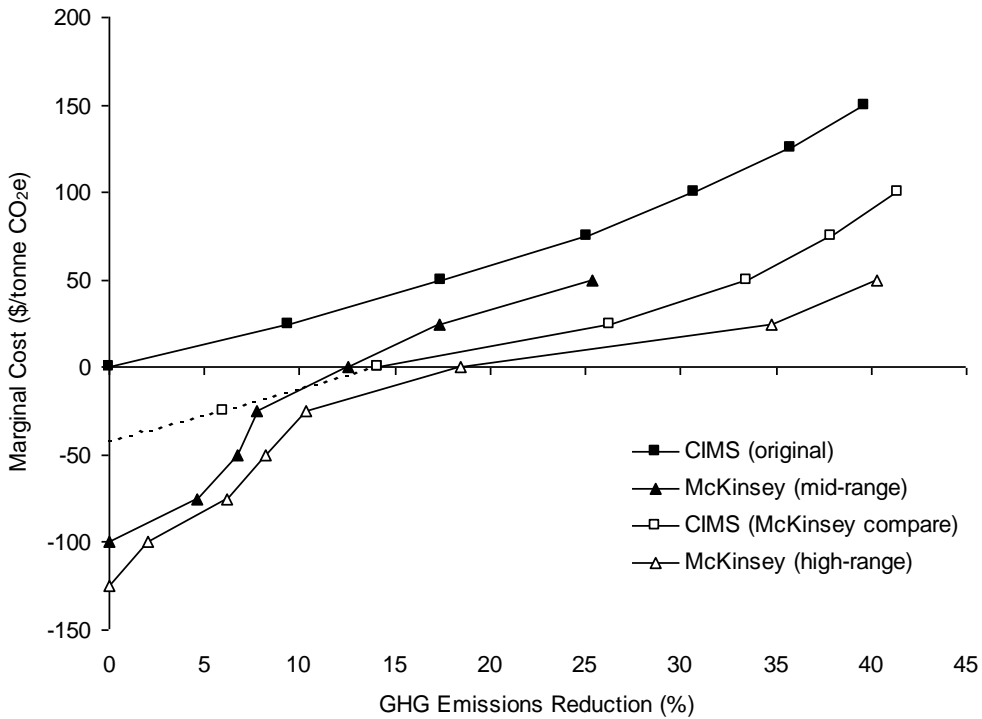


Figure 4.6: GHG abatement cost curves for the US in 2030 including a modified CIMS curve

The CIMS cost curve generated with these adjustments is much lower than the original CIMS curve, demonstrating the importance of these aspects of model design. At a cost of \$50/tonne CO₂e, abatement potential in 2030 is 33% according to the new curve, as opposed to 17% for the original curve. When costs are moderate (in the range of \$50/tonne CO₂e), the most important of the modifications to CIMS proved to be the change to a 7% social discount rate. Removing the intangible cost parameters would have had more of an impact than it did if we had not constrained a number of key consumer choices in order to hold utility constant in accordance with the assumptions of the McKinsey analysis.

At positive marginal costs, the modified CIMS curve is even lower than the McKinsey mid-range curve. However, it is higher than a representation of the McKinsey high-range curve also included in Figure 4.6. In the high-range case, economic, technical, and regulatory constraints are relaxed to approximate “urgent national mobilization.” The McKinsey report focuses on the mid- and high-range cases because

only the high-range case achieves GHG abatement levels implied by an analysis of proposed US federal legislation. At the positive carbon prices tested, abatement potential estimated in the modified version of CIMS falls roughly halfway between the McKinsey mid-and high-range cases. This finding is compatible with our hypothesis that improvements incorporated into hybrid models to address the shortcomings of conventional bottom-up models account for much of the difference in estimated abatement costs.⁴⁶ At negative marginal costs, we indicate the modified CIMS curve with a dashed line. While it is possible to run a negative carbon price in CIMS, the model has been designed and used primarily as a policy simulation tool in which positive prices for carbon result from climate policy.

We repeated the exercise of comparing the contributions from different categories of abatement opportunities in the CIMS and McKinsey analyses, this time using the modified version of CIMS (Figure 4.7). The share of emissions reductions from energy efficiency in CIMS doubled relative to the original simulation, bringing it close to the share estimated for McKinsey. The contributions from fuel switching and carbon capture and storage decreased in CIMS, again getting closer to the McKinsey analysis. Our results suggest that key methodological developments incorporated into the CIMS hybrid model but not the McKinsey bottom-up approach can explain discrepancies in the proportion of emissions reductions from different categories of abatement opportunities, in particular energy efficiency.

⁴⁶ Huntington (2011) reaches a similar conclusion, starting with an energy-efficiency cost curve based on McKinsey and mathematically adjusting it to take into account achievable energy savings rather than optimal energy savings.

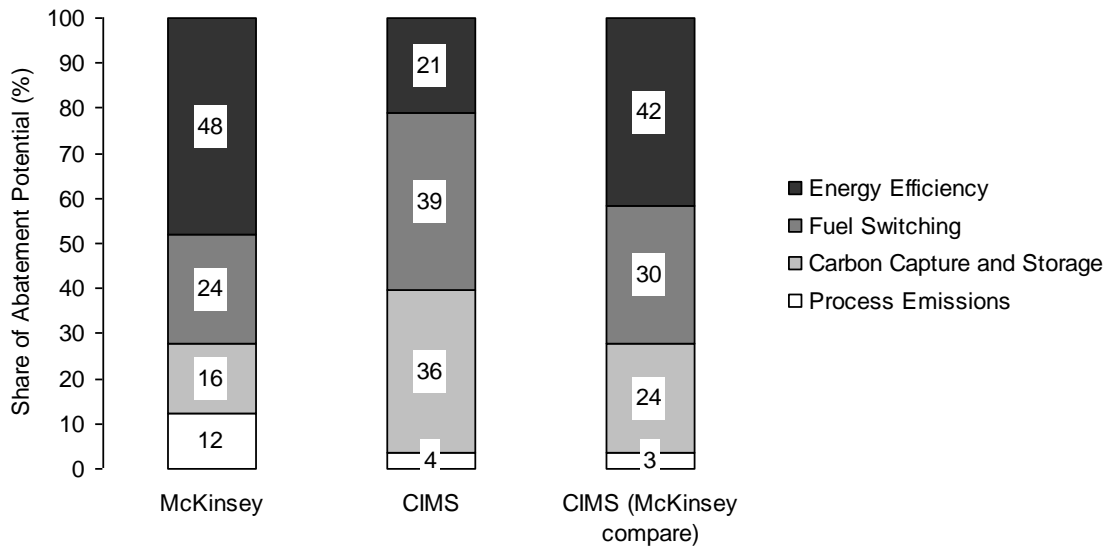


Figure 4.7: Contributions to GHG emissions abatement in 2030 at \$50/tonne CO₂e, with modifications to CIMS

4.7. Conclusion

The low cost estimates for energy conservation and GHG emissions abatement generated by the McKinsey consulting firm and other analysts using a conventional bottom-up approach have caught the attention of policy-makers. The results are appealing because they suggest that politically acceptable measures such as information and education programs, as well as targeted subsidies and regulations, are sufficient to address climate change, especially by driving what appear to be low-cost energy efficiency improvements. In this context, comprehensive regulatory or taxation policies that establish a moderate to high price on carbon emissions can appear to be unnecessary. Conventional bottom-up analysis, however, does not incorporate substantial improvements in energy modeling of the past two decades. Hybrid energy-economy models have been developed that explicitly combine engineering and economic analysis, taking into account costs associated with risk and quality differences between technologies.

In this paper, we conducted simulations using the CIMS hybrid model and compared the results with those provided by the McKinsey consulting firm in their

bottom-up assessment of GHG abatement potential in the US. This allowed us to explore how fundamental differences between the hybrid and bottom-up analytical frameworks can impact the results. Our findings suggest that the way in which costs are defined can have a substantial influence on estimates of GHG abatement potential, as well as the importance of energy efficiency in achieving this potential. In fact, the behavioral parameters that influence technology acquisition in hybrid models may account for a considerable portion of the discrepancy between the results of these two types of analysis, especially when the marginal cost of emissions reduction is low enough not to trigger sizeable macroeconomic feedbacks.

The low cost estimates provided by McKinsey appear to be explained by assumptions about costs and risks that have been refuted to a considerable degree by research leading to the development of hybrid models. Bottom-up studies such as those produced by the McKinsey group may lead to decisions in the US and elsewhere in favor of policies that place too much emphasis on energy efficiency, and that are not comprehensive or stringent enough to reduce GHG emissions substantially.

4.8. Acknowledgements

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Appendix: Decomposition methodology

The CIMS decomposition analysis was carried out separately for each energy supply and energy demand sub-model. The decomposition identity for combustion GHG emissions by sector or sub-sector is given in Eq. (4.2):

$$C_R = Q \frac{E}{Q} \frac{C_G}{E} \frac{C_R}{C_G} = QIFS_C \quad (4.2)$$

where C_R is the combustion emissions released to the atmosphere, Q is the output or activity level, E is the energy consumption and $I (= E/Q)$ is the energy intensity of output, C_G is the combustion emissions generated and $F (= C_G/E)$ is the emissions intensity of energy consumption, and $S_C (= C_R/C_G)$ is the ratio of combustion emissions released to combustion emissions generated.

The decomposition identity for process GHG emissions by sector or sub-sector is given in Eq. (4.3):

$$P_R = Q \frac{P_G}{Q} \frac{P_R}{P_G} = QAS_P \quad (4.3)$$

where P_R is the process emissions released to the atmosphere, Q is the output or activity level, P_G is the process emissions generated and $A (= P_G/Q)$ is the process emissions intensity of output, and $S_P (= P_R/P_G)$ is the ratio of process emissions released to process emissions generated.

For both combustion and process emissions, we decomposed the difference between the reference case and \$50/tonne CO₂e carbon price simulations in 2030 using the logarithmic mean Divisia index (LMDI) approach (Ang, 2005). Reductions in combustion emissions associated with changes in the I , F , and S_C variables in Eq. (4.2) were attributed to energy efficiency, fuel switching, and carbon capture and storage, respectively. Reductions in process emissions associated with changes in the S_P variable in Eq. (4.3) were also attributed to carbon capture and storage, while reductions

associated with changes in the A variable were attributed to other process emissions abatement.

We used a partial substitution method to calculate the primary energy equivalent of electricity generated from solar, hydro, and wind. The conversion efficiency assumed for these sources was therefore based on the efficiency of conventional thermal power plants. Another option would have been to use a physical energy content method and assume 100% efficiency. We chose the partial substitution method so that when there is an increase in the share of electricity generation from renewables, the emissions reduction is allocated to the fuel switching category by the decomposition analysis, rather than a portion being allocated to energy efficiency. This is consistent with how we categorized the abatement options presented in the McKinsey report.

Carbon capture is primarily implemented in fossil fuel electricity generation plants in our analysis. A plant with carbon capture requires more energy than an equivalent plant without; however, this is not reflected in the emissions reduction allocated to carbon capture and storage by our decomposition methodology. Instead, implementation of carbon capture and storage technology in a particular sector or sub-sector leads to greater energy intensity (I) in Eq. (4.2), and therefore less emissions abatement from the energy efficiency category. To correct for this, we removed a portion of the emissions reduction allocated to carbon capture and storage and added it to energy efficiency.

The abatement potential allocated to each category as described above was summed across all the individual sub-models of CIMS. For the energy demand sub-models, emissions reductions associated with changes in the Q or output variable in Eqs. (4.2) and (4.3) due to macroeconomic feedbacks are negligible at a carbon price of only \$50/tonne CO₂e (we did not identify any abatement potential for an output category in the McKinsey analysis either).⁴⁷ However, emissions increase due to increases in the output of the electricity generation and natural gas production sub-sectors. Because these changes are associated with fuel switching in the energy demand sectors, we

⁴⁷ The revenue recycling function that was activated in the CIMS carbon price simulations would have mitigated any macroeconomic feedback effects occurring at the low carbon price.

reallocated the emissions increase to the fuel switching category when summing across the individual sub-models.

5. An econometric analysis of afforestation offsets for carbon sequestration

5.1. Abstract

According to some analysts, forest carbon sequestration has the potential to remove substantial amounts of the greenhouse gas carbon dioxide from the atmosphere at relatively low costs. Based on such findings, policy-makers have developed protocols to award offset credits for forestry projects under emissions cap and tradable permits programs. Most studies of the cost-effectiveness and sequestration capacity of forest carbon sink programs use bottom-up engineering methods; however, these methods do not offer a realistic portrayal of landowner behavior. In order to incorporate the revealed preferences of landowners, I develop and estimate an econometric model of afforestation on private land in Ontario, Canada, which I then use to simulate a hypothetical afforestation offsets program. My simulations indicate that across a range of offset prices and assumptions about the rate of carbon sequestration, the potential for forest carbon sequestration is much smaller than the potential estimated by comparable bottom-up studies. Furthermore, the simulations suggest low levels of additionality, which could lead to emissions exceeding the cap of an emissions cap and tradable permits program if afforestation offsets are allowed.

5.2. Introduction

For the past few decades, there has been interest in the potential for enhanced forest carbon sinks to remove substantial amounts of the greenhouse gas carbon dioxide (CO₂) from the atmosphere at relatively low costs. As forests grow, they remove CO₂ and sequester carbon in trees and other plants, litter and soil. Afforestation, reforestation, changes in forest management practices, and reducing emissions from

deforestation and degradation (REDD) have been embraced as climate mitigation options.

The promise of forest carbon sequestration has led policy-makers to explore offset credits as a way of fostering the desired land-use and land management changes. Offsets are relevant in the context of an emissions cap and tradable permits program, such as the Kyoto Protocol or the European Union Emission Trading Scheme (EU-ETS). Under this type of program, the governing body sets a maximum level for emissions (the emissions cap) and then allocates tradable emissions permits that allow total emissions equal to the level of the cap. In order to recognize emissions removals associated with tree growth, forestry projects may be awarded offset credits, which can then be sold and used as emissions permits. Forest carbon offsets are being considered as part of ongoing negotiations to establish a post-Kyoto international climate regime. In particular, “[a]n international system that enables countries to earn carbon credits by ... (REDD) will almost certainly be a prominent feature of whatever post-2012 international climate architecture emerges from ongoing negotiations” (Blackman, 2010, p. 4). Forest carbon offsets are also permitted under a number of sub-national emissions trading systems that are being developed in the US and Canada, including the Regional Greenhouse Gas Initiative (Northeast and Mid-Atlantic States), the California Cap-and-Trade Program, and the Alberta Offset System.

The legitimacy of forest carbon offsets can be undermined by three key issues: additionality, permanence and leakage (see, for example, van Kooten and Sohngen, 2007). Projects that are awarded offset credits must be additional to what would have occurred in the absence of the incentives created by the offsets mechanism, otherwise the integrity of the emissions cap and tradable permits program is threatened. It is extremely difficult to demonstrate additionality, because it is impossible to have knowledge of the counter-factual scenario that would have been observed if the offsets system had not been in place. Permanence is an issue because CO₂ is released from forests when trees are harvested, or burn down in a fire or succumb to a pest outbreak. Leakage can occur if enough land is converted from farms to forests, resulting in higher

agricultural land prices and increased deforestation of land that is not regulated by the offsets system.⁴⁸

While policy-makers have been developing offsets protocols, analysts have been evaluating the cost-effectiveness and sequestration capacity of forest carbon sink programs. Since the late 1980s, numerous studies (as reviewed by Richards and Stokes, 2004; Stavins and Richards, 2005; van Kooten and Sohngen, 2007) have yielded dramatically different cost estimates, even among studies with the same geographic scope. Direct comparison of the results is not possible because of the inconsistent use of terminology, wide ranging assumptions with respect to key parameter values, and different methodological approaches. In particular, three methods have been applied to estimating land opportunity costs, which are the most important factor influencing carbon sequestration costs: bottom-up engineering, sectoral optimization and econometric analysis. The majority of studies are bottom-up studies.

The three methods of estimating land opportunity costs may be summarized as follows. In the bottom-up approach, analysts typically base their estimates either on observed prices for land rental or land purchase, or on the revenues and costs associated with alternative land uses. Sectoral optimization models represent interactions between the forest products and agricultural markets, and are therefore able to address the problem of “leakage” associated with forest-based carbon sequestration programs. Econometric studies use historical data to characterize relationships between relative returns to alternative land uses and landowner behavior. The resulting carbon sequestration cost estimates implicitly take into account the (revealed) preferences of landowners.

