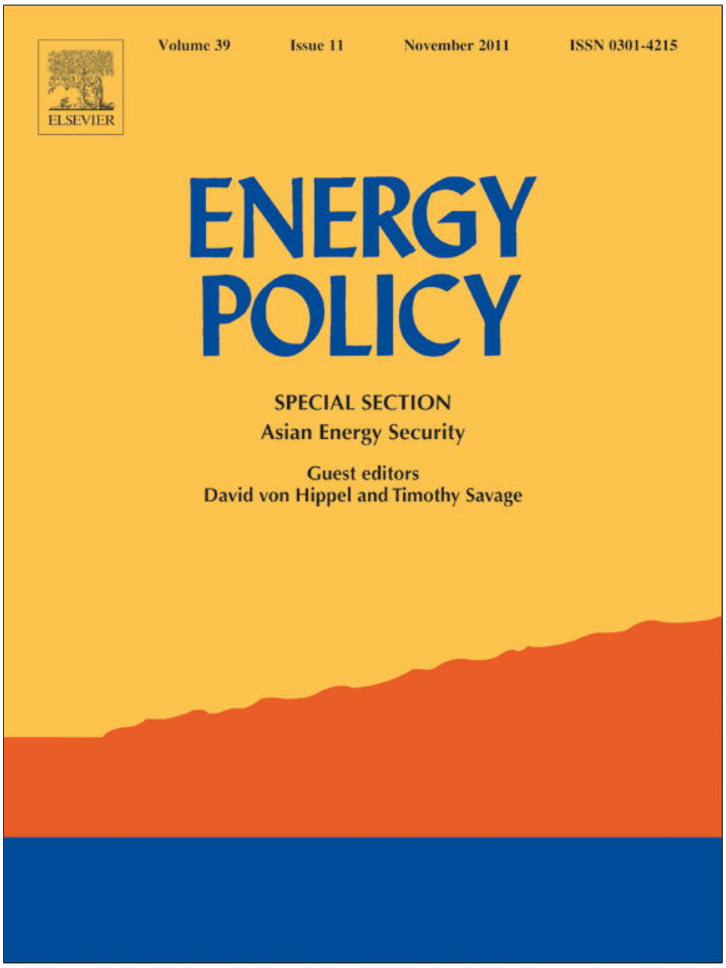
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Energy efficiency and the cost of GHG abatement: A comparison of bottom-up and hybrid models for the US

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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.

1. 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 Fig. 1—upward

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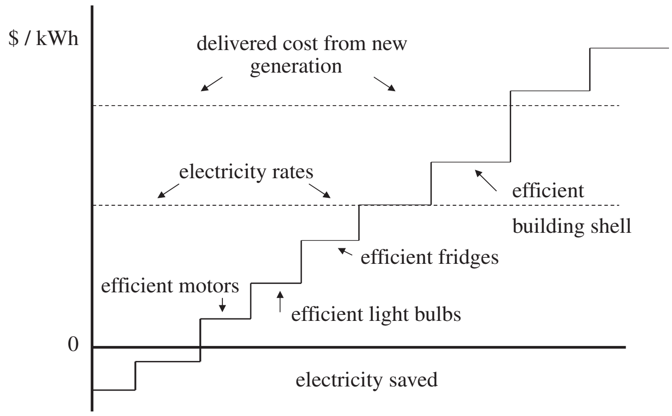

Fig. 1. Example of a least-cost energy efficiency curve.

sloping curves showing the amount of energy savings that is profitable at each energy price level based on the life-cycle cost calculations.

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 3, 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, 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 5, we revisit the comparisons made in Section 4, 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.

2. 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 (CO_2e) 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).

3. 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 (2009b) 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 alterative 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).[1] 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 Fig. 2. Energy supply and energy demand components are each made up of a number of sub-models representing particular sectors or subsectors. 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, 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 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

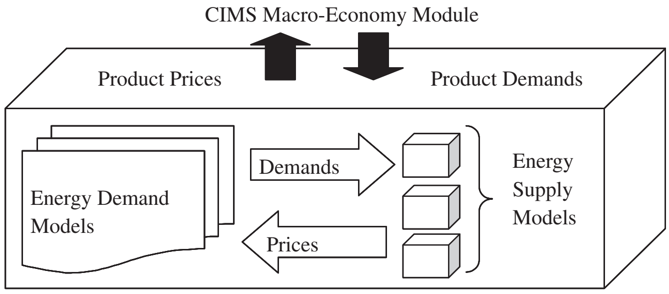

Fig. 2. Basic structure of the CIMS model.

