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From my perspective

Representing spatial technology diffusion in an energy system optimization model

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ABSTRACT

In this study, we develop a series of technology diffusion formulations that endogenously represent empirically observed spatial diffusion patterns. We implement these formulations in the energy system optimization model MESSAGE to assess their implications for the market penetration of low-carbon electricity generation technologies. In our formulations, capacity growth is constrained by a technology's knowledge stock, which is an accumulating and depreciating account of prior capacity additions. Diffusion from an innovative core to less technologically adept regions occurs through knowledge spillover effects (international spillover effect). Within a cluster of closely related technologies, knowledge gained through deployment of one technology spills over to other technologies in the cluster (technology spillover effect). Parameters are estimated using historical data on the expansion of extant electricity technologies. Based on our results, if diffusion in developing regions relies heavily on earlier deployment in advanced regions, projections for certain technologies (e.g., bioenergy with carbon capture and storage) should be tempered. Our model illustrates that it can be globally optimal when innovative economies deploy some low-carbon technologies more than is locally optimal as it helps to accelerate diffusion (and learning effects) elsewhere. More generally, we demonstrate that by implementing a more empirically consistent diffusion formulation in an energy system optimization model, the traditionally crude—or nonexistent—representation of technology diffusion in energy-climate policy models can be significantly improved. This methodological improvement has important implications for the market adoption of low-carbon technologies.
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1. Introduction

1.1. Integrated assessment models

The preponderance of scientific evidence indicates that continued emission of greenhouse gases (GHGs) will cause further increases in global temperatures, likely resulting in severe and irreversible negative impacts (IPCC, 2014). Growing concern about climate change has led governing bodies at all levels to implement or at least to consider policies to reduce emissions. Example policy instruments include emissions pricing, emissions trading schemes with quantity limits, renewable portfolio standards, and feed-in tariffs. A key question is how do these policies affect the market deployment of different technology options—and hence GHG emissions—and how do policies in one jurisdiction (e.g., a country) potentially affect the market uptake of new technologies in other jurisdictions. These research questions are traditionally explored via formal models and in assessing alternative future policy and technology scenarios.

To evaluate the economic and environmental consequences of potential climate policies, researchers have developed a host

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of integrated assessment models (IAMs) that combine elements of the linked energy, economic, and environmental systems (including land-use) in a unified inter-disciplinary framework (Wilkerson et al., 2015). The primary intention of IAMs is not to provide exact forecasts, but rather to suggest plausible future scenarios based on model assumptions about population growth, economic growth, technological change, and other factors (Moss et al., 2010). These models feature a diverse set of methodologies, and several attempts have been made to classify them into distinct categories (Schneider and Lane, 2005; Schneider, 1997; Stanton et al., 2009). Although these taxonomies differ, it is fairly straightforward to identify several broad classes of IAMs that differ in terms of level of integration, detail represented, and the applied solution method, each with distinct strengths and weaknesses that make it well suited for certain applications and research questions, but not others.

Cost–benefit IAMs contain reduced-form representations of the climate system and represent feedbacks from the climate to the economy. By placing an economic value on damages caused by GHG emissions, these models weigh the benefits of reducing emissions against the costs it would entail. Cost–benefit IAMs are designed to address the question of the best climate policy, such as an optimal carbon price schedule. They are typically simple and transparent in structure, but feature little (if any) regional or technological detail. Cost–benefit IAMs include the DICE, FUND, and PAGE models employed by the Interagency Working Group on Social Cost of Carbon to inform U.S. government policy (Interagency Working Group on Social Cost of Carbon, 2010).

General equilibrium IAMs include detailed representations of the economy, often disaggregated into different regions and sectors. Firms maximize profit, consumers maximize utility, and the model solves for the equilibrium prices that equilibrate supply and demand across all markets. Most general equilibrium models rely on a recursive-dynamic solution approach rather than an inter-temporal optimization scheme. General equilibrium IAMs are well suited for evaluating the economic impact of a policy, particularly when feedbacks between economic sectors could be significant. Partial equilibrium IAMs follow a similar modeling paradigm but solve for equilibrium prices only within certain markets of interest such as energy commodities or electricity generation. The EPPA model (Paltsev et al., 2005) is a prototypical general equilibrium IAM, while GCAM (Kim et al., 2006) is representative of partial equilibrium models.