Stavins (1999) argues that bottom-up engineering analyses do not portray landowner behavior in a realistic manner for a number of reasons. First, a change in land use may require an irreversible investment on the part of the landowner, and this investment may be associated with considerable uncertainty (Parks, 1995). In such cases, option value becomes an important consideration (Pindyck, 1991). Second, a

⁴⁸ This is of particular concern for tropical forests where weak regulatory institutions, corruption and the remoteness of forested areas make illegal land conversion difficult to control. See Chomitz (2007) for a discussion of the factors that contribute to forest loss in the tropics.

landowner may experience non-monetary (non-market) returns from forests (Plantinga, 1997) or agricultural land. Third, there may be a delay in the response of a landowner to economic incentives, due to liquidity constraints or “decision-making inertia.” Fourth, the analyst may be unaware of some of the (private) market costs and benefits to which the landowner is responding. Plantinga et al. (1999) also note that agricultural landowners may not possess the knowledge and skills necessary to manage forest land; becoming familiar with forestry practices therefore represents an additional cost of afforestation.

Given these concerns about the bottom-up methodology, I develop and estimate an econometric model of afforestation on private land, which I then use to simulate a hypothetical afforestation offsets program. Econometric studies of forest carbon sequestration cost have been undertaken in the US (Lubowski et al., 2006; Newell and Stavins, 2000; Plantinga et al., 1999; Stavins, 1999); however, there is a lack of this type of research for Canada. The Canadian literature is dominated by bottom-up engineering analyses (McKenney et al., 2004; van Kooten et al., 1992; van Kooten et al., 2000; Yemshanov et al., 2005). I estimate an econometric model for the Canadian province of Ontario using a backcast database of afforestation activity between 1990 and 2002 developed by the Canadian Forest Service. This is a novel application of the dataset, as far as I am aware. The results provide insight into the carbon sequestration potential at various marginal costs (offset prices), as well as the proportion of sequestration that is expected to be additional.

This paper begins with a review of afforestation programs in Ontario during the timeframe of my study in section 5.3. An understanding of these programs is necessary for the development of the econometric model and measurement of the independent variables influenced by policy, as discussed in the following two sections. In section 5.4, I provide the theoretical framework for the analysis, followed by a discussion of the empirical implementation of this theory. In section 5.5, I describe how the dependent and independent variables are measured, and provide data sources. In section 5.6, I test for statistical problems with the empirical estimation, explore remedies where such problems are identified, and discuss the corrected results. In section 5.7, I describe the hypothetical offsets program and method of simulation. Results are compared to those of studies using the bottom-up approach. I offer my conclusions in section 5.8.

5.3. Historical afforestation programs in Ontario

During my study period, which is from 1990 to 2002, changes in provincial tree planting programs are believed to have been a major influence on afforestation in Ontario (White and Kurz, 2005). A review of these policies is therefore necessary prior to developing the econometric model for this research. Puttock (2001) describes nine different programs in detail in a report prepared for the Ontario Ministry of Natural Resources (OMNR). I take into account only those programs that were exclusively focused on tree planting, or that had a large-scale tree planting component, on land owned by private individuals. I am only interested in programs that helped establish block plantations, rather than those that encouraged linear plantations, such as shelterbelts. The four programs I consider are: the Woodlands Improvement Act program, the Conservations Authorities, Project Tree Cover and the Over-The-Counter Nursery Stock Program.⁴⁹

Under the Woodlands Improvement Act, the OMNR planted trees for landowners with a minimum of 5 acres (approximately 2 hectares) available. The landowner was responsible for purchasing the trees; however, these were available at a subsidized rate from provincial nurseries. The landowner also agreed to commit the land to forest for a period of 15 years, and to provide adequate protection for the plantation. The program was extremely popular with landowners, but was phased out beginning in 1993 as a result of provincial government restructuring. Staff funding cuts and subsequent closure of the provincial nurseries contributed to the end of the program. The last year in which trees were planted under the Woodlands Improvement Act program was 1996.

As of 2001, there were 38 Conservation Authorities operating in Ontario (mostly in the southern part of the province), and more than half of these had established afforestation programs for private land. While the Woodlands Improvement Act program was in effect, the Conservation Authorities primarily assisted landowners with less than the minimum 2 hectare (ha) requirement. The cost of nursery stock was borne by the

⁴⁹ The programs I do not consider are as follows: the Agreement Forests program, agroforestry programs, the Wetland Habitat Fund, Stewardship Councils, and Ontario Power Generation's Carbon Sequestration and Biodiversity Management program.

landowner under 60% of the Conservation Authority programs, with cost-sharing under the other 40%. There were similar arrangements in place for planting costs. The Conservation Authorities obtained stock from the provincial nurseries until 1997-98, when these nurseries were closed or privatized. The closure of the provincial nurseries significantly affected the afforestation programs of the Conservation Authorities. Stock from private nurseries was costly, and there were issues with stock quality and the availability of suitable species and seed sources.

Project Tree Cover was a partnership launched in 1992 under Tree Plan Canada between the National Community Tree Foundation, Forestry Canada, the OMNR and Trees Ontario. Like the Conservation Authorities, Project Tree Cover targeted rural landowners with relatively small properties. Once the Woodlands Improvement Act program was discontinued, larger areas could also receive funding. Landowners were to contribute \$0.20 per tree planted under the program, either in cash or by performing work of equal value. Plantations could not be established primarily for commercial production, and landowners had to commit to maintain the trees for five years. Seedlings were supplied by the provincial nurseries until they were shut down, at which point seedlings were obtained privately. Trees were planted starting in 1993, but because of start-up delays the number of trees was well below the target that had been established. Over time, Project Tree Cover did not receive the expected levels of funding and support. As a result, targets for 1994 and 1995 were revised downward, and the landowner contribution was increased to \$0.35 per tree in 1996 and \$0.50 per tree in 1997. The program ended in 1997 for a number of reasons including funding constraints, staff reductions at the OMNR, closure of the provincial nurseries and difficulties coordinating the various organizations involved.

The first provincial tree nursery opened in 1905 and the last one closed in 1999. While the nurseries were in operation, landowners and public organizations were able to obtain stock at reduced prices through the Over-The-Counter Nursery Stock Program. The provincial nurseries were authorized to provide stock at a price of \$0.075 per seedling from 1988 to 1990, \$0.10 from 1991 to 1996 and \$0.28 from 1997 until the end of the nursery program. An administration fee of \$10 per order was also applied. A minimum order of 100 trees was required, increasing in multiples of 50 trees, and the minimum size of the area to be planted by an individual landowner was 2 ha. The public

nursery system ensured a continuity of supply that facilitated long-term planning and budgeting by the Conservation Authorities and provincial programs. However, the availability of stock at subsidized rates may have had a negative impact on the development of private nursery capacity, which proved to be insufficient once the provincial nurseries were shut down.

5.4. Theoretical background and empirical implementation

The theoretical model for my study is drawn from the research on non-industrial private forest management, which includes timber harvesting, timber stand improvement and reforestation. This choice with respect to theoretical basis was influenced by the data source for the dependent variable: a backcast database developed by the Canadian Forest Service in support of the Government of Canada's Feasibility Assessment of Afforestation for Carbon Sequestration (FAACS) initiative (White and Kurz, 2005). The afforestation events captured in the FAACS database typically involve abandoned farmland. Reforestation after a timber harvest is a reasonable analogue for this type of land-use change, because neither reforestation nor the afforestation of abandoned land involves the conversion of productive farmland into forest.⁵⁰

Leading econometric analyses of the cost of forest carbon sequestration develop models of land use, rather than focusing on a particular land-use change, such as afforestation. The dependent variable considered by Stavins (1999) is the change in forest land as a share of total county area available for conversion; this variable is influenced by both afforestation and deforestation. Plantinga et al. (1999) explain the allocation of land-use shares among forestry, agriculture and urban/other, and Lubowski et al. (2006) model six major private land uses. Of course, to conduct this type of analysis requires land-use data for the geographical area in question, preferably tracked over time. Stavins (1999) and Plantinga et al. (1999) derive land-use share observations from periodic surveys conducted by the US Forest Service, while Lubowski et al. (2006) rely on repeated observations at over eight hundred thousand sample points from the

⁵⁰ I use the term "reforestation" here to refer to a voluntary activity that, although possibly influenced by government policy, is not mandated by regulation.

US Department of Agriculture's National Resources Inventory. Canada has compiled periodic forest inventories; however, the system historically did not provide information on changes over time.⁵¹ Since I do not have time series data characterizing Canada's forest land base, the land-use models cited above are not an appropriate template for my analysis; however, I did review them as a check to make sure all relevant independent variables were included in my econometric specification.

Beach et al. (2005) review and synthesize the empirical literature on non-industrial private forest management, and provide a useful analytical framework for landowner behaviour based on utility-maximization theory. The theoretical model assumes that landowners make management decisions to generate optimal combinations of forest products income and non-market amenities, in such a way as to maximize their utility. These management decisions involve selecting levels of harvesting, reforestation and timber stand improvement. The factors that influence these choices are divided into four sets: market drivers (*MD*), policy variables (*PV*), owner characteristics (*OC*) and plot/resource conditions (*PR*). The reduced form determinants of reforestation (*REF*) are therefore as shown in Eq. (5.1):

$$REF = f(MD, PV, OC, PR) \quad (5.1)$$

A number of specific variables within each of the four primary categories have been used to explain reforestation behavior (Beach et al., 2005). It is also common practice for studies where the dependent variable is the area of land planted in trees (as opposed to binary choice models of the probability of reforestation taking place) to include a measure of the timber harvest volume as an independent variable (Kline et al., 2002; Li and Zhang, 2007; Sun, 2007). This variable represents the amount of land that is available for replanting.

In my analysis, the dependent variable is afforestation (*A*) on private land in Ontario, and I use the total area of farms (*FA*) to approximate the amount of land available for this activity (analogous to the timber harvest variable described above).

⁵¹ A new forest inventory system is being implemented for Canada that does take changes over time into account.

Although farm area likely underestimates to some degree the amount of land available for afforestation (since other land uses can also be converted to forest), it is a reasonable approximation. As mentioned earlier in this section, the authors of the FAACS database note that, although the scope is all afforestation on private land in Canada, the data generally reflects afforestation on abandoned agricultural land (White and Kurz, 2005). In fact, discussions of the cost of forest carbon sequestration often assume that afforestation occurs on agricultural land.⁵²

The other theoretical variables I use to explain afforestation are discussed below in the context of the four primary categories identified by Beach et al. (2005). Table 5.1 provides the expected effect of each theoretical variable on the dependent variable, along with an explanation.

Table 5.1: Expected effects of theoretical variables

Theoretical variable	Expected effect	Explanation
Farm Area (<i>FA</i>)	+	Total area of farms is an approximation of the amount of private land available for afforestation.
Planting Revenues (<i>TR</i>)	+	Higher timber revenues are expected to encourage afforestation.
Planting Expenses (<i>PE</i>)	-	Higher planting expenses are expected to discourage afforestation.
Agricultural Revenues (<i>AR</i>)	-	Higher agricultural revenues increase the opportunity cost of investing in afforestation as opposed to agriculture.
Agricultural Expenses (<i>AE</i>)	+	Higher agricultural expenses decrease the opportunity cost of investing in afforestation as opposed to agriculture.
Short-term Interest Rate (<i>STI</i>)	-	Short-term interest rates are a general measure of the opportunity cost of investing in afforestation.
Other Program Benefits (<i>PB</i>)	+	Support from government programs is expected to encourage afforestation.

⁵² For example, a summary table of forestry practices for carbon sequestration that appears in both Richards and Stokes (2004) and Stavins and Richards (2005) equates afforestation with the afforestation of agricultural land, as does the accompanying discussion.

Theoretical variable	Expected effect	Explanation
Access to Capital (<i>AC</i>)	+	Landowners with greater access to capital (and greater wealth) are expected to conduct more afforestation.
Site Quality (<i>SQ</i>)	+/-	Landowners are more likely to conduct afforestation on higher quality sites; however, higher site quality could also increase the opportunity cost of investing in afforestation as opposed to agriculture.

Market drivers are represented using five theoretical variables: tree planting (timber) revenues (*TR*), tree planting expenses (*PE*), agricultural revenues (*AR*), agricultural expenses (*AE*) and the short-term interest rate (*STI*). As in other jurisdictions, agricultural land in Ontario is subject to pressures from urban development. There is no variable in my theoretical model of afforestation that takes into account the incentives for farmers to sell their land to developers; however, such choices would be reflected in the farm area variable.

In terms of policy variables, a variable accounting for tree planting subsidies provided under the programs described in section 5.3 is not necessary, since these subsidies directly impacted planting expenses. In addition to subsidies, the historical tree planting programs provided technical expertise and made suitable planting stock available. For the programs to function effectively, they also had to have sufficient capacity to deliver service to potential participants across the province. I include a theoretical variable to account for these other program benefits (*PB*).

Income is the only owner characteristic for which the empirical literature supports an influence on reforestation; the influence is theoretically positive because landowners with higher incomes should have better access to the capital needed to conduct reforestation (Beach et al., 2005). Also, wealthier landowners may place a higher value on forests (Li and Zhang, 2007). In this analysis, I use access to capital (*AC*) directly as a theoretical variable instead of income. Per capita income in rural areas is conceptually too close to agricultural revenues. Furthermore, per capita income does not necessarily represent the income of private landowners, who are only a subset of the total population.

Plot/resource conditions for reforestation have been represented by plot size and site quality (Beach et al., 2005). Plot size is relevant in the context of replanting trees following a harvest; however, the size of the plot of trees is, by definition, undefined prior to afforestation. I include site quality (*SQ*) as a theoretical variable in my analysis.

The specific theoretical model of afforestation developed above is summarized as Eq. (5.2):

$$A = f(FA, TR, PE, AR, AE, STI, PB, AC, SQ) \quad (5.2)$$

Some changes were made to move from the theoretical model to its empirical implementation. I found agricultural revenues (*AR*) and agricultural expenses (*AE*) to be highly correlated. To avoid multicollinearity problems, I replaced these two variables with the ratio of agricultural expenses-to-revenues (*AER*).⁵³ The consequence of this change is that separate coefficients cannot be estimated for *AR* and *AE*; however, these coefficients are not necessary for my analysis. The expected impact of *AER* on afforestation is positive because as agricultural expenses increase relative to revenues, the opportunity cost of afforestation diminishes and the activity becomes more attractive.

Other program benefits (*PB*) are difficult to measure, but are represented in the empirical model using the operating budget of the Ontario Ministry of Natural Resources (*OMNR*). The operating budget of the *OMNR* is an appropriate measure of these additional benefits because funding for the *OMNR* was integral to all of the key programs considered in my analysis. “Operating budgets cover expenditures dedicated to, primarily, personnel and programs, and reflect how many people a ministry has available to carry out its mandate” (Environmental Commissioner of Ontario, 2007, p. 3). More detailed budget information would have been useful – spending on individual afforestation programs for example – but is simply not available for the timeframe of my study.

⁵³ Expenses-to-receipts ratios are also calculated by Statistics Canada and used in their financial analysis of Canadian farms (Statistics Canada, no date(b)).

Access to capital (*AC*) is represented by the average value of land and buildings owned per farm (*FV*) in the empirical model. Land and buildings can be used by a landowner as collateral to secure a mortgage. However, a number of other factors, including savings, income, debt load and other collateral, also influence access to capital. Use of farm value as a proxy for access to capital in this analysis is based on the assumption that these two variables are approximately proportional to each other.

Although site quality (*SQ*) is a theoretically important variable, it is not included in the empirical model. The FAACs database I use to provide data for the dependent variable does not describe afforestation events in terms of site quality, so this information is not available.

The implicit form of the empirical model of afforestation that I use in this study is presented as Eq. (5.3) below:

$$A = f(FA, TR, PE, AER, STI, OMNR, FV) \quad (5.3)$$

The empirical specification including the coefficients to be estimated is represented by Eq. (5.4):

$$\begin{aligned} \ln(A_{it} + 1) = & \beta_0 + \beta_1 \ln FA_{it} + \beta_2 \ln TR_t + \beta_3 \ln PE_t + \beta_4 AER_{it} + \beta_5 STI_t \\ & + \beta_6 \ln OMNR_t + \beta_7 \ln FV_{it} + c_i + \mu_{it} \end{aligned} \quad (5.4)$$

where *i* identifies the cross-sectional dimension of each panel in terms of census divisions, *t* identifies the time dimension of each panel, *c* is an unobserved intercept specific to each census division and μ is a stochastic error term. I assume a double-log relationship between the aforementioned dependent and independent variables.⁵⁴ A preliminary estimation that was linear in the variables did not perform well. The double-log form was tested next because it can accommodate some of the non-linear relationships that can be expected to exist in the real world, while still offering the

⁵⁴ The dependent variable is increased by 1 prior to taking the natural log because sometimes no afforestation is carried out.

simplicity of a model that is linear in its coefficients. Also, this functional form prevents the model from solving for a negative value of afforestation.