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. (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.

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

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. (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_j parameter represents all intangible costs and benefits that consumers and businesses perceive, additional to the simple

[1] 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).

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. 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 CO_2e 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 Fig. 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 2. The initial energy price and output forecasts in CIMS are standardized to the Energy Information Administration's Annual Energy Outlook (AEO) for (2009a).[2] 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 CO_2e 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). 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.

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 CO_2e, 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.[3]

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

[3] 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

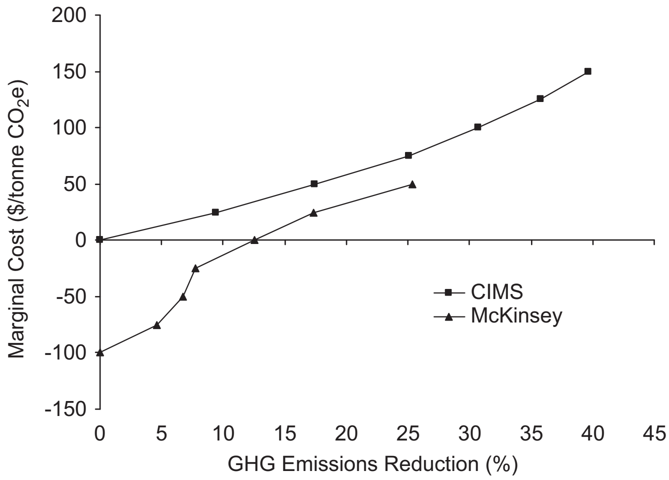

Fig. 3. GHG abatement cost curves for the US in 2030.

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 CO_2e 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.[4] 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 Appendix A). 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 Fig. 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 from this action under GHG pricing.[5] 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.

In the CIMS reference case simulation, energy intensity is reduced considerably over the forecast period. An examination of end-use intensity trends (Fig. 5) reveals substantial reductions for residential buildings, manufacturing industry, and light-duty vehicle transportation.[6] 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 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.[7] As shown in Fig. 5, for residential buildings, manufacturing industry, and

(*footnote continued*)
in the US was not high enough to warrant recalibrating the CIMS model to $2005 US.

[4] 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.

[5] 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.

[6] 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.

[7] 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

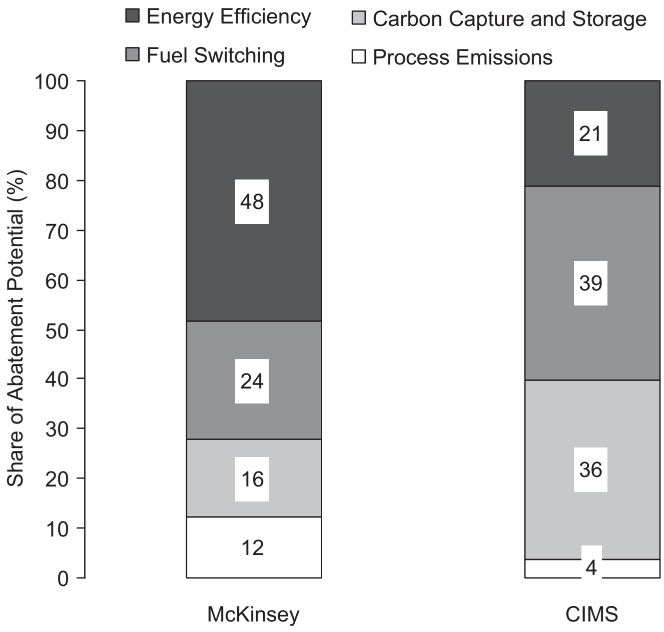

Fig. 4. Contributions to GHG emissions abatement in 2030 at \$50/tonne CO_2e.

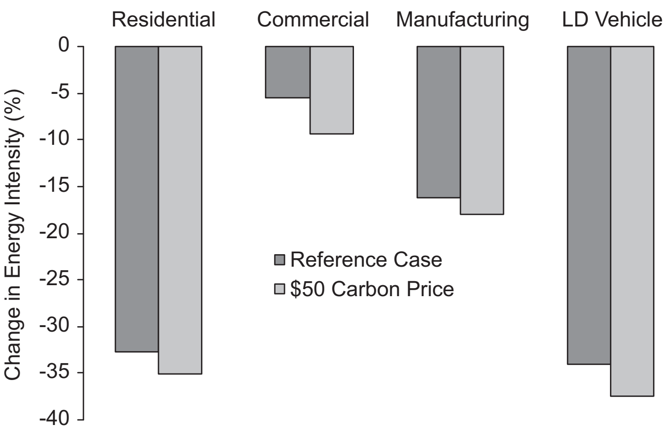

Fig. 5. Reduction in energy intensity between 2005 and 2030.