IAMs based on energy system optimization models take the perspective of an energy system planner whose problem is to select the set of energy technology investments that minimizes total cost subject to a variety of constraints. These constraints reflect the need to meet energy end-use demands, the finite availability of energy resources, limits on technology diffusion rates, and possibly caps on GHG emission quantities. Energy system optimization IAMs often feature many technologies represented in great parametric detail, including fixed and variable costs, conversion efficiencies, capacity factors, and lifetimes. As a result, these models are frequently applied to assess the prospects for, or value of, individual energy technologies under a range of assumptions. Examples of this model class include TIAM (Loulou and Labriet, 2007; Loulou, 2007), based on the MARKAL/TIMES energy system model (Loulou et al., 2004), and MESSAGE (Riahi et al., 2007), the modeling framework utilized in this study.

1.2. Energy technology assessments

Technology-detailed IAMs have been used to conduct a wide range of energy technology assessments. The goals of such assessments vary, but common objectives are to develop scenarios for the adoption of a technology, determine its economic value, evaluate its environmental impact, and investigate how these results change under different assumptions about end-use demands, technological change, climate policy, and other parameters. In this subsection, we briefly review some recent, multi-model energy technology assessments to demonstrate how IAMs are applied in this context and highlight the challenges that arise.

The Stanford Energy Modeling Forum Study 27 (EMF 27) examined the role of technology for achieving climate policy objectives by comparing results from 18 IAMs (Weyant and Kriegler, 2014). Scenarios varied in their assumptions about technology availability, placing different constraints on technologies like nuclear, bioenergy, solar, wind, and carbon capture and storage (CCS). For each technology scenario, the models produce a range of global mitigation costs required to meet 450 ppm and 550 ppm atmospheric carbon dioxide equivalent (CO_2e) concentration targets. Comparing the cost ranges across technology scenarios establishes the value of individual technologies, or groups of technologies, for meeting the climate policy objective. The study results suggest that bioenergy and CCS are particularly valuable mitigation technologies due to their potential applications beyond the electricity generation sector and their combined ability to produce negative emissions (Kriegler et al., 2014).

Similar to EMF 27, the European Union's Adaptation and Mitigation Strategies—Supporting European Climate Policy (ADAM) project employed a collection of IAMs to assess the value and competitive potential of certain energy technologies for achieving low atmospheric GHG concentration targets (Edenhofer et al., 2015). Across the participating models, the ranking of individual technology options by importance was fairly robust (Edenhofer et al., 2010). Renewables and CCS are the most valuable technologies, and biomass is also important if its availability is high and the climate target is ambitious. Nuclear was found to be of lesser importance. Many energy transition pathways are possible to achieve modest climate policy goals, but stringent targets imply heavy reliance on particular technologies and a loss of flexibility to substitute technologies within the energy mix. The project results suggest that understanding limits to the availability of technologies with potentially adverse side effects, such as bioenergy and CCS, should be a high priority of future research.

The Report on Energy and Climate Policy in Europe (RECIPE) project analyzed the economic and technical dimensions of decarbonization using three IAMs and a variety of policy and technology scenarios (Edenhofer et al., 2012). Echoing the results of the ADAM studies, the RECIPE project findings indicate that CCS and renewables are the most valuable low-carbon technology options due to their flexibility and broad applicability (Tavoni et al., 2011). Nuclear is again found to have comparatively lesser importance. Prospects for renewables are highly sensitive to assumptions about technological change and diffusion. The project demonstrates the importance of building a diversified portfolio of mitigation technologies and fostering technological innovation.