The empirical specification above allows the intercept to differ according to the census division. In addition to these cross-section fixed effects, I attempted to include a dummy variable in Eq. (5.4) representing census divisions in northern Ontario; however, this dummy interacted with the fixed effects dummies to produce a multicollinearity problem that prevented estimation of the equation.⁵⁵ The cross-section fixed effects account for unobserved heterogeneity, thereby preventing bias. The province of Ontario is a large geographic area that spans three ecozones⁵⁶ and includes communities with varying socioeconomic characteristics. Average site quality (SQ) is expected to vary by census division; however, this theoretical variable is not included in the empirical model. Data on planting revenues and planting expenses are only available in the time dimension of the panels, although these variables are expected to vary by census division as well. Furthermore, landowners in different regions may have different perspectives on the non-monetary value of forests compared to agricultural land; something I was not able to quantify in this analysis.

5.5. Variable measurement and data sources

The measurement of the dependent and each of the independent variables for the panel data model specified as Eq. (5.4) is discussed below, along with data sources. A more in-depth description of how I obtained data for the dependent variable from the FAACS database is provided in Appendix A. Details of the calculations and sources for the independent variables are located in Appendix B. All dollar amounts were deflated to real 2002 dollars; however, only the derivation of nominal prices is discussed in section 5.5.2 below. Table 5.2 summarizes the statistical characteristics of the variables.

⁵⁵ According to (Nautiyal et al., 1995), there are marked differences between northern and southern Ontario in terms of forest type, industrial structure and land ownership patterns.

⁵⁶ Ecozones are the largest-scale classification within the National Ecological Framework for Canada.

Table 5.2: Descriptive statistics for the dependent and independent variables

	Mean	Max	Min	St. dev.
Dependent variable				
Afforestation (ha/yr)	16.3	361.7	0	34.9
Independent variables				
Farm Area ('000 ha)	125.5	680.7	5.7	114.6
Planting Revenues (\$2002/ha/yr)	121	156	78	24
Planting Expenses (\$2002/ha/yr)				
Discount rate 5%	54	93	15	33
Discount rate 20%	185	328	43	120
Agricultural Expenses-to-Revenues (%)	88.6	149.4	75.8	9.7
Short-term Interest Rate (%)	5.7	12.8	2.6	2.6
OMNR Operating Budget ('000 000 \$2002)	546	768	366	141
Average Value per Farm ('000 \$2002)	406	1,638	171	215

As discussed below and in Appendix A, five census divisions were amalgamated to preserve records of afforestation events for which detailed geographic information is not available in the FAACS database. The amalgamation was included in the calculation of the descriptive statistics presented in Table 5.2. This explains in part why the maximum value for farm area is so much greater (more than two orders of magnitude) than the minimum value. If the amalgamation is excluded, the minimum value remains at 5.7, while the maximum value is only 297. Within the amalgamation, the maximum farm area is approximately twice the minimum farm area, and the standard deviation is only about a quarter of the size of the mean.

5.5.1. Dependent variable

The FAACS backcast database (White and Kurz, 2005) contains information on afforestation events that occurred on private land in Canada between 1990 and 2002. Data are recorded on the size of the area planted, the location of the plantation and the year the site was planted. I had initially planned to conduct my analysis on a national

scale, but decided to narrow the focus to the province of Ontario for a number of reasons. Most notably, there are data inconsistencies between provinces (missing data, data recorded in different ways and at different levels of precision),⁵⁷ and I had difficulty matching output from the version of the database I received to the data published by White and Kurz.⁵⁸ The geographical data for Ontario are available with enough precision and consistency to suit my purposes, and I was able to obtain a close match with the published results (see Appendix A). An examination of afforestation in Ontario over time (Figure 5.1) indicates a peak in 1992 followed by sharp declines in 1993, 1996 and 1998. There is a small recovery in 2001, which is maintained in 2002.

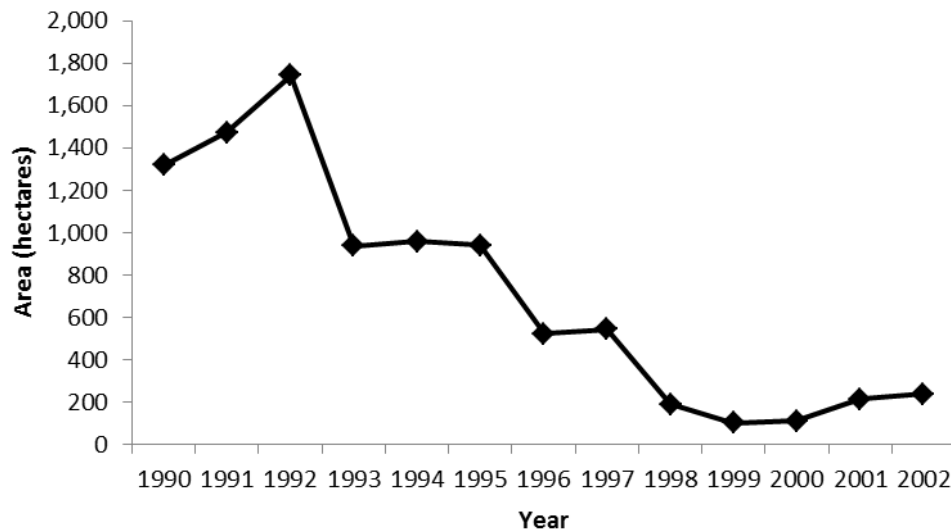


Figure 5.1: Annual area afforested in Ontario from 1990 to 2002

There were 49 census divisions in Ontario as of 2001 (the year used to define the census divisions). However, the Census of Agriculture, which is the data source for several of the independent variables, does not include the Toronto Division, and the FAACS database does not contain any records for this division either, leaving only 48 census divisions. Five census divisions were amalgamated to preserve records of afforestation events for which detailed geographic information is not available (see

⁵⁷ Data for the FAACS backcast were collected from a variety of agencies that did not necessarily share common procedures.

⁵⁸ Many years have passed since the database was compiled, and no other versions are available. Also, many key contacts have moved on to new projects and/or new positions.

Appendix A), further reducing the number of cross-sectional observations to 44. Figure 5.2 shows afforestation by census division (CD) number for each of these cross-sections, including the amalgamation (amal). The FAACS database spans the period from 1990 to 2002. Therefore, the time dimension of the panels is 13 years, and a total of 572 panel data observations on the dependent variable are available for this analysis.

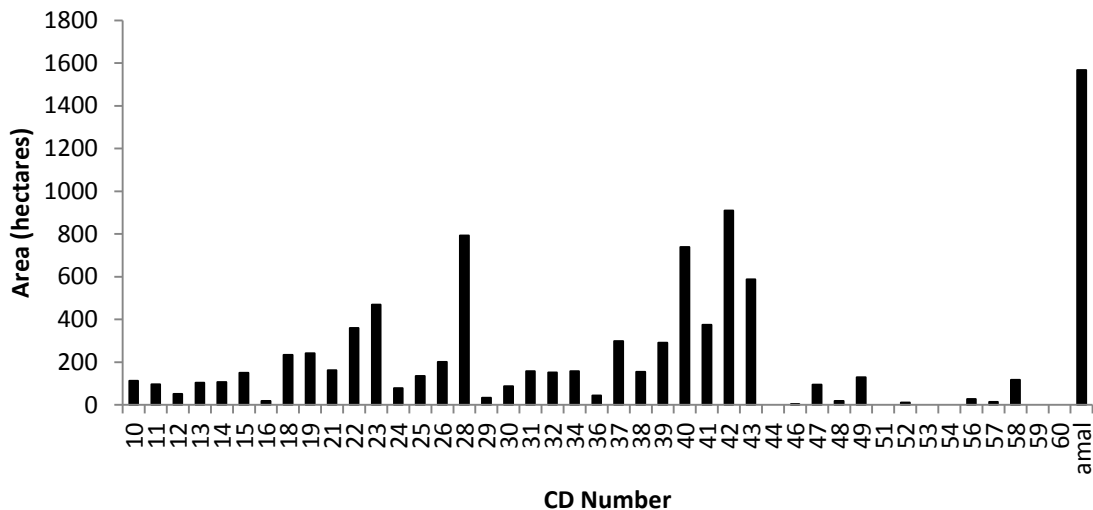


Figure 5.2: Area afforested from 1990 to 2002 in Ontario by census division

White and Kurz (2005, p. 496) provide an important caveat with respect to the data source for the dependent variable:

Most data contained in the FAACS database were collected from records maintained by agencies that sponsored afforestation on private lands – typically using public funds – and for which records have been maintained. These data provide a partial picture of afforestation activity in Canada from 1990 to 2002, and may under-represent the total area afforested during this period. It is probable that information on some privately financed efforts is missing from the dataset – particularly small plantings by private landowners that would easily escape general notice.

Since the FAACS database may underrepresent plantings that were privately financed, it seems quite plausible that wealth and access to capital, represented in the empirical model by average value per farm, could have a negative relationship with the dependent variable, rather than the positive relationship hypothesized in section 5.4. While a wealthy landowner might be expected to conduct more afforestation than

average (holding all else equal), he or she might also be expected to participate less in afforestation programs. It is easier for a wealthy landowner to privately finance their tree planting efforts, thereby avoiding application procedures, limitations on the future use of their land, and other downsides associated with obtaining agency funding. As a result, wealthy landowners may be underrepresented in the FAACS database.⁵⁹

5.5.2. *Independent variables*

To generate planting revenues, I assumed a softwood timber price of \$18/m³ in 2005 (McKenney et al., 2006), and estimated nominal prices from 1990 to 2002 from the 2005 price using a price index for softwood lumber for Ontario. The softwood price was used because softwoods account for 84% of the area planted in Ontario according to the FAACS database (White and Kurz, 2005). I then multiplied the derived softwood timber prices by an average annual growth in harvestable biomass of 6m³/ha (McKenney et al., 2006) to calculate the annual revenue per ha that a landowner would have expected from planting trees.⁶⁰ This methodology assumes that landowners base their expectations of future revenues on prices in the current year.

I derived planting expenses by estimating the cost per tree planted (seedling cost plus planting cost) from the point of view of the landowner. Most of the afforestation events in the FAACS database are associated with programs that sponsored afforestation using public funds (White and Kurz, 2005). Therefore, cost per tree was based on an analysis of the main afforestation programs in Ontario over the timeframe of the analysis, as summarized in Table 5.3.

The cost of participating in the Woodlands Improvement Act (WIA) program was equal to the price per seedling of obtaining stock from the provincial nurseries (through the Over-The-Counter Nursery Stock Program), as shown in the first row of Table 5.3. The WIA program was in place at the beginning of my study period and ended in 1996.

⁵⁹ Given this discussion, it is possible that the FAACS data exhibits selection bias. In this case, a system instrumental variables estimator, in particular a two-stage least squares estimator, is a potential remedy.

⁶⁰ The cost of harvesting and/or thinning was not taken into account in estimating planting revenues.

The cost of participating in Project Tree Cover (PTC) is given in the second row of the table. Although the program was launched in 1992, the first trees were not planted until 1993; the program ended in 1997.⁶¹

Table 5.3: Landowner cost per tree planted (nominal \$)

	1990	1991-1992	1993	1994-1995	1996	1997	1998	1999	2000-2002
WIA (provincial nurseries)	0.075	0.10	0.10	0.10	0.10	NA	NA	NA	NA
PTC	NA	NA	0.20	0.20	0.35	0.50	NA	NA	NA
Basis for <i>PE</i>	0.075	0.10	0.10	0.20	0.35	0.50	0.75	0.76	0.80

The estimate of cost per tree used as the basis for calculating planting expenses (*PE*) is provided in the third row of Table 5.3. Both the WIA program and PTC were in place from 1993 to 1996; however, I used the cost of participating in the WIA program to calculate planting expenses from 1990 to 1993 because PTC experienced start-up delays in its first year. According to OMNR Statistics and Annual Reports (as summarized by Puttock, 2001), the number of trees planted under the WIA dropped precipitously from approximately 3.59 million in 1993 to approximately 580 thousand in 1994, as the program was being phased out. Therefore, from 1994 to 1997, I used the cost of participating in PTC as the cost per tree in order to derive planting expenses. Once this program ended, I assumed landowners faced market costs for tree planting. In 1998, a market cost of \$0.75 was used as the basis for planting expenses: this was the full per unit cost associated with PTC according to Puttock (2001). From 1999 to 2002, the 1998 cost was inflated using the industry price index (producer price index) from Statistics Canada.

⁶¹ In developing my estimate of the cost of per tree planted, I did not include the cost of participating in the tree planting programs of the Conservation Authorities. The Conservation Authority programs were in operation at the same time as the WIA and PTC programs, and targeted the same group of landowners as PTC. Also, each Conservation Authority designed its own afforestation program, and data on the specific planting costs and cost-sharing arrangements are no longer available going back to 1990.

I derived annual planting expenses per ha from the cost per tree by assuming a planting density of 2,000 seedlings per ha, and annualizing the up-front planting costs (deflated to \$2002) over a 50-year rotation period. Real discount rates of 5% (social discount rate) and 20% (personal discount rate) were tested.⁶² After annualizing the up-front costs, I added an annual cost of \$5 per ha to represent the costs of tending and managing a plantation (Yemshanov et al., 2005).

Measurement of the other independent variables is more straightforward. Total area of farms, the ratio of agricultural expenses-to-revenues, and average value per farm are either calculated from or based directly on data collected by Statistics Canada's Census of Agriculture. The short-term interest rate is measured by Canadian 3-month treasury bill rates, as reported by Statistics Canada. The operating budget of the OMNR is from the Public Accounts of the Ontario Ministry of Finance.

The operating budget of the OMNR is highly (negatively) correlated with planting expenses (Table 5.4). This is not surprising, since both variables are influenced by government policy. Despite the apparent multicollinearity, I retained both variables due to their theoretical importance. It is sometimes possible to address multicollinearity by combining variables; however, in this case, there was no sensible way to do so. Also, the effects of planting expenses and program spending had to be kept separate in order to perform the simulations reported in section 5.7.

⁶² Discount rates in the range of 5% have been applied in bioeconomic models of afforestation (e.g. McKenney et al., 2006; Yemshanov et al., 2007) and forest carbon sequestration cost studies (Richards and Stokes, 2004). Warner and Pleeter (2001) review past studies of the personal discount rate: "the rate at which individuals trade current for future dollars" (p. 33). These rates are generally very high, but decrease with the sum of money involved and the time delay. The literature on the personal discount rate does not provide a clear analogue for afforestation (many studies focus on either household appliance purchases or decisions with respect to lump sum payments or retirement plans); therefore, the 20% discount rate should be viewed simply as a sensitivity test for this higher class of discount rates.

Table 5.4: Simple correlation coefficients between the independent variables

	$\ln FA_{it}$	$\ln TR_t$	$\ln PE_t$ 5%	$\ln PE_t$ 20%	AER_{it}	STI_t	$\ln OMNR_t$	$\ln FV_{it}$
$\ln FA_{it}$	1							
$\ln TR_t$	0.003	1						
$\ln PE_t$ 5%	-0.009	0.462	1					
$\ln PE_t$ 20%	-0.008	0.476	NA	1				
AER_{it}	-0.576	0.136	0.158	0.159	1			
STI_t	0.005	-0.758	-0.711	-0.720	-0.147	1		
$\ln OMNR_t$	0.009	-0.507	-0.926	-0.926	-0.151	0.742	1	
$\ln FV_{it}$	0.362	-0.048	0.011	0.009	-0.372	0.005	-0.013	1

Note: Planting expenses ($\ln PE_t$) are included in the correlation matrix twice, according to which discount rate was used to annualize the up-front costs. The correlation coefficient between $\ln PE_t$ 5% and $\ln PE_t$ 20% is not relevant because these two variables are never included in the same equation.

5.6. Empirical estimation

5.6.1. Nonstationarity

Prior to estimating Eq. (5.4), I tested for nonstationarity due to a unit root. Nonstationarity is of concern because the panels have a time dimension; variables may therefore follow a random walk through time (i.e. have a unit root). Nonstationarity can result in spurious correlation(s) between a nonstationary dependent variable and any independent variables that are also nonstationary, leading to an inflated R^2 and t-values. I tested the dependent variable (natural log transformed) for nonstationarity due to a unit root by conducting a suite of panel unit root tests, the results of which are summarized in Table 5.5.⁶³ All of the tests reject the null hypothesis of a unit root at the 5% significance level.