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.

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 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.[8] 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.

5. 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 Fig. 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 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.

(*footnote continued*)
in the baseline forecast can have a significant effect on estimates of the cost-effective and/or achievable efficiency potential.

[8] 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 CO_2e avoided, depending on the utilization rate. The Interagency Task Force on Carbon Capture and Storage (2010) provides a similar range for the incremental costs of new coal-fired plants with carbon capture and storage of between \$60 and \$95/tonne CO_2 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 (rebuilds and new builds) of \$44/tonne CO_2e.

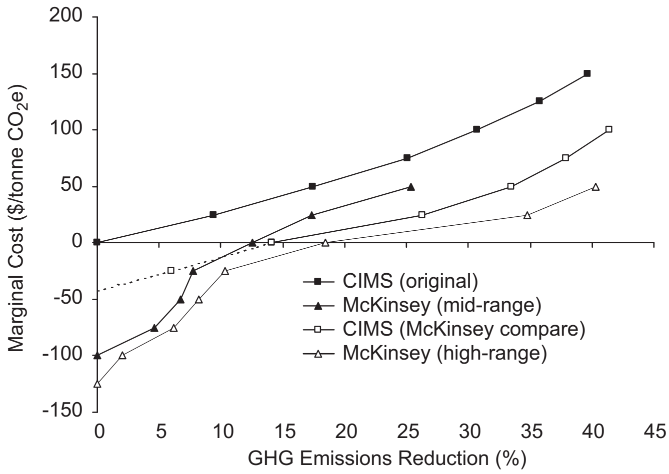

Fig. 6. GHG abatement cost curves for the US in 2030 including a modified CIMS curve.

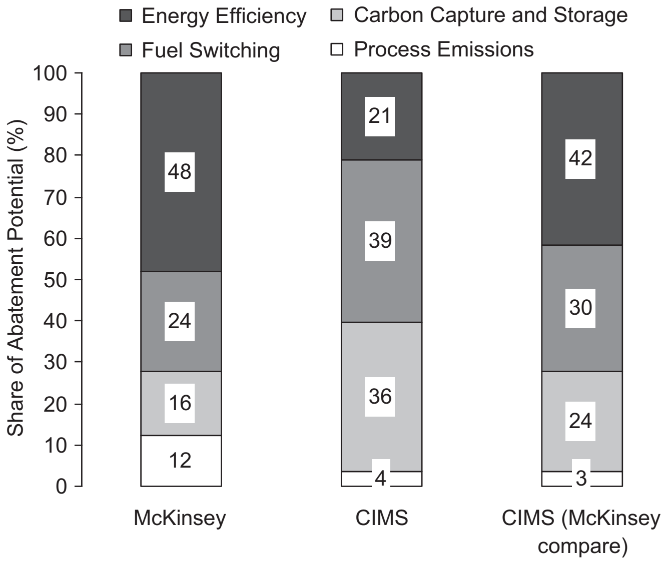

Fig. 7. Contributions to GHG emissions abatement in 2030 at $50/tonne CO_2e, with modifications to CIMS.

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.

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 CO_2e, 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 CO_2e), 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 Fig. 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. 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 (Fig. 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.

6. 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.

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Appendix A. 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

$$C_R = Q\frac{E}{Q}\frac{C_G}{E}\frac{C_R}{C_G} = QIFS_C \qquad (\mathrm{A}-1)$$

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

$$P_R = Q\frac{P_G}{Q}\frac{P_R}{P_G} = QAS_P \qquad (\mathrm{A}-2)$$

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 CO_2e 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. (A-1) 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. (A-2) 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. (A-1), 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. (A-1) and (A-2) due to macroeconomic feedbacks are negligible at a carbon price of only \$50/tonne CO_2e (we did not identify any abatement potential for an output category in the McKinsey analysis either).[9] 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 reallocated the emissions increase to the fuel switching category when summing across the individual sub-models.

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[9] 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.

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