The Assessment of Climate Change Mitigation Pathways and Evaluation of the Robustness of Mitigation Cost Estimates (AMPERE) project, funded by the European Union, analyzed the effects of delayed international action to address climate change on the achievability of long-term climate policy goals (Kriegler et al., 2015a). Several studies in this project evaluated the effects of near-term policy choices on energy transitions throughout this century. An analysis featuring nine IAMs (Bertram et al., 2015) found that delayed climate policy implementation causes significantly more coal capacity to be installed over the next several decades. To meet a long-term climate goal such as limiting warming to 2 °C above pre-industrial temperatures, much of this coal capacity would need to be prematurely retired and bioenergy with CCS would need to be deployed to produce negative emissions. Another AMPERE study determined that if bioenergy with CCS is unavailable in the long-term, the optimal transition to a low-carbon energy system includes much greater emission reductions in the near-term (Eom et al., 2015). The majority of this transition occurs in the period 2030–2050, with nuclear, solar, and wind power all scaling up dramatically, particularly if CCS is banned. The project also found that limits on diffusion rates of low-carbon technologies become more formidable obstacles to climate stabilization if mitigation is delayed (Iyer et al., 2015). Constraints on the market penetration of CCS and renewables are more costly than those on nuclear and bioenergy. A combination of delayed policy action and stringent diffusion rate limits renders ambitious long-term climate policy objectives infeasible.

The conclusions of IAM-based energy technology assessments are only as credible as the structural and parametric assumptions contained in the models. To model extremely complex socioeconomic systems, IAMs necessarily resort to simplified representations that abstract away from the innumerable interactions and factors that are present in reality. One important process that IAMs model in a very simplified fashion is technology diffusion. In the next subsection, we describe how energy system optimization models typically represent technology diffusion. Our focus is on this class of IAMs because energy system optimization models include the most technological detail and offer the most transparent structural framework for diffusion analyses. In Subsection 1.4, we review historical evidence on the diffusion of energy technologies to investigate whether the model formulations properly respect empirically observed patterns.

1.3. Technology diffusion: Model formulations

Energy system optimization models select technology investments on the basis of cost, but the relative costs of different technologies change over time as a result of technological change, evolving climate policy, and other factors. Without constraints on technology diffusion, models would initiate a drastic and instantaneous shift in the technology investment portfolio as soon as a new technology becomes cost-competitive with an incumbent. For example, a model might not invest in solar photovoltaic (PV) capacity at all until exogenous technological progress and a rising carbon price make it cost-competitive with fossil generation, causing the model to suddenly switch all its investment from fossil to solar PV. Such behavior is clearly inconsistent with the gradual nature of historical energy transitions (see next subsection), so many energy system optimization models include constraints to limit the rate of deployment of new technologies, or technology growth rates.

The standard modeling approach is to impose exogenous constraints on annual scale-up rates for individual technologies within each region. These diffusion constraints are specified in either absolute or percentage terms. Heterogeneous maximum scale-up rates can be applied to different technologies and possibly to different regions. Models that include advanced technology options which are currently in development or envisioned for the future exogenously specify when these technologies will become available. These availability dates may or may not vary by region. Models with percentage growth constraints that include technologies which do not currently constitute an appreciable portion of the technology mix must allow for some amount of deployment in the initial adoption period.

The popular and well-documented Market Allocation (MARKAL) model, developed and maintained by the IEA, is a quintessential energy system optimization model with a standard technology diffusion formulation. It exogenously imposes maximum annual growth rates on capacity expansion and also enables the user to place exogenous upper bounds on total capacity or investment in new capacity (Loulou et al., 2004). For technologies that have not yet been deployed, MARKAL allows for some initial build in the first adoption period. The IEA has recently developed The Integrated MARKAL-EFOM System (TIMES) as a successor to MARKAL (Loulou and Labriet, 2007; Loulou, 2007). TIMES has some additional features but its reference energy system and description of technologies are largely inherited from MARKAL. As MARKAL and TIMES are model generators used in many different applications, diffusion constraint parameterizations depend on the particular implementation. The upgraded Dynamic New Earth 21 (DNE21+) energy system optimization model, maintained by the Research Institute of Innovative Technology for the Earth in Japan, provides global coverage with many regions and technologies (Akimoto et al., 2012; Akimoto et al., 2004). It has been included in major inter-model comparison studies including the aforementioned AMPERE and EMF 27 projects. DNE21+ imposes a percentage scale-up constraint on nuclear power generation, but not on other technologies. It also places exogenous upper bounds on wind, solar PV, and nuclear generation as shares of total generation (RITE Systems Analysis Group, 2009; Krey, 2011). Availability dates are exogenously specified for new technologies; for example, CCS generation options can be deployed starting in 2020. The Regionalized Model of Investments and Development (REMIND) operated at the Potsdam Institute for Climate Impact Research employs adjustment costs to allow an acceleration of technology diffusion compared to average technology deployment (Leimbach et al., 2010). The Joint Global Change Research Institute's Global Change Assessment Model (GCAM) is a recursive-dynamic IAM rather than an energy system optimization model. Although GCAM does not normally feature explicit technology scale-up constraints, the AMPERE study which employed GCAM to analyze the implications of diffusion limits for climate stabilization pathways added exogenous generation growth constraints on top of the model's logit choice technology selection formulation (Iyer et al., 2015).