⁶³ The statistical software package used in this analysis is EViews (version 7.2).

Table 5.5: Results of panel unit root tests

Method	Statistic	Probability
Common root		
Levin, Lin, Chu	-4.881	0.000
Individual root		
Im, Pesaran, Shin	-2.177	0.015
Fisher – ADF	102.679	0.010
Fisher – PP	119.080	0.000

Note: The unit root tests were computed on the levels of the series. Individual fixed effects were included as exogenous regressors in the test equation. For tests that perform regressions on lagged difference terms, lag length was automatically selected according to the Schwarz criterion (no maximum was specified). For tests that are based on kernel weighting, the kernel type was Bartlett and the bandwidth was selected automatically according to the Newey-West method.

5.6.2. Serial correlation

Given the results of the unit root tests, I proceeded to estimate Eq. (5.4) using the panel fixed effect methodology. I tested for serial correlation by running a regression in which the dependent variable is composed of the residuals (estimated error terms) from the initial estimation and the independent variables are the residuals lagged by one and two time periods.⁶⁴ The estimated coefficient on the residual lagged by one time period is significant at the 1% level, indicating that serial correlation is a problem in Eq. (5.4).

I attempted to correct for serial correlation by adding a simple time trend as an independent variable to Eq. (5.4). The results of the estimation are reported in Table

⁶⁴ My test is based on the simple test for serial correlation suggested by Wooldridge (2010, pp. 198-199). The results in the form of the equation are as follows for a discount rate of 5%:

$$\hat{\mu}_{it} = -0.004 + 0.274^{***} \hat{\mu}_{it-1} - 0.015 \hat{\mu}_{it-2},$$

(-0.104) (6.071) (-0.328)

No. obs. = 484 Adj. R² = 0.072

and a discount rate of 20%:

$$\hat{\mu}_{it} = -0.004 + 0.274^{***} \hat{\mu}_{it-1} - 0.015 \hat{\mu}_{it-2},$$

(-0.107) (6.075) (-0.346)

No. obs. = 484 Adj. R² = 0.072

5.6. The coefficient on the time trend variable is not significant at the 10% level; therefore, I failed to reject the null hypothesis of no time trend and concluded that adding a time trend is not an appropriate remedy for serial correlation in this case. This result further indicates that Eq. (5.4) does not suffer from nonstationarity due to an underlying time trend.

Table 5.6: Estimation results with time trend (panel fixed effects)

	Discount rate 5%	Discount rate 20%
Constant	20.135 (1.245)	19.686 (1.216)
$\ln FA_{it}$	-0.937 (-0.791)	-0.928 (-0.782)
$\ln TR_t$	-0.130 (-0.377)	-0.129 (-0.370)
$\ln PE_t$	-0.561*** (-2.792)	-0.472*** (-2.580)
AER_{it}	-0.004 (-0.254)	-0.003 (-0.244)
STI_t	-0.033 (-0.904)	-0.037 (-1.004)
$\ln OMNR_t$	0.528 (1.139)	0.559 (1.207)
$\ln FV_{it}$	-1.174*** (-3.906)	-1.176*** (-3.903)
T_t	-0.036 (-0.703)	-0.043 (-0.831)
No. obs.	572	572
Adj. R ²	0.682	0.681

* significant at 10%, ** significant at 5%, *** significant at 1%. t-values in parentheses.

To obtain results corrected for serial correlation, I reran the initial estimation with the White period standard errors and covariance correction (d.f. corrected). The results are shown in Table 5.7, according to the (real) discount rate used to annualize up-front planting expenses (columns 1 and 3). The estimated coefficient covariance matrix is of

reduced rank for the White correction due to the relatively small cross-sectional dimension of the panel.

Table 5.7: Estimation results (panel fixed effects)

	Discount rate 5%		Discount rate 20%	
	Correct SC 1.	Correct hetero. 2.	Correct SC 3.	Correct hetero. 4.
Constant	15.656 (0.701)	(1.076)	14.351 (0.644)	(0.933)
ln FA _{it}	-0.852 (-0.384)	(-0.811)	-0.823 (-0.370)	(-0.778)
ln TR _t	-0.001 (-0.002)	(-0.002)	0.029 (0.067)	(0.074)
ln PE _t	-0.660*** (-4.136)	-0.660*** (-2.528)	-0.579*** (-3.972)	-0.579** (-2.299)
AER _{it}	-0.005 (-0.188)	(-0.470)	-0.005 (-0.188)	(-0.473)
STI _t	-0.018 (-0.502)	(-0.515)	-0.019 (-0.526)	(-0.530)
ln OMNR _t	0.693** (2.272)	0.693* (1.522)	0.758*** (2.472)	0.758* (1.556)
ln FV _{it}	-1.194*** (-3.270)	-1.194*** (-2.665)	-1.200*** (-3.280)	-1.200*** (-2.677)
No. obs.	572		572	
Adj. R ²	0.682		0.681	

* significant at 10%, ** significant at 5%, *** significant at 1%. t-values in parentheses.

5.6.3. Heteroskedasticity

Heteroskedasticity is likely to be a problem in this analysis because the standard deviation of the dependent variable is large relative to the mean (Table 5.2). The area afforested by census division exhibits a wide range, and this is exacerbated by the amalgamation of five census divisions (due to a lack of precise geographic information for a number of records, see Appendix A). The variance of the errors may be higher for cross-sections with a larger land area, or, more specifically, a larger land area available for afforestation, which is measured by total area of farms in this analysis. A scatter plot

of the residuals from Eq. (5.4) against farm area, shown in Figure 5.3, suggests that heteroskedasticity is present, but that the residuals are, in fact, contracting as farm area increases.⁶⁵ The data points at the far right of the figure represent the amalgamation referred to above. The residuals may be contracting because census divisions with a larger agricultural base had better systems in place for recording afforestation activity during my study period.

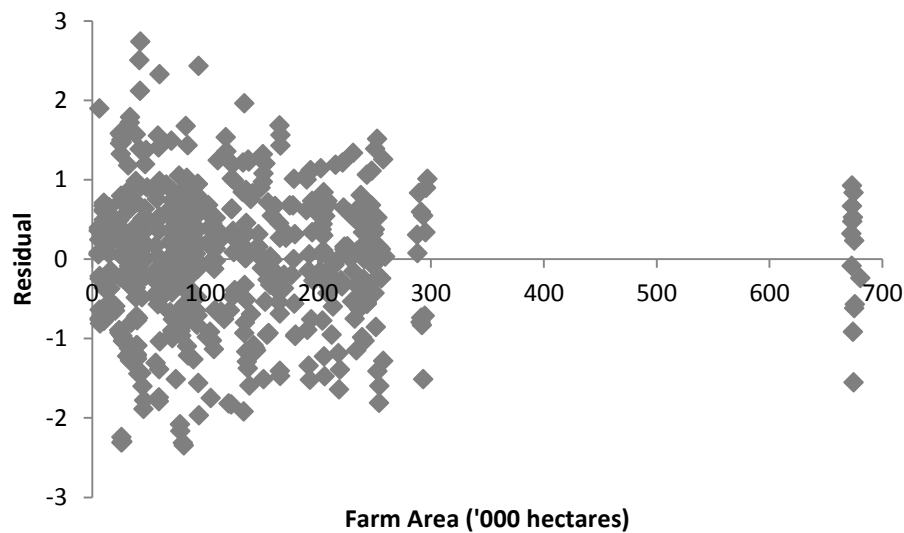


Figure 5.3: Visual inspection of the residuals for heteroskedasticity

To obtain results corrected for heteroskedasticity, I reran the initial estimation with the White cross-section standard errors and covariance correction (d.f. corrected). The results are reported in columns 2 and 4 of Table 5.7. Only the t-values are reported, because estimated coefficients are unaffected by the White corrections.⁶⁶ I also attempted to correct for heteroskedasticity using a polynomial specification in which the ratio of agricultural expenses-to-revenues (*AER*) and the average value per farm (*FV*) are squared, as in Eq. (5.5):

⁶⁵ The residuals in Figures 5.3 and 5.4 are from the 5% discount rate test; however, the pattern is very similar for the 20% discount rate.

⁶⁶ Changes in the t-values were observed relative to the initial estimation (without correction of the standard errors), confirming that some heteroskedasticity is present in Eq. (5.4).

$$A_{it} = \beta_0 + \beta_1 FA_{it} + \beta_2 TR_t + \beta_3 PE_t + \beta_4 AER_{it} + \beta_5 (AER_{it})^2 + \beta_6 STI_t + \beta_7 OMNR_t + \beta_8 FV_{it} + \beta_9 (FV_{it})^2 + c_i + \mu_{it} \quad (5.5)$$

The ratio of agricultural expenses-to-revenues is expected to have a positive influence on afforestation because as agricultural expenses increase relative to revenues, the opportunity cost of afforestation is reduced. However, after a certain point, decreasing profits (or increasing losses) from agriculture could threaten the finances of rural landowners and discourage spending on afforestation. Under this hypothesis, β_4 would have a positive sign and β_5 would have a negative sign, resulting in an inverted U-shaped relationship between afforestation and the expenses-to-revenues ratio.

The average value per farm is also expected to have a positive impact on afforestation, since the owners of more valuable farms have greater access to the capital needed to conduct afforestation. However, as noted in section 5.5.1, the FAACS database essentially represents the area planted under afforestation subsidy programs, and may underestimate total afforestation. The owners of the most valuable farms may choose to conduct afforestation using their own private funds. Since these plantings might not be included in the database, the relationship between afforestation and farm value could also have an inverted U shape, with β_8 expected to be positive and β_9 expected to be negative.

The results of the estimation using the polynomial specification are given in Table 5.8. The estimation output is very similar regardless of the discount rate used to annualize up-front planting expenses. Although all of the estimated coefficients are significant at the 10% level, only the coefficients on planting expenses (PE), the short-term interest rate (STI) and the operating budget of the OMNR are of the expected sign. In particular, the coefficients on the polynomial variables are highly significant with unexpected signs. Furthermore, the residuals from the polynomial specification still exhibit heteroskedasticity (Figure 5.4), although this time they appear to be expanding as farm area increases. I therefore concluded that the polynomial specification tested is not an appropriate means of correcting for heteroskedasticity in this case.

Table 5.8: Estimation results using polynomial specification (panel fixed effects)

	Discount rate 5%	Discount rate 20%
Constant	590.916*** (5.166)	590.267*** (5.161)
FA _{it}	-0.001*** (-2.794)	-0.001*** (-2.794)
TR _t	-0.114* (-1.581)	-0.114* (-1.581)
PE _t	-0.185*** (-2.379)	-0.051*** (-2.379)
AER _{it}	-6.671*** (-3.490)	-6.671*** (-3.490)
(AER _{it}) ²	0.028*** (3.321)	0.028*** (3.321)
STI _t	-1.556** (-2.093)	-1.556** (-2.093)
OMNR _t	0.000* (1.490)	0.000* (1.490)
FV _{it}	-0.000*** (-3.587)	-0.000*** (-3.587)
(FV _{it}) ²	0.000*** (2.855)	0.000*** (2.855)
No. obs.	572	572
Adj. R ²	0.540	0.540

* significant at 10%, ** significant at 5%, *** significant at 1%. t-values in parentheses.

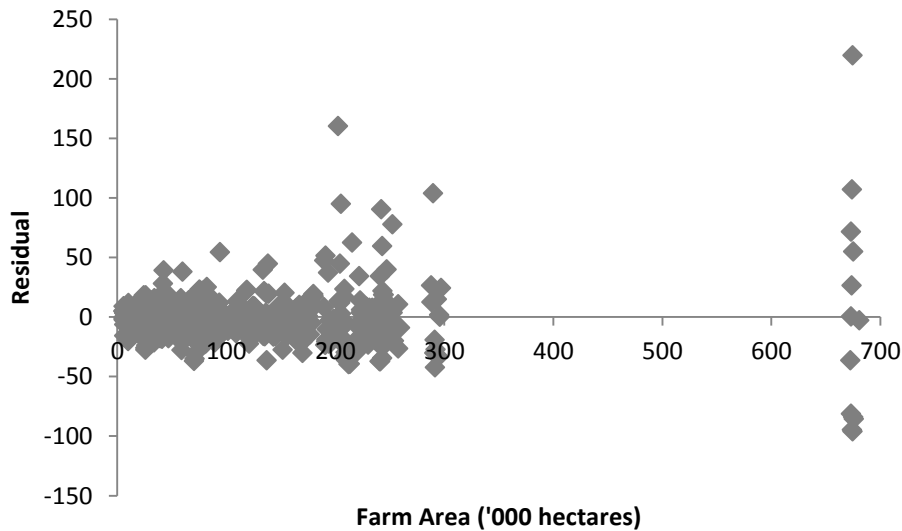


Figure 5.4: Heteroskedasticity in the polynomial specification

To address the heteroskedasticity problem, I considered redefining the dependent variable as the percentage of available land afforested, approximated by dividing the total area afforested by the total area of farms. This would eliminate the natural log of farm area as an independent variable, and would control for heteroskedasticity due to the amalgamation of census divisions. I decided against this change; however, on the basis that the dependent variable would potentially be distorted. Although farm area is a reasonable measure of the amount of land available for afforestation, it is not a perfect measure, since some afforestation must also have occurred on non-agricultural land.

I did not take further steps to correct for heteroskedasticity because: 1) the t-values estimated with the White correction for heteroskedasticity are generally quite close in magnitude to those from the initial estimation, and 2) serial correlation is likely to be more important than heteroskedasticity in certain applications of panel data models (Wooldridge, 2010). The coefficients reported in Table 5.7 must be interpreted with caution due to the reduced rank problem with the serial correlation correction, and the fact that I was not able to correct for both serial correlation and heteroskedasticity at the same time.

5.6.4. Multicollinearity

Imperfect multicollinearity is of concern in this analysis because, as noted in section 5.5.2, the operating budget of the OMNR is highly (negatively) correlated with planting expenses ($r = -0.926$). Imperfect multicollinearity is not a violation of the classical assumptions of ordinary least squares, and is not expected to severely undermine forecasting, as long as the multicollinearity in the forecast data is similar to the multicollinearity in the sample data used for estimation. However, in section 5.7 (below), I perform simulations in which planting expenses vary, while the operating budget of the OMNR is held constant.

To investigate the potential impact of multicollinearity between planting expenses (*PE*) and the operating budget of the OMNR (*OMNR*), I removed each of these explanatory variables in turn and reran the estimation. The results, which are reported in Appendix C, suggest that the multicollinearity may have had a substantial impact on the estimated coefficients. In particular, when the explanatory variable *PE* is removed, the (positive) coefficient on *OMNR* becomes much larger, and is of greater significance with the discount rate set at 5%. When the explanatory variable *OMNR* is removed, the absolute value of the (negative) coefficient on *PE* increases as well. The potential impact of multicollinearity on the simulation results is discussed in section 5.7.4.

5.6.5. Estimation results

Returning to the results corrected for serial correlation in columns 1 and 3 of Table 5.7, the estimated coefficients on the variables measuring the impact of government policy – planting expenses (*PE*) and the operating budget of the OMNR – are significant at the 1% and 5% level, respectively, and are both of the expected sign.⁶⁷ The elasticity of afforestation with respect to planting expenses is estimated to be approximately -0.66 for the 5% discount rate and -0.58 for the 20% discount rate, holding the other independent variables constant. The elasticities of afforestation with respect to the operating budget of the OMNR are estimated at 0.69 and 0.76 for the 5%

⁶⁷ This result was obtained despite evidence of severe multicollinearity between these two variables.

and 20% discount rates, respectively. The estimated coefficient on the short-term interest rate (*STI*) is negative, as expected, but is not significant. For farm area (*FA*), planting (timber) revenues (*TR*) and the ratio of agricultural expenses-to-revenues (*AER*), the estimated coefficients have unexpected signs when the discount rate is set at 5% (the sign for planting revenues is as expected at the 20% discount rate); however, none are even weakly significant. The estimated coefficient on the average value per farm (*FV*) is significant at the 1% level and has an unexpected sign. The adjusted R^2 of the equation is 0.682 when the discount rate is set at 5%, and is almost unchanged at 0.681 when the discount rate is 20%.

There are plausible explanations for the lack of significance in the estimated model. The correlation matrix presented in Table 5.4 suggests there is relatively strong multicollinearity (below 0.8 but above 0.7) between the short-term interest rate and planting revenues, as well as between the interest rate and planting expenses. This may have contributed somewhat to the insignificant coefficients and unexpected signs.

Farm area is not found to have a significant (positive) impact on afforestation, despite being an approximation of the amount of private land available for this activity. A possible explanation may be that the area afforested in Ontario during my study period represented only a tiny fraction of the total farm area in the province. According to the FAACS database, the total area afforested between 1990 and 2002 was some 9,297 ha, which was about a fifth of a percent of the available farm area.⁶⁸ Since such a small percentage of farm area was actually afforested, even census divisions with small farm areas could have accommodated relatively large amounts of afforestation, given the right circumstances.

Planting revenues are also not found to have a significant (positive) relationship with afforestation. Theoretically, landowners should factor planting revenues into their land-use decisions. In the case of afforestation in Ontario during my study period, however, there is evidence that landowners were, for the most part, not interested in harvesting the trees they planted. An Environics Research Group (2003) survey asked a

⁶⁸ Total farm area changes slightly from year to year; the 9,297 ha afforested in Ontario between 1990 and 2002 was just under 0.20% of the total farm area in the province, as measured in any year during the study period.

sample of farmers who had conducted afforestation on their land between 1990 and 2002 their reasons for doing so. In Ontario, 65% of respondents listed “aesthetics,” “conservation and wildlife habitat” or “improve water and soil” as their purpose. An additional 18% were creating shelterbelts. Only 18% cited “commercial wood supply.” If landowners were primarily concerned with non-monetary forest amenities rather than revenues from various alternative investments, this could explain the insignificant coefficients on the short-term interest rate and the ratio of agricultural expenses-to-revenues as well.

Another reason why the landowners in my study may not have considered revenues from timber harvesting is that many of the afforestation programs in place during the 1990s required an agreement to maintain the forest for a set period of time. The Woodlands Improvement Act program, for example, required land to be committed to forest for 15 years. It is also possible that landowners do not appear to take planting revenues into account because they apply high discount rates to future benefits. However, even when a 20% personal discount rate is used to calculate annualized planting costs, the estimated coefficient on planting revenues is still not significant (although the sign is now positive, as expected).

The highly significant (negative) unexpected sign on average value per farm could be due to the fact that the FAACS database does not necessarily represent all of the afforestation that took place on private land in Ontario during my study period. The database potentially underrepresents plantings by wealthy individuals with access to large amounts of capital, measured in this case by the average value per farm (see discussion in section 5.5.1). The unexpected sign could also be the result of unobserved heterogeneity in the time dimension of the panels caused by an omitted variable.⁶⁹ In particular, an omitted variable that is expected to have a positive coefficient but that is negatively correlated with average value per farm over time, or one that is expected to have a negative coefficient but that is positively correlated with average value per farm, could be the cause. Based on the literature review, all relevant

⁶⁹ Unobserved heterogeneity between census divisions is already accounted for by the cross-section fixed effects. It was not possible to include time fixed effects in my model. Estimation using time fixed effects dummies (even without cross-section fixed effects) produced a multicollinearity problem that prevented estimation of the equation.

independent variables that can be measured are included in my analysis; however, I considered additional variables highlighted in analysis of the 2006 Census of Agriculture by Statistics Canada.

Land rental has been increasing over several censuses in Canada (Statistics Canada, no date(a)), as has the (real) value of land and buildings owned per farm in Ontario, suggesting a positive correlation. Since neither landowners nor tenants are likely to invest in planting trees on rented land, the expected coefficient on a variable measuring land rental is negative, making it a candidate for correcting the potential bias. I used data from the Census of Agriculture to calculate the percentage of total farm area that was rented or leased (*RL*) in Ontario during my study period, and added this as an independent variable to Eq. (5.4), resulting in Eq. (5.6):

$$\ln(A_{it} + 1) = \beta_0 + \beta_1 \ln FA_{it} + \beta_2 \ln TR_t + \beta_3 \ln PE_t + \beta_4 AER_{it} + \beta_5 STI_t + \beta_6 \ln OMNR_t + \beta_7 \ln FV_{it} + \beta_8 RL_{it} + c_i + \mu_{it} \quad (5.6)$$

The estimation results are reported in Table 5.9 (columns 2 and 5). The coefficient on the rent or leased variable has an unexpected (positive) sign, and is not even remotely significant. The problem of the highly significant (negative) unexpected sign on average value per farm is not resolved. Therefore, I did not include the new variable in further estimations.

Table 5.9: Estimation results with *RL* and *M* added (panel fixed effects)

	Discount rate 5%			Discount rate 20%		
	Initial estimate 1.	Add <i>RL</i> 2.	Add <i>M</i> 3.	Initial estimate 4.	Add <i>RL</i> 5.	Add <i>M</i> 6.
Constant	15.656 (0.701)	15.611 (0.706)	27.531 (1.134)	14.351 (0.644)	14.335 (0.650)	27.466 (1.132)
$\ln FA_{it}$	-0.852 (-0.384)	-0.863 (-0.373)	-1.165 (-0.522)	-0.823 (-0.370)	-0.826 (-0.356)	-1.168 (-0.524)
$\ln TR_t$	-0.001 (-0.002)	0.001 (0.002)	-0.438 (-0.891)	0.029 (0.067)	0.030 (0.068)	-0.451 (-0.925)
$\ln PE_t$	-0.660*** (-4.136)	-0.663*** (-3.961)	-0.550*** (-3.153)	-0.579*** (-3.972)	-0.580*** (-3.796)	-0.473*** (-2.998)

	Discount rate 5%			Discount rate 20%		
	Initial estimate 1.	Add <i>RL</i> 2.	Add <i>M</i> 3.	Initial estimate 4.	Add <i>RL</i> 5.	Add <i>M</i> 6.
AER_{it}	-0.005 (-0.188)	-0.005 (-0.181)	-0.005 (-0.190)	-0.005 (-0.188)	-0.005 (-0.187)	-0.005 (-0.191)
STI_t	-0.018 (-0.502)	-0.017 (-0.477)	-0.044 (-1.198)	-0.019 (-0.526)	-0.018 (-0.506)	-0.047 (-1.277)
$\ln OMNR_t$	0.693** (2.272)	0.697** (2.120)	0.346 (1.001)	0.758*** (2.472)	0.759** (2.298)	0.370 (1.063)
$\ln FV_{it}$	-1.194*** (-3.270)	-1.191*** (-3.088)	-1.112*** (-2.973)	-1.200*** (-3.280)	-1.199*** (-3.105)	-1.110*** (-2.962)
RL_{it}	NA	0.002 (0.026)	NA	NA	0.001 (0.009)	NA
M_t	NA	NA	-0.440* (-1.504)	NA	NA	-0.479** (-1.656)
No. obs.	572	572	572	572	572	572
Adj. R^2	0.682	0.681	0.682	0.681	0.680	0.682

* significant at 10%, ** significant at 5%, *** significant at 1%. t-values in parentheses. White period standard errors and covariance correction (d.f. corrected).

The number of million dollar farms in Canada (at real prices) is also increasing, and these farms are more likely to be incorporated operations (Statistics Canada, no date(b)). It can be hypothesized that the operators of large, corporately run farms are less inclined to engage in tree planting than are the owners of smaller, unincorporated farms. This would be the case if the corporate operators are less interested in alternative sources of revenue and/or the non-monetary values of forests. A variable representing the percentage of million dollar farms would therefore have a negative expected sign, and could also correct the problem. Information on the percentage of farms in Ontario with total gross receipts of one-million dollars or more is available from the Census of Agriculture. I tested the percentage of million dollar farms (M) as an independent variable, according to Eq. (5.7):⁷⁰

⁷⁰ Million dollar farms data are available by census division, but only as a custom tabulation from Statistics Canada. Due to cost considerations, only the time dimension of the variable was used in the estimation.

$$\ln(A_{it} + 1) = \beta_0 + \beta_1 \ln FA_{it} + \beta_2 \ln TR_t + \beta_3 \ln PE_t + \beta_4 AER_{it} + \beta_5 STI_t + \beta_6 \ln OMNR_t + \beta_7 \ln FV_{it} + \beta_8 M_t + c_i + \mu_{it} \quad (5.7)$$

In the new estimation (Table 5.9, columns 3 and 6), the coefficient on the million dollar farms variable is negative as expected, but is significant at the 5% level only when the discount rate used to annualize planting expenses is set at 20% (it is significant at the 10% level when the discount rate is set at 5%). The coefficient on average value per farm is still negative, highly significant and of similar magnitude. Furthermore, the million dollar farms variable is highly correlated with the operating budget of the OMNR ($r = -0.878$), leading to a lack of significance for the latter variable. Because the million dollar farms variable is not significant at the standard level for both discount rates, does not fix the unexpected sign, introduces multicollinearity and is not supported by the theoretical literature, I did not include it in further estimations.

There is one final interpretation of the significant unexpected sign on average value per farm that is worth considering. Average value per farm is the product of average land value (per ha) and average farm size (ha). The expected impact of land value on tree planting is ambiguous because land can represent both an input to timber production (less tree planting as land values increase) and an alternative to plantations (more tree planting as land values increase) (Lee et al., 1992; Kline et al., 2002). If the impact is negative in this case, it is possible that land value, as a component of value per farm, is influencing the estimated coefficient to produce the unexpected sign. It seems unlikely, however, for a factor whose impact is ambiguous to result in a coefficient of the magnitude and significance observed here.

5.7. Simulation of a hypothetical offsets program

In this section, I describe the procedure used to simulate a hypothetical afforestation offsets program; report results in terms of carbon sequestration potential, cost and additionality; and investigate the potential impact of multicollinearity. The results presented here are subject to simulation error, especially given the problems encountered with the empirical estimation – insignificant coefficients, unexpected signs, multicollinearity, and difficulties correcting for serial correlation and heteroskedasticity.

As discussed in section 5.5.1, the data source for the dependent variable may underrepresent plantings that were privately financed (as opposed to subsidized by afforestation programs). The policy tested in the simulation is not the same as the policies that were in place during the time frame of the econometric analysis (some of these issues are discussed below). Also, the data used in the empirical estimation are from some time ago, and the parameters may not be accurate given changes in policy (e.g. agricultural policies and subsidies) and other factors that have occurred or that may occur in the future. Despite such issues, this study is illustrative of the econometric approach to evaluating the potential for forest carbon sequestration in Canada. Better data would help to further define the numerical results presented below; however, the results as they are provide information on the magnitude of carbon sequestration potential and cost relative to bottom-up studies, and suggest that we should not dismiss additionality as a concern when considering forest carbon offsets.

5.7.1. Simulation procedure

I used the econometrically estimated coefficients in columns 1 and 3 of Table 5.7 to simulate a hypothetical carbon offsets program for Ontario. The program is open to new afforestation projects on private land for 20 years, and projects that qualify are awarded offset credits on an annual basis for up to 50 years. I tested a range of offset prices starting at \$10/tonne carbon (\$2002) and increasing in \$10 increments. These offset prices are equivalent to permit prices if the offsets are part of an emissions cap and tradable permits program. Offset prices are assumed to remain constant through time. The offsets simulation results are evaluated relative to a base case scenario in which offsets are not awarded for afforestation projects.

In the simulations, offsets revenues were used to reduce annualized planting expenses (PE). The natural way to have simulated the offsets program using Eq. (5.4) would have been by increasing the annual planting (timber) revenues (TR) variable. However, the estimated coefficient on this variable is not significant, possibly because landowners were not interested in harvesting. My methodology therefore rests on the assumption that landowners react to an increase in revenues in the same way as an equivalent decrease in expenses. Furthermore, since offsets revenues are acquired on an annual basis, while the seedling cost and planting cost components of planting

expenses are incurred up-front, the choice of discount rate is paramount.⁷¹ I provide simulation results based on the two estimations described in section 5.6: one applying a social discount rate of 5% and the other a personal discount rate of 20%.

I assume my hypothetical offsets system is implemented under conditions similar to those that existed during the timeframe of the econometric analysis (1990 to 2002). Therefore, average values are used for all the variables in the simulation, except those influenced by government policy. For planting expenses, the base case value (assuming no offsets revenues) is set to correspond to the market planting cost of \$0.80 per tree (\$2002), experienced once the main provincial programs subsidizing afforestation had ended (see Table 5.3). Different values for total (annualized) planting expenses are used according to the discount rate.

In my simulations, instead of using the average value for the operating budget of the OMNR calculated over the entire simulation period, I use the average value over the five years between 1998 and 2002, after the phase-out of the main provincial afforestation programs. The operating budget of the OMNR is included in the analysis to represent other benefits of these provincial programs, in addition to afforestation subsidies. Other benefits include the provision of technical expertise, the availability of suitable planting stock and the capacity to deliver services to participants. In simulating a hypothetical afforestation offsets program, I did not want to assume that these other benefits would be provided, primarily because it would no longer be possible to interpret offset prices as representing marginal costs of forest carbon sequestration. In order to derive marginal costs, the cost of providing the additional benefits would have to be estimated and factored into the analysis. Since I only have information on the operating budget of the OMNR in its entirety – rather than information detailing spending on afforestation programs in particular – these calculations would not have been possible.

In order to calculate offsets revenues (and adjust base case planting expenses) according to the offset price, information is required on carbon sequestration rates for

⁷¹ Planting expenses also include an estimate of the annual cost of tending and managing a plantation (see section 5.5.2 above).

forest plantations.⁷² Carbon sequestration potential depends on several factors not specified in my analysis, including site quality, tree species and management regime. Carbon is stored in a number of components within a forest ecosystem (tree trunks, branches, leaves, roots, soils, litter and understory), and previous studies vary in terms of which of these components are included (Richards and Stokes, 2004). Actual sequestration may differ from what was expected due to fire and pest outbreaks. Finally, different assumptions regarding carbon sequestration on agricultural land influence how much of the forest carbon sequestration is counted as additional. To address uncertainty with respect to carbon sequestration, I tested the following four rates: one, two, five and ten tonnes carbon per ha per year.⁷³

To estimate carbon sequestration potential, the sequestration rates described above were also applied to the simulated afforestation outcomes. In each of the 20 years that afforestation projects are accepted under the hypothetical offsets program, a new cohort of tree plantations is established. In my simulation model, the total area planted is the same in every year, because the values for the independent variables are unchanged.⁷⁴ I assume that a new forest plantation captures carbon at the specified sequestration rate for at least 50 years, which implies no harvesting by the landowner over this period. The assumption regarding harvesting is not unreasonable, given that my econometric analysis suggests landowners were not particularly interested in harvesting. Also, the afforestation offsets program may require landowners to commit their land to forest for a period of time. In reality, however, the rate of carbon sequestration would vary over time for a given plantation, even without harvesting. Different profiles of carbon flows are observed according to tree species and region (Richards and Stokes, 2004). Therefore, the carbon sequestration rates I tested should

⁷² I use the same sequestration rates to calculate offsets revenues as I do to estimate carbon sequestration from the simulated afforestation outcomes (see the following paragraph). In doing so, I implicitly assume that those administering the offsets program have perfect information with respect to carbon sequestration.

⁷³ Sequestration rates range from two to ten tonnes/ha/yr for most US studies of forest carbon sequestration cost (Richards and Stokes, 2004; Stavins and Richards, 2005). I include the rate of one tonne/ha/yr to reflect lower expected growth rates in Canadian forests. The ten tonnes rate is probably unlikely, but was included to cover the potential for the development of faster growing clones.

⁷⁴ To simulate total area planted in Ontario in a given year, I multiplied the output of Eq. (5.4) by 44 because there are 44 cross-sections in my analysis.

be thought of as “average” rates calculated using a discounting/levelization methodology similar to that which is described below (in the context of calculating an “average” value for total annual carbon sequestration).

I tested three different scenarios with respect to what happens to the carbon sink established by a cohort of tree plantations after 50 years. In the first scenario (which I have named “augment”), the trees are not harvested and carbon continues to accumulate at the same rate as before. I track this accumulation until the last cohort reaches the age of 50 (in the 69th and final year of the program). In the second scenario (“release”), harvest occurs once the cohort reaches age 50 and all the stored carbon is released; there is no replanting.⁷⁵ The third scenario (“maintain”) represents an intermediate between these two extremes: carbon does not continue to accumulate after 50 years, but is not released either. One might assume the trees are harvested to manufacture long-lived products that maintain the carbon sink, at least until far enough into the future that discounting of carbon flows (see discussion below) makes the release negligible.