As these examples demonstrate, energy system optimization models typically limit technology diffusion through some combination of exogenously specified availability dates and exogenous constraints on capacity or generation growth, level, and share. MESSAGE, the energy system optimization framework utilized in this study, represents technology diffusion in much the same manner. It includes constraints on generation growth, although these limits can be exceeded by incurring a penalty cost to expand generation faster than the constraint implies. We summarize MESSAGE in greater detail in Subsection 2.1.

1.4. Technology diffusion: Historical evidence

No new technology spreads instantaneously. Instead, rates of adoption, or technology diffusion, observed empirically vary widely spanning time scales of months to years (e.g., for fashion items) to decades, even centuries (as for large-scale, long-lived infrastructures). In turn, diffusion rates and levels depend on a host of factors including characteristics of the technology (e.g., profitability) and characteristics of the adoption environment. The diffusion literature is vast and a comprehensive review is beyond the scope of this paper. A useful literature synthesis is provided through the successive editions of Everett Rogers' *Diffusion of Innovations* (Rogers, 2003), which the energy and climate-related technology diffusion literature, reviewed here, draws upon.

As summarized above, energy system optimization models limit technology diffusion rates due to ample historical evidence indicating that most energy technologies require time scales of decades or even centuries to achieve widespread adoption. Previous studies have computed characteristic diffusion time scales for a wide range of technology transitions, usually defined as the time required to scale up from 10% to 90% of maximum adoption[1] (Grubler et al., 1999; Wilson, 2009; Nakićenović, 1990; Cleveland, 2012; Meyer et al., 1999; Ray, 1989). Historically observed time scales include 130 years for the transition from traditional renewables to coal steam power and 80 years for the transition from coal to oil, gas, and electricity (Grubler, 2012). End-use technologies typically diffuse faster than supply-side technologies, but heterogeneity is substantial. Global diffusion took place over durations of 60 years for railways (Grubler, 1990), 25 years for basic oxygen steel furnaces (Nakićenović, 1990), and 12 years for substituting steam by diesel or electric locomotives (Grubler et al., 1999). Diffusion rates do not appear to be changing significantly over time, in contrast to the common perception that technologies are being adopted faster in the present than they were in the past (Wilson, 2009). To parameterize diffusion constraints, energy system optimization model developers and users can calculate the equivalent annual growth rates from the empirical data. The slow global diffusion of coal power took place with an annual growth rate of just 2% (Iyer et al., 2015).

There is no generally accepted theory that explains diffusion rate heterogeneity across technologies, but several factors are considered important. Greater unit scale and larger market size contribute to slower diffusion. Requirements for interrelated technologies or complex infrastructures also hinder the diffusion process (Grubler, 2012). For example, a major obstacle confronting the potential expansion of hydrogen fuel cell vehicles is that it would require significant advances and investments in hydrogen production technologies and distribution networks (Grubler et al., 1999). Certain factors can accelerate diffusion. A powerful one is the presence of niche markets in which the unique performance advantages of a new technology offer a substantial upgrade relative to conventional competitors (Wilson, 2012). The new technology is likely imperfect and expensive, but the market niche shields it from competition and provides valuable opportunities for performance enhancement and cost reduction. History provides many examples of technologies that benefited from such niches. The light water reactor initially thrived as a power source for nuclear submarines, and the benefits of this experience left the technology well placed to diffuse into the civilian electricity sector (Cowan, 1990). Mobile phones benefited from early deployment in recreational boats and automobiles, where the traditional competitor was not a viable option. In the early stages of diffusion, performance is a more important driver of adoption than cost competitiveness. Typically, significant cost reductions only occur once the technology reaches a deployment level capable of supporting standardization and mass production (Wilson, 2012).