The carbon sequestration rate is the same across cohorts and through time; therefore, the amount of carbon captured per cohort per year does not vary for a given sequestration rate up to the age of 50. However, because a new cohort is added in each year, the sum of carbon sequestration across cohorts increases with time for the 20 years during which new afforestation projects are added under the offsets program. Total annual carbon sequestration then remains constant until year 50, when changes may begin to occur according to the scenarios described in the previous paragraph. To summarize these results in terms of an “average” value for total annual carbon sequestration over the 69 years during which the afforestation offsets program is active, I took the sum across cohorts in each year, and discounted back to the present using a

⁷⁵ Harvest revenues are not accounted for in the simulation because the estimated coefficient on the tree planting revenues variable is not significant (and has an unexpected sign with a discount rate of 5%).

real social discount rate of 5%.⁷⁶ I then annualized this present equivalent over 69 years, again at a discount rate of 5%.

5.7.2. Carbon sequestration potential and cost

The results of the calculations described above are presented in Table 5.10 for selected offset prices. Simulation outcomes are also summarized in Figures 5.5-5.9 by plotting the offset price on the vertical axis and additional (relative to the base case) carbon sequestration on the horizontal axis. Figures 5.5-5.9 may be interpreted as marginal cost curves for forest carbon sequestration through the afforestation of private land. The cost curves do not, however, include the costs associated with administering an afforestation offsets program. Administrative costs include the costs of measuring and monitoring the carbon uptake of projects. Van Kooten and Sohngen (2007, p. 243) argue that for ephemeral sinks such as grasslands and short-rotation tree plantations: “transaction costs [associated with measuring and monitoring] could greatly exceed the value of the sequestered carbon.” Administrative procedures such as benefit-cost tests may also be required to demonstrate additionality, even though it is impossible to determine with certainty whether or not a project is truly additional. Therefore, if administrative costs were included, the marginal cost curves would be higher, perhaps much higher, than those presented here.

Carbon sequestration potential increases at an increasing rate in the cost curves due to the double-log specification of Eq. (5.4). Lubowski et al. (2006) generate a marginal cost function for forest-based carbon sequestration in the US that is also concave at lower levels of carbon sequestration (i.e. lower marginal costs), becoming convex at higher marginal costs because the size of the land base is fixed. As discussed below, in the simulations reported here, the scale of afforestation is not sufficient for the constraint on available land to become an issue.

⁷⁶ Discounting carbon flows at the social discount rate assumes that the (real value of) marginal damage from the release of an additional tonne of carbon to the atmosphere is constant over time (Stavins, 1999).

Table 5.10: Annual carbon (C) sequestration (relative to the base case) in tonnes at selected offset prices

Sequestration rate (tonnes C/ha/yr)	\$10/tonne C		\$30/tonne C		\$50/tonne C		\$100/tonne C	
	Discount rate		Discount rate		Discount rate		Discount rate	
	5%	20%	5%	20%	5%	20%	5%	20%
Augment								
1	114	27	428	84	973	148	NA	346
2	506	109	2,886	365	NA	691	NA	2,153
5	4,865	740	NA	3,140	NA	9,750	NA	NA
10	NA	3,456	NA	NA	NA	NA	NA	NA
Maintain								
1	110	26	413	81	938	143	NA	333
2	488	105	2,781	352	NA	666	NA	2,075
5	4,688	713	NA	3,026	NA	9,395	NA	NA
10	NA	3,330	NA	NA	NA	NA	NA	NA
Release								
1	83	20	314	62	714	108	NA	253
2	371	80	2,117	268	NA	507	NA	1,579
5	3,569	542	NA	2,303	NA	7,151	NA	NA
10	NA	2,535	NA	NA	NA	NA	NA	NA

The range of offset prices tested depends on the assumed sequestration rate and the discount rate used to annualize up-front planting expenses. I did not test outside the range of historically-based planting expenses used to estimate Eq. (5.4).⁷⁷ At the discount rate of 5%, the base case planting expense is low relative to when a 20% discount rate is used. Therefore, the offset price does not need to be as high for offsets revenues to reduce planting expenses below the historical range. This is especially true

⁷⁷ The reason is well articulated by Kennedy (2003, p. 359): “Inside the X [independent variable] data set we have information on the behavior of Y [dependent variable] and so can be fairly confident about our forecasts; outside the data set the opposite is the case.”

when higher sequestration rates are assumed, because then offsets revenues are higher for a given offset price.

For the scenario in which the carbon sink is maintained after 50 years, and the carbon sequestration rate is two tonnes/ha/yr (SR2 in Figure 5.5), my simulations indicate that if landowners annualize up-front planting expenses at a 5% social discount rate (DR5), the potential exists at an offset price of \$30/tonne of carbon to sequester an additional 2,781 tonnes of carbon per year during the 69 years that the afforestation offsets program is active. This is the result of an increase in cumulative afforestation of 2,248 ha over the 20-year policy period (relative to the base case). When a 20% discount rate (DR20) is assumed, the corresponding sequestration potential is much lower, at 352 tonnes per year (increase in cumulative afforestation of 285 ha). At the higher discount rate, the base case annualized planting expense is higher, and the percentage change associated with offsets revenues is smaller for a given offset price. Also, the absolute value of the estimated coefficient on planting expenses is lower, indicating a lower elasticity of afforestation with respect to planting expenses. However, as described above, the 20% discount rate allowed me to test a greater range of offset prices, up to a price of \$140/tonne, which resulted in an estimate of 6,024 tonnes (additional) of carbon sequestered annually (increase in cumulative afforestation of 4,870 ha).

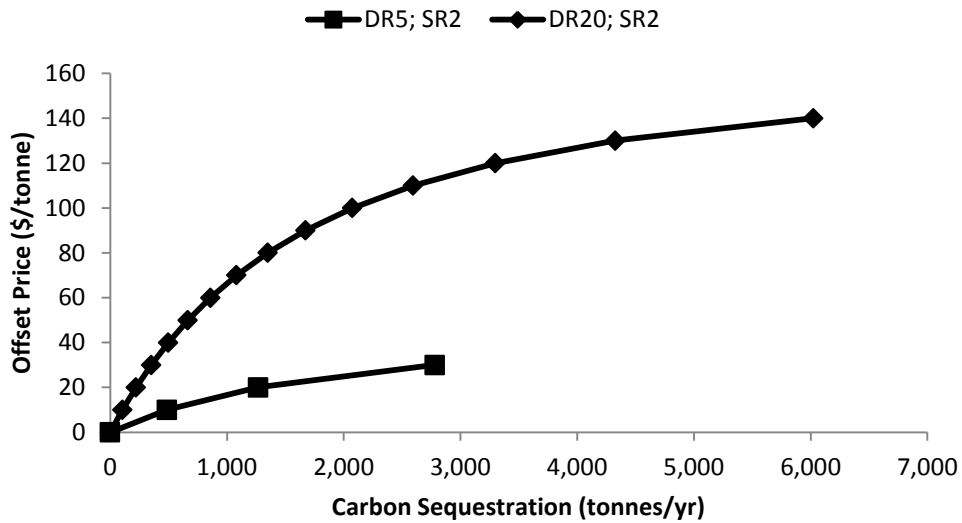


Figure 5.5: *Additional forest carbon sequestration at increasing offset prices, sequestration rate 2, carbon sink maintained (impact of the discount rate)*

The assumed carbon sequestration rate also has a dramatic impact on the results. Figures 5.6 and 5.7 illustrate this impact, again for the “maintain” scenario. Higher sequestration rates result in greater percentage reductions in planting expenses in the simulations, all else being equal, and therefore greater percentage increases in the estimated area afforested. Furthermore, for a given plantation size, annual carbon sequestration clearly increases with the sequestration rate. The figures therefore indicate more carbon sequestration at a given offset price as the sequestration rate increases. As suggested above, as the carbon sequestration rate increased, the maximum offset price I could test decreased. In fact, a sequestration rate of ten tonnes/ha/yr could not be tested with the discount rate set at 5% because offsets revenues were greater than annualized planting expenses, even at the \$10 offset price.

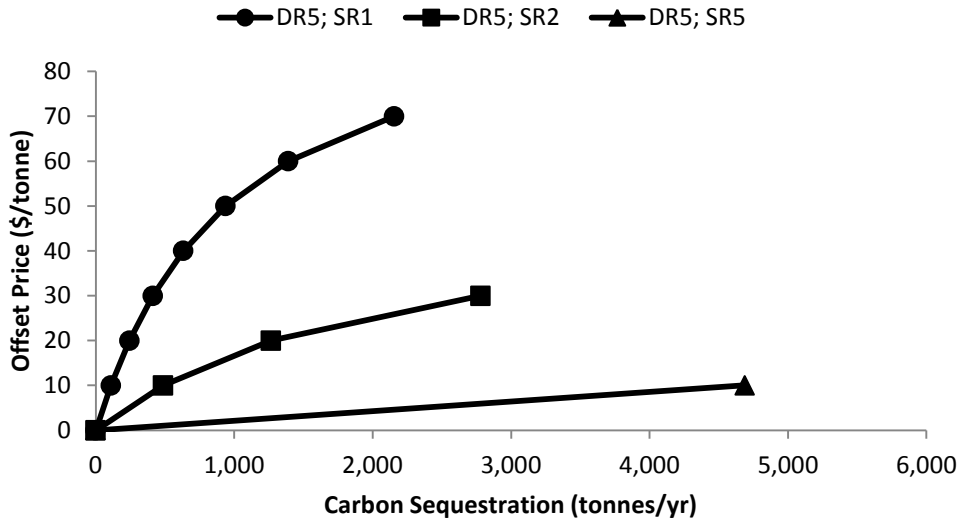


Figure 5.6: *Additional forest carbon sequestration at increasing offset prices, discount rate 5%, carbon sink maintained (impact of sequestration rate)*

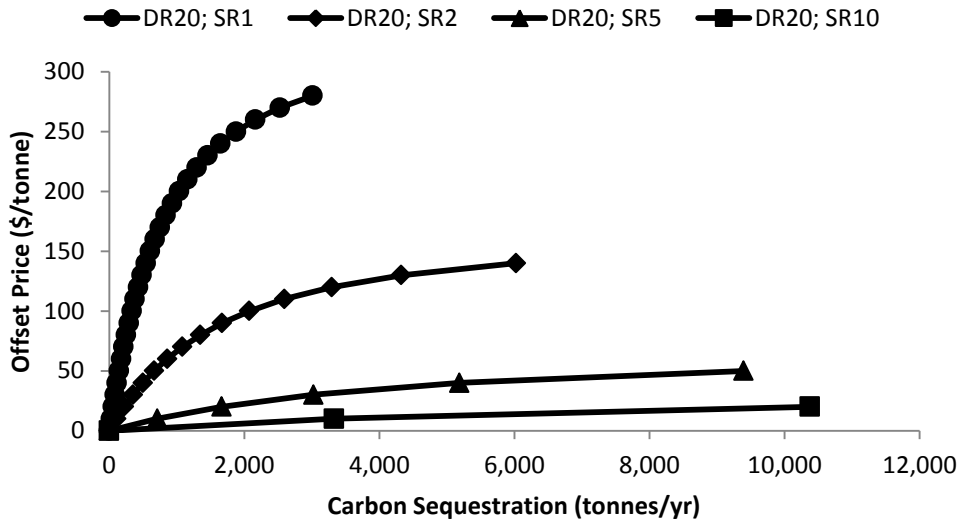


Figure 5.7: *Additional forest carbon sequestration at increasing offset prices, discount rate 20%, carbon sink maintained (impact of sequestration rate)*

The different scenarios with respect to fate of the sequestered carbon after 50 years are illustrated in Figures 5.8 and 5.9 for a carbon sequestration rate of two tonnes/ha/yr. In my simulations, the fate of the carbon sink is not as important as the choice of discount rate or the assumed rate of carbon sequestration. In fact, the

“augment” scenario is almost indistinguishable from the “maintain” scenario. Of course, if carbon flows were not discounted, the fate of the carbon sink would be much more important. In particular, the “release” scenario would result in zero net carbon sequestration. On the other hand, if carbon flows were discounted at a higher rate, carbon fate after 50 years would be even less important.

The most remarkable feature of the results is that across a range of offset prices and sequestration rates, and despite testing alternative assumptions with respect to discounting and the fate of sequestered carbon, estimated annual carbon sequestration is almost negligible in relative terms. In a jurisdiction the size of Ontario, the potential for carbon sequestration (and reducing CO₂ emissions) would normally be measured in millions of tonnes (megatonnes, Mt), whereas the results for this study are measured in thousands of tonnes (kilotonnes, kt). The amount of land afforested in my simulations is correspondingly low – almost certainly not enough to trigger any price changes that would lead to carbon leakage. This outcome is not surprising given the historical data on which the econometric modeling is based. According to the FAACS backcast database, only a tiny fraction of the agricultural land base of Ontario was afforested throughout the 1990s and early 2000s, despite subsidies and program support, which were substantial in the early 1990s.

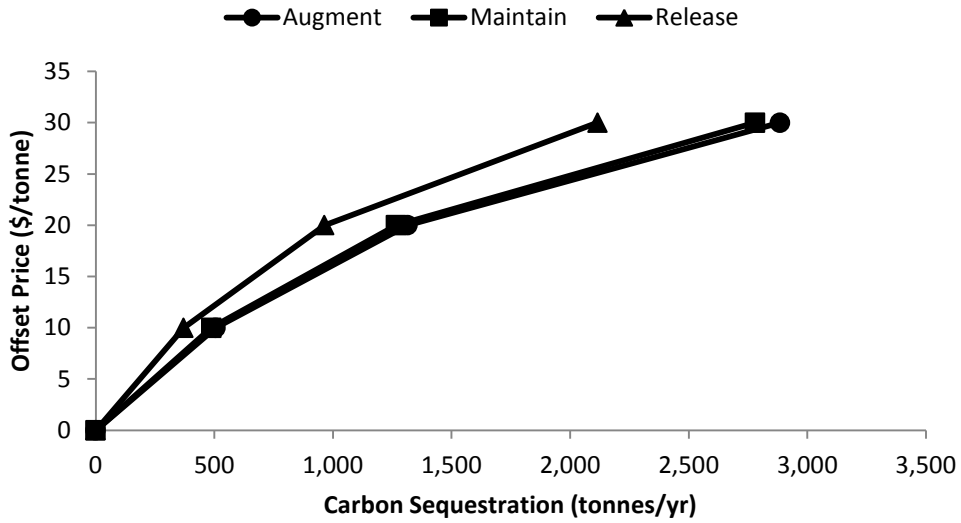


Figure 5.8: *Additional forest carbon sequestration at increasing offset prices, sequestration rate 2, discount rate 5% (impact of carbon fate)*

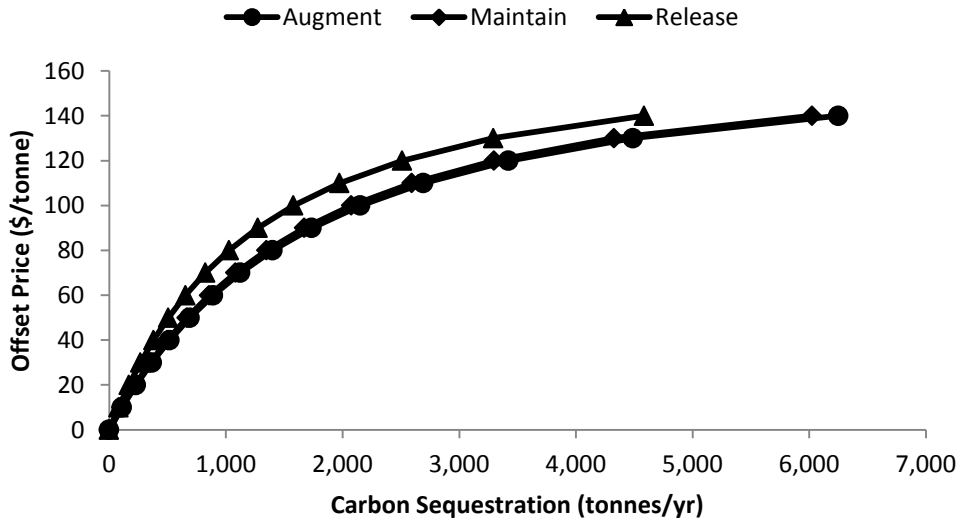


Figure 5.9: *Additional forest carbon sequestration at increasing offset prices, sequestration rate 2, discount rate 20% (impact of carbon fate)*

A number of Canadian studies that use the bottom-up engineering approach to estimate land opportunity costs find sequestration potential to be much greater than the current analysis. Van Kooten et al. (2000) generate marginal cost curves for afforestation in Northeast BC and Alberta using fast-growing hybrid poplar. Applying a 4% discount rate to both costs and carbon flows, they estimate that at a marginal cost of

between \$80 and \$90 per tonne, there is the potential to sequester an average of 20 Mt per year over a 50-year time horizon; at a marginal cost of \$20 per tonne, average sequestration is just over 5 Mt per year.⁷⁸ McKenney et al. (2004) developed the Canadian Forest Service – Afforestation Feasibility Model (CFS-AFM); a spatial model of the biology and economics of afforestation that calculates “break even” carbon prices (akin to marginal costs) at which afforestation becomes financially attractive. Five growth and yield scenarios for hybrid poplar were tested. The modeling indicates that at a price of \$10/tonne CO₂ (\$36.67/tonne carbon) the amount of land in Eastern Canada that would potentially be made available for afforestation would range (across the growth and yield scenarios) from less than 10 thousand ha to 1.91 million ha, and at a price of \$25/tonne CO₂ (\$91.67/tonne carbon) land availability would range from 20 thousand ha to 8.34 million ha.⁷⁹ Yemshanov et al. (2005) use an enhanced version of the same model to explore the economic potential of slower growing hardwoods and softwoods, as well as hybrid poplar. They find that in Eastern Canada, at a price of \$10/tonne CO₂, 2.218 million ha would be potentially attractive for afforestation using hybrid poplar, five thousand ha would be attractive for hardwood plantations, and 1.930 million ha would be attractive for softwood (conifer) plantations.⁸⁰

Putting aside various sources of simulation error, the discrepancy between my results (and the historical record) and the results of bottom-up studies for Canada may be explained by revisiting the critiques of “engineering” or “least-cost” analyses offered by Stavins (1999) and Plantinga et al. (1999). The existence of non-monetary returns to agriculture, inertia with respect to land-use change, and costs associated with agricultural landowners learning how to manage a forest would bias bottom-up analyses towards low estimates of afforestation and carbon sequestration costs.

⁷⁸ Van Kooten et al. (2000) appear to have discounted carbon for the purpose of calculating marginal cost; however sequestration potential is measured in undiscounted carbon.

⁷⁹ The growth and yield scenarios of McKenney et al. (2004) are analogous to my tests of alternative carbon sequestration rates. The huge range in potential land availability in McKenney et al. across growth and yield scenarios is consistent with my finding that the results are highly sensitive to carbon sequestration rates.

⁸⁰ Despite the considerable land-use changes implicated in the bottom-up studies discussed here, no attempt is made to address the potential impact of increased land prices as the agricultural land base is reduced. Likewise, carbon leakage is not factored into the analyses.

Notwithstanding these explanations, a review of forest carbon sequestration costs in the US by Stavins and Richards (2005) suggests that the difference between the econometric and bottom-up approaches should not be so drastic. The authors identified eleven previous studies whose results could be made mutually consistent by performing a number of straightforward calculations. Bottom-up engineering, sector optimization and econometric methodologies were included. After normalizing the results, the authors found that, for a massive program resulting in 300 million tons of annual carbon sequestration, nearly all the marginal cost estimates were between \$25 and \$75 (US) per short ton of carbon.

There are a number of specific factors that may have contributed to minimal afforestation on private land in Ontario despite the incentives offered, and in contrast to the optimistic forecasts of Canadian bottom-up studies. In the final report on the FAACS initiative, the Canadian Forest Service (2006) notes that Canada has historically lacked a culture of farm forestry. The report explains the influence of Canadian land-use and taxation policies, which promote agriculture at the expense of forest plantations. Cultural biases are also important in the Canadian context, as described by DeMarsh (1999, in Canadian Forest Service, 2006, p. 12):

The most significant non-physical, non-financial constraint to expanding afforestation is landowner feelings that the land in question may/should be returned to agricultural production at some point in the future. This sense of keeping trust with the ancestors who cleared the land, or romantic attachment to a picture of cattle grazing in lush pasture around the homestead can be dismissed as sentimentality, but is a real and powerful motivation for some rural landowners.

This is presumably in contrast to the US, where a large percentage of timberland is controlled by non-industrial private forest landowners.

The extent to which all landowners in Ontario were aware of and able to access the afforestation programs in place during the study period must also be taken into consideration. The econometric model assumes that all landowners made land-use decisions based on the subsidized planting costs. In reality, program capacity may not have been nearly sufficient to justify this assumption. A legitimate offsets program would

likely also face capacity constraints, in light of the administrative requirements discussed previously.

5.7.3. *Additionality and free riders*

Protocols for quantifying offset credits may assume additionality for afforestation projects, either because the land has not been forested for a period of time,⁸¹ or because afforestation does not appear to be financially viable. Alberta's draft protocol for afforestation offsets projects (Government of Alberta, 2011) requires that lands must not have been forested for at least 20 years prior to the start of the project, and asserts that (p. 18):

Given the number of years since the land may have been treed, and has since been under other land use(s) such as agriculture, it is reasonable to assume that the land would not become a treed area without the project. Also, given the capital-intensive nature of all afforestation projects relative to limited or no expectations of financial return, afforestation project developers must demonstrate that the project is not required by law in order to establish additionality.

Van Kooten et al. (2002) calculate the costs and benefits of planting native tree species on marginal agricultural land in Canada and find that landowners would lose money as a result of their afforestation efforts. They assume that any environmental benefits of tree planting are external (i.e. not captured by the landowner), and therefore conclude that landowners will not plant trees unless they are provided with subsidies or other incentives.

Looking at the issue from another perspective, human beings are heterogeneous in terms of their preferences and perceptions; therefore, some landowners who have the money to do so will plant trees for aesthetics, recreation or conservation purposes, even if there is no financial reward. That is to say, the environmental benefits of afforestation are not always external, and some landowners may incur monetary losses to capture them. My econometrically-based simulations indicate that some afforestation (and

⁸¹ By definition this must be the case, otherwise the activity would be "reforestation" instead of "afforestation."

therefore some carbon sequestration) will occur even in the absence of offsets revenues. This means that not all afforestation under the hypothetical program is additional, and if offset credits are granted to all projects, there will be “free riders” who obtain credits even though they were going to plant trees anyway. Allocating offset credits to projects that are not additional under an emissions cap and tradable permits program leads to emissions exceeding the cap.

The percentage of total carbon sequestration that is additional, according to my simulations, is presented in Figure 5.10 for a sequestration rate of two tonnes carbon per ha per year, and assuming the forest carbon sink is maintained after 50 years. Since the amount of sequestration that would have occurred in the absence of the offsets incentive is static across offset prices, the proportion of sequestration that is additional increases with the offset price. At an offset price of \$30 per tonne of carbon, approximately 60% of the carbon sequestration is estimated to be additional, assuming landowners annualize up-front costs at a discount rate of 5%. When a discount rate of 20% is applied, total sequestration is substantially lower, and therefore the percentage estimated to be additional is lower as well, at only 17%. These low rates of additionality (high rates of free-ridership) would seriously compromise the integrity of a real-world offsets program.⁸²

⁸² Free-ridership may be lower than what is suggested by my analysis if landowners whose projects are not additional do not apply for offset credits. This point is particularly relevant given my hypothesis that wealthy landowners are underrepresented in the FAACS database because they may not have claimed available subsidies for afforestation projects (see section 5.5.1).

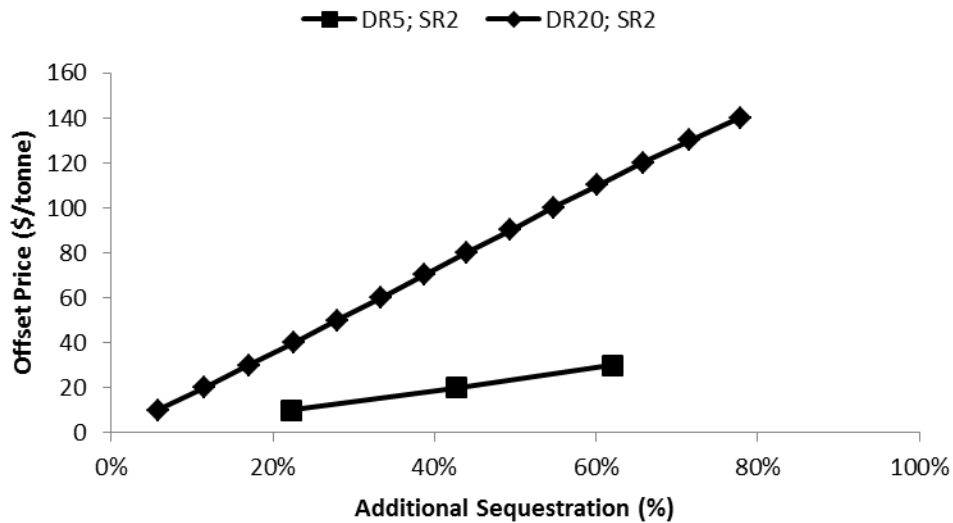


Figure 5.10: Percentage of total carbon sequestration that is additional, sequestration rate 2, carbon sink maintained

5.7.4. Impact of multicollinearity

As discussed in section 5.6.4, I investigated the potential impact of multicollinearity between planting expenses (*PE*) and the operating budget of the OMNR (*OMNR*) on the empirical estimation by removing each of these explanatory variables in turn and rerunning the estimation (results are provided in Appendix C). Although the estimated coefficients reported in Table 5.7 and used in the simulations may have been influenced by multicollinearity, the main conclusions drawn from these simulations are not affected by changes of the magnitude shown in Appendix C.

Taking first the case in which *OMNR* is removed, the estimated elasticity of afforestation with respect to planting expenses increases in absolute value. This results in greater estimates of the additional (relative to the base case) carbon sequestration potential, as illustrated in Figure 5.11.⁸³ Although large increases are observed when *OMNR* is removed, the sequestration potentials are still within the range estimated when testing higher sequestration rates (see Figures 5.6 and 5.7 above). The sequestration

⁸³ The results presented in Figures 5.11 and 5.12 were obtained by rerunning the simulations using the constants and coefficients shown in columns 3 and 6 of Table 5.11 of Appendix C (instead of the initial estimates shown in columns 1 and 4).

potentials remain orders of magnitude less than what might be expected based on bottom-up engineering estimates. Additionality is improved only somewhat, as shown in Figure 5.12.

On the other hand, the specification in which the explanatory variable representing planting expenses (PE) is removed is correct if this is an irrelevant variable. In that case, offset pricing alone (without additional program support) would be assumed to have no effect on afforestation, and no additional carbon sequestration would occur regardless of the offset price. This is not a realistic scenario; we know that high offset prices should have some impact on afforestation. A more relevant possibility is that the initial estimate of the elasticity of afforestation with respect to planting expenses is too great in absolute value. If this were true, sequestration potentials would be lower than the estimates provided in section 5.7.2, further undermining the case for forest carbon offsets.

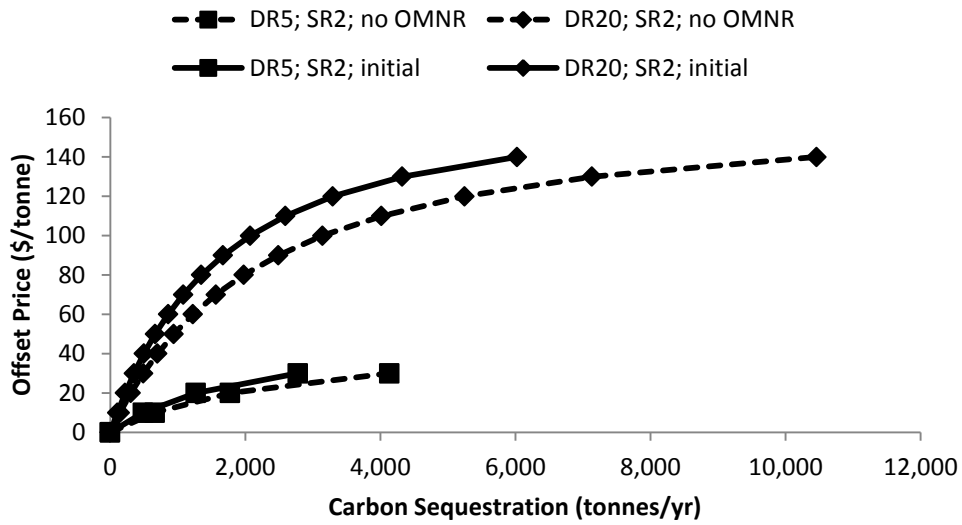


Figure 5.11: Impact of removing OMNR on forest carbon sequestration (sequestration rate 2, carbon sink maintained)

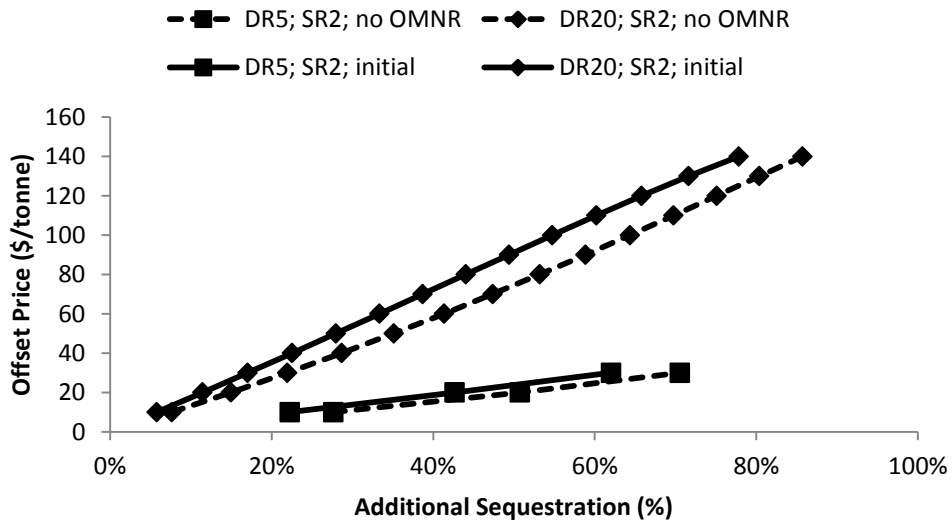


Figure 5.12: Impact of removing OMNR on additionality (sequestration rate 2, carbon sink maintained)

5.8. Conclusions

In this analysis, I develop and estimate an econometric model of afforestation on private land in order to address concerns regarding the bottom-up engineering approach

that is often used to evaluate the potential for forest carbon sequestration. I then use the estimated model to simulate a hypothetical afforestation offsets program, which allows me to draw some conclusions about the potential for forest carbon sequestration at varying marginal costs, as well as the expected additionality of carbon offsets projects. The data for my dependent variable is from an afforestation database compiled by the Canadian Forest Service for the period 1990 to 2002; the database has not been applied in this context before. I use data for the province of Ontario specifically. My study helps to fill a gap in the literature for Canada, which is dominated by bottom-up studies of the cost of forest carbon sequestration.

The econometric analysis yields a number of insights, not all of which are expected. I find that tree planting expenses, which were reduced by historical tree planting programs, especially in the early 1990s, have a significant negative impact on afforestation. A variable measuring afforestation program spending has a significant positive impact. None of the other variables included in the econometric specification have significant coefficients with the expected sign. These results provide empirical support for the notion that tree planting programs were the most important factor influencing afforestation in Ontario during my study period. A variable measuring average wealth and access to capital by census division is found to have a significant negative impact on afforestation. This is not the expected relationship, and the result may be due to an underrepresentation of plantings by wealthy landowners in the database used to provide data for the dependent variable. Serial correlation and heteroskedasticity both appear to be present in the initial estimation, and there were some difficulties correcting these problems. However, the significance of the coefficient on the planting expenses variable, which is of prime importance to the simulations discussed below, is robust to the corrections tested. Although multicollinearity is present and may have had a substantial impact on the estimated coefficients, an analysis of this problem indicates that the main conclusions drawn from the simulations are not affected.

My simulations indicate that across a range of offset prices and assumptions about the rate of carbon sequestration, the potential for forest carbon sequestration is much smaller than the potential estimated by Canadian bottom-up studies. Furthermore, the simulations suggest low levels of additionality, which could lead to emissions exceeding the cap of an emissions cap and tradable permits program if afforestation

offsets are allowed. Although caveats must be raised with respect to potential simulation error, policy makers should still give serious consideration to this analysis. It provides a rare illustrative case of applying the econometric approach to Canada, and while I do not claim that the specific numerical results are robust, this study represents an important first step in terms of incorporating the revealed preferences of landowners. Better data on land use in Canada would help refine the estimates. It is reasonable to conclude, however, that before investing public funds in major afforestation programs targeting private land, policy makers in Canada should consider the various aspects of landowner behavior discussed in this paper, cultural barriers to farm forestry in this country, and distortions created by existing land-use and taxation policies that favor agricultural land use. If my findings with respect to additionality are correct, the contribution of afforestation offsets should be limited under emissions cap and tradable permits programs.