Diffusion is a spatial (Hagerstrand, 1967) as well as a temporal process, and historical evidence confirms that technologies diffuse at different times, at different rates, and to different extents in different places, and can be significantly influenced by policies (Victor, 1993). An illustrative empirically based theory for technology diffusion across multiple regions is suggested by “Schmidt's Law” (Grubler, 1990). With respect to a specific technology, it divides regions into three groups: core, rim, and periphery. The core is where the technology is invented, subject to experimentation, and first deployed commercially. To develop the technology, the core must have both sufficient innovative ability and economic motivation to make the necessary resource commitment. As the technology spreads from the core to the rim and eventually to the periphery, later adopters have the advantage of benefiting from the experiences of earlier adopters via knowledge spillover effects (Verdolini and Galeotti, 2011). At this point, the technology has likely been refined and costs have likely declined significantly. Schmidt's Law claims that, as a result, diffusion proceeds at a faster rate in regions which adopt the technology later. However, diffusion tends to be less pervasive in regions where adoption is delayed, ultimately saturating at a lower extent than in regions where adoption occurred earlier. This is often attributed to a lack of proper institutions and infrastructures in later adopters, markets which may not be as favorable to a technology, or the availability of yet newer options that invite technological leapfrogging.

Empirical evidence supports the validity of Schmidt's Law over a wide range of technologies, time periods, and geographical contexts. A recent meta-analysis of technology up-scaling found that diffusion accelerated moving from the core to the rim and periphery for technologies as diverse as natural gas power, oil refineries, and automobiles (Wilson, 2009). One historical example that conforms particularly well to Schmidt's Law is the diffusion of coal power in Europe (Grubler, 2012).

[1] This convention is based on the parameters of the logistic growth functions (S-shaped curves) that are frequently used to describe technology diffusion. See Wilson (2012) for more information on this diffusion rate metric.

England emerged as the core region for coal power because it had legal and economic institutions that incentivized scientific pursuits, domestic coal reserves, and a clear industrial motivation to replace water power with coal. The diffusion of steam-based coal power in England was slow (spanning most of the 18th and 19th centuries) but very pervasive, ultimately providing almost all the nation's primary energy. England developed an effective infrastructure for mining, transporting, and using coal. The next European nations to adopt coal power were Germany, France, and the Netherlands, which constituted the rim. Benefiting from the earlier experience of England, diffusion in these countries took place much faster. In general, and in accordance with Schmidt's Law, the maximum extent of diffusion in the rim was lower, with coal power saturating at roughly 85% of primary energy in France and the Netherlands. The European periphery for coal power included Spain, Italy, Sweden, and Portugal. Diffusion in the periphery took place later and proceeded at a pace similar to that observed in the rim. The maximum extent of diffusion was much lower in the periphery than anywhere else, which can be explained by several factors. The periphery countries lacked the large coal reserves of England and Germany, never developed as comprehensive a supporting infrastructure for coal, and adopted coal power when new competitors like oil and gas were entering the primary energy mix. It is interesting to note that the regions which adopted coal power earliest and most heavily also retained a large share of coal power the longest as new competitors arose. This is an example of lock-in, the idea that significant technological experience and the existence of a complex infrastructure supporting the incumbent technology help it persist even when superior competitors enter the market.

The simple, exogenous constraints used to limit technology diffusion in most energy system optimization models do not respect these empirical observations regarding the spatial dimensions of technology diffusion. They do not distinguish among core, rim, and periphery regions, and do not represent important feedbacks such as knowledge or technology spillover effects where diffusion in one region facilitates adoption in other regions.

1.5. Purpose and Overview

In this study, we develop a series of progressively more detailed technology diffusion formulations that endogenously represent empirically observed spatial diffusion patterns. We implement these formulations in the MESSAGE energy system optimization model and parameterize them using historical data on the expansion of several extant electricity generation technologies. We analyze results from several scenarios to explore the implications of our formulations for the market adoption of low-carbon electricity technologies. More generally, this study serves as a proof of concept. We demonstrate that implementing a more empirically consistent technology diffusion formulation than the crude approach typically featured in energy system optimization models is feasible, is not overly complicated, and has significant implications for energy transition pathways throughout this century.

The remainder of this article is organized as follows. In the next section, we characterize the MESSAGE modeling