Appendix A: Methodology for extracting data for the dependent variable from the FAACS database

I requested the FAACS database from the Canadian Forest Service and received a copy in Microsoft Access™ 2000 format. I had to perform a number of steps to extract data for the dependent variable from the version of the database that I received. First, I designed a system of queries in consultation with current and former Canadian Forest Service employees to replicate the results published by White and Kurz (2005) for Ontario. Once a good match was obtained, I made changes to reflect recent developments in how Canada defines its forests, and to take into account factors specific to my analysis. Finally, I coded the records in the FAACS database by census division to create cross-sectional observations for the panel analysis.

Design of a system of queries in Microsoft Access to replicate the published results

The developers of the FAACS database sought to record afforestation events that would qualify under Article 3, paragraph 3 of the Kyoto Protocol to the United Nations Framework Convention on Climate Change (United Nations, 1998). “Afforestation” is defined as “the direct human-induced conversion of land that has not been forested for a period of at least 50 years to forested land through planting, seeding and/or the human-induced promotion of natural seed sources.” “Forest” is defined as “a minimum area of land of 0.05–1.0 ha with tree crown cover (or equivalent stocking level) of more than 10–30 per cent with trees with the potential to reach a minimum height of 2–5 metres [m] at maturity in situ” (UNFCCC, 2006, p. 5). For the purposes of calculating net changes in greenhouse gas emissions from direct human-induced land-use change and forestry activities, countries must select a single minimum value for each of tree crown cover, land area and tree height. When the White and Kurz (2005) paper was published, Canada had not yet finalized the values to define its forests. The FAACS database identified a planting event as afforestation if it was at least 0.05 ha in size, with tree crown cover of at least 30%, and with trees having the potential to reach a height of at least 5 m.

In consultation with contacts involved with the FAACS database (B. Simpson, February 6, 2009 – June 1, 2009; T. White, February 12-18, 2010), I designed a system of queries to replicate the results published by White and Kurz (2005) for Ontario:

1. An existing query in the version of the database I received from the Canadian Forest Service uses detailed cadastral data recorded for the afforestation events to remove any duplicate records in Ontario. There are no duplicate records removed by this query; however, the query does remove a number of records for which the cadastral information necessary to avoid duplication was not recorded.
2. Plantings and portions of plantings that were not categorized as either “hardwood” or “softwood” were removed from the results. This was done to remove plantings of shrubs, as these would generally not be capable of reaching 5 m at maturity.
3. For each afforestation event, I used data on total stems planted and area of the plantation to calculate stem density. Those records with a density of less than 250 stems per ha were removed because these would be highly unlikely to reach the 30% crown closure requirement.
4. Plantings categorized as “linear” in the database were removed. Linear plantations were excluded from the FAACS database because at the time it was not known whether Canada would define its forests in such a way as to include linear activities such as shelterbelts and corridors.
5. Afforestation events smaller than the 0.05 ha were removed to meet the minimum area requirement of the FAACS database.

Once these queries were in place, the output from my version of the database matched very well with the published results for Ontario. I was not able to obtain numerical results from the Canadian Forest Service; however, when my output is superimposed on a graph of annual area planted by province from White and Kurz (2005), it is difficult to distinguish two separate lines for Ontario.

Changes to the query system for the current analysis

After matching my results with the published results for Ontario, I made three additional changes to the query system in the FAACS database:

1. Canada has now identified single minimum values to define its forests for reporting under the United Nations Framework Convention on Climate Change. Forests are defined as having the potential to achieve minimum tree crown cover of 25%, minimum land area of 1

ha and minimum tree height of 5 m (Government of Canada, 2007). I therefore altered my query on minimum size to require an area of 1 ha instead of 0.05 ha.

2. I added a query to remove afforestation events on land where ownership was classified in the FAACS database as “federal,” “provincial,” “municipal,” “conservation authority” or “industrial,” since I am interested in the response of non-industrial private landowners to incentives for afforestation.⁸⁴
3. The FAACS database includes afforestation events that took place under the City of Greater Sudbury Land Reclamation Program (now the Regreening Program). Unlike the other afforestation programs addressed by this analysis, the Sudbury program was not a cost-sharing program – private landowners were not required to make any contribution in order to have trees planted on their land. Furthermore, most of the non-industrial plantings were done on residential properties on the outskirts of the city, rather than on agricultural land (S. Monet, City of Greater Sudbury, personal communication, March 23, 2012). For these reasons, the afforestation activity that took place under this program does not fit well with the theoretical model of tree planting behaviour or the econometric model specified for this analysis. I therefore removed approximately 300 records from the database that were located within the Greater Sudbury municipality.

Coding by Statistics Canada census division

After applying the queries described above to the FAACS database, 2597 records remained for the province of Ontario. Of these, approximately 93% included information on “upper tier municipality” (UTM). I used this information to code the records by Statistics Canada census divisions, as defined in the 2001 census agricultural regions and census divisions map for Ontario (Statistics Canada, 2002a). Usually, the UTM corresponded directly to the name of a census division. In some cases, the UTM entry provided geographic data at a finer level of resolution, such as a township. In these cases, I used Statistics Canada’s 2001 Community Profiles to look up the correct census division (Statistics Canada, 2002b). In a few instances, the UTM

⁸⁴ The FAACS database likely excluded planting activities on government-owned land as well, but may have retained events on land owned by the Conservation Authorities. Note the distinction between afforestation taking place on land *owned* by the Conservation Authorities, and afforestation taking place on private land with the *assistance* of the Conservation Authorities. The latter is retained in the database output for the dependent variable, while the former is not.

information was ambiguous. Information on “administrative boundary” and/or “township” contained within the database was used to code these entries.

Records that did not include information on UTM were coded based on “township,” “geographic township” or “postal code” information where possible. After this was done, 133 records remained that could not be coded by census division. Of these, 123 were contained within the administrative boundary of Kemptville in eastern Ontario.⁸⁵ The five census divisions comprising the Kemptville district were amalgamated so that these 123 records could be retained.⁸⁶ The 10 remaining uncoded records were associated with several different administrative regions, each of which contained more than one census division. These records were dropped from the results because retaining them would have required additional amalgamations that would have substantially reduced the number of cross-sectional observations.

⁸⁵ Administrative boundaries correspond to the map of Ontario Ministry of Natural Resources (2002) regions and districts.

⁸⁶ The amalgamated census divisions, listed by number and name are: 1. Stormont, Dundas and Glengarry United Counties, 2. Prescott and Russell United Counties, 6. Ottawa Division, 7. Leeds and Grenville United Counties, and 9. Lanark County.

Appendix B: Details of variable measurement and data sources

Dependent variable

Afforestation *A* Total area afforested on non-industrial, private land by census division and year from the Feasibility Assessment of Afforestation for Carbon Sequestration (FAACS) database (White and Kurz, 2005).
Units: ha/yr

Independent variables

Farm Area *FA* Total area of farms by census division and year from Statistics Canada's Census of Agriculture, available every five years. Data from the 1986, 1991, 1996, 2001 and 2006 census were used, with missing years filled by interpolation.
Units: ha

Planting (timber) Revenues *TR* A softwood timber price of \$18/m³ in 2005 (McKenney et al., 2006) was adjusted for 1990-2002 using Statistics Canada's price index for softwood lumber for Ontario (2002=100; CANSIM Table 329-0062). The result was deflated using the industry price index (producer price index) for all commodities (2002=100) from Statistics Canada (CANSIM Table 329-0056). It was then multiplied by an average annual growth in harvestable biomass of 6m³/ha (McKenney et al., 2006) to calculate planting revenues. This variable is available by year only.
Units: \$2002/ha/yr

Planting Expenses *PE* Landowner planting costs per tree were estimated based on an analysis of historical afforestation programs (summarized by Puttock, 2001), and deflated using the industry price index. A planting density of 2,000 seedlings per ha was assumed to convert to expenses per ha. These up-front planting expenses were then annualized over a rotation period of 50 years. Real discount rates of 5% and 20% were tested. An annual cost of \$5 per ha was added to represent the costs of tending and managing a plantation (Yemshanov et al., 2005). This variable is available by year only.
Units: \$2002/ha/yr

Agricultural Expenses-to-Revenues *AER* Total gross farm receipts and total farm operating expenses from the Census of Agriculture were each deflated using the industry price index, and then divided by the total area of farms to give \$2002/ha/yr. Both measures are available by census division every five years. Missing years were filled by interpolation (after deflating prices).
Units: %

Short-term Interest Rate *STI* Canadian 3-month treasury bill rates, as reported by Statistics Canada (CANSIM Table 176-0043); annual values were calculated as the average of monthly values. Interest rates were not adjusted for inflation because they are short-term rates.
Units: %

OMNR Operating Budget *OMNR* Obtained from the Public Accounts of the Ontario Ministry of Finance for fiscal years 1990-1991 to 2002/2003. The operating budget (for the fiscal year that begins in the year in question) was deflated using the consumer price index for all items (2002=100) for Canada from Statistics Canada (CANSIM Table 326-0021).
Units: \$2002

Average Value per Farm *FV* Total value of land and buildings owned from the Census of Agriculture was deflated using the industry price index, and then divided by the total number of farms. Both measures are available by census division every five years. Missing years were filled by interpolation (after deflating prices).
Units: \$2002/farm

Appendix C: Potential impact of multicollinearity on the empirical estimation

Table 5.11: Estimation results with PE and OMNR removed in turn (panel fixed effects)

	Discount rate 5%			Discount rate 20%		
	Initial estimate 1.	Remove PE 2.	Remove OMNR 3.	Initial estimate 4.	Remove PE 5.	Remove OMNR 6.
Constant	15.656 (0.701)	-20.329 (-1.025)	28.834 (1.271)	14.351 (0.644)	-20.329 (-1.025)	28.767 (1.264)
ln FA _{it}	-0.852 (-0.384)	-0.637 (-0.303)	-0.666 (-0.300)	-0.823 (-0.370)	-0.637 (-0.303)	-0.608 (-0.273)
ln TR _t	-0.001 (-0.002)	0.173 (0.407)	-0.035 (-0.081)	0.029 (0.067)	0.173 (0.407)	0.000 (0.001)
ln PE _t	-0.660*** (-4.136)	NA	-0.864*** (-6.820)	-0.579*** (-3.972)	NA	-0.781*** (-6.758)
AER _{it}	-0.005 (-0.188)	-0.016 (-0.612)	-0.005 (-0.182)	-0.005 (-0.188)	-0.016 (-0.612)	-0.005 (-0.178)
STI _t	-0.018 (-0.502)	0.001 (0.037)	-0.008 (-0.223)	-0.019 (-0.526)	0.001 (0.037)	-0.008 (-0.232)
ln OMNR _t	0.693** (2.272)	2.226*** (7.342)	NA	0.758*** (2.472)	2.226*** (7.342)	NA
ln FV _{it}	-1.194*** (-3.270)	-1.167*** (-3.005)	-1.233*** (-3.341)	-1.200*** (-3.280)	-1.167*** (-3.005)	-1.245*** (-3.364)
No. obs.	572	572	572	572	572	572
Adj. R ²	0.682	0.669	0.681	0.681	0.669	0.679

* significant at 10%, ** significant at 5%, *** significant at 1%. t-values in parentheses. White period standard errors and covariance correction (d.f. corrected). Note: When the explanatory variable describing planting expenses (PE) is removed, the discount rate used by landowners to annualize up-front planting costs becomes irrelevant; therefore, the results in columns 2 and 5 are identical.

6. Conclusions

My thesis aims to better inform climate policy decisions, given that devastating impacts may be irreversible if we do not act quickly and appropriately. I do this by critically evaluating claims that energy efficiency and forest carbon sequestration actions each offer the potential to mitigate climate change at low costs. These claims are seemingly confirmed by conventional bottom-up analyses that do not realistically portray human behavior or feedback effects within the economy. The papers comprising my thesis describe how I develop and apply new models to test the findings of the bottom-up approach. These models incorporate behavioral parameters that have been econometrically estimated from quasi-experimental data – an empirical basis that is in contrast to the untested and subjectively determined assumptions about human behavior that drive conventional bottom-up models. Economic feedbacks within the economy are also represented, as necessary, in the models I use in my thesis. In this concluding chapter, I discuss notable differences between the three papers presented here, as well as the common prescriptions for climate policy that are nonetheless supported.

Some dissimilarities between the three papers are worth highlighting. First, while all of the research seeks to improve upon the conventional bottom-up methodology, two different models are used for this purpose, and these models address the shortcomings of the bottom-up approach in different ways. In the first two papers, I use the CIMS model to assess the potential role of energy efficiency in US climate policy. This model has three key empirically-based behavioral parameters, and also takes partial economic feedbacks into account. Recent efforts at parameterization use revealed preference data from “natural experiments” and stated preference data from “hypothetical experiments” to estimate the behavioral parameters of CIMS. The two types of data are used (separately or in combination) to estimate discrete choice econometric models, and the CIMS parameters are derived from these models. In the third paper, I develop an econometric model of afforestation to investigate the magnitude and cost of carbon sequestration in forests. This model is based on revealed preference data from a

“natural experiment” created through policies that subsidized afforestation in Ontario in the 1990s. It implicitly takes landowner behavior into account through the historical data used for estimation. The amount of afforestation that is expected based on my simulations is not enough to trigger feedback effects.

A second difference is evident in comparing the range of actions modeled. In the first two papers, I use CIMS to model economy-wide GHG emissions from energy extraction, processing and use. I compare actions in different sectors of the economy in terms of their contribution to emissions reductions. The version of CIMS applied in these studies does not deal with carbon sequestration in forests or agricultural soils. In the last paper, on the other hand, I use an econometric model to address only one action: afforestation as a means of forest carbon sequestration.

Third, there are discrepancies between the papers with respect to policy simulation. In the first and last papers, I simulate and evaluate specific policy measures, while in the second paper I do not. In the first paper, I use CIMS to model end-use efficiency standards and an economy-wide carbon tax as part of a comparative modeling exercise organized by the Energy Modeling Forum at Stanford University (EMF-25). In the third paper, I simulate a hypothetical afforestation offsets program using an econometric model; the offsets could be part of an emissions cap and tradable permits program. Because the econometric model allows for simulation of a counterfactual scenario in which offsets are not awarded for afforestation projects, I am able to estimate levels of additionality associated with the program. Additionality was found to be low, which is the same as saying that free-ridership was found to be high. In the second paper, I apply carbon price signals within the CIMS model to represent the costs GHG emissions abatement. This methodology allows for comparison with the McKinsey report. I do not specify a particular policy measure in the second paper, although the carbon price can be interpreted as the result of a carbon tax or cap-and-trade program.

A fourth difference between the papers is the degree to which their results are compared with the bottom-up approach I am critiquing. In the second paper, I set up a direct comparison between the CIMS model and the conventional bottom-up approach of McKinsey in order to isolate the impact of behavioral parameters in CIMS. In the third paper on afforestation, such a direct comparison is not possible due to methodological

differences, although bottom-up results are provided and discussed alongside results from the econometric model. I do not explicitly compare my results with the bottom-up approach in the first paper, since this was produced as part of a larger exercise in which a number of different energy-economy models for the US were compared and contrasted.

Despite these differences, my thesis supports a number of general climate policy prescriptions, given the assumptions about methodology and data collection that I have applied in this research. I find that neither energy efficiency nor forest carbon sequestration is the “magic bullet” for GHG emissions mitigation. Conventional bottom-up analyses may suggest otherwise, but this is because these models do not realistically portray human behavior or the relevant economic feedbacks. Addressing climate change by targeting either of these actions primarily would not provide the needed emissions reductions or CO₂ removals and would be more costly than necessary. Subsidy programs designed to achieve these actions – including subsidies in the form of offsets – would require large public expenditures, especially due to free-rider problems. Information programs may have a role, depending on the importance of information-related market failures that prevent cost-effective actions from being undertaken; however, the economist’s definition of a market failure is much narrower than the bottom-up modeler’s definition of a market barrier. To successfully meet the challenge of climate change, policy-makers must implement broad-based policies that impose a substantial financial or regulatory constraint on GHG emissions.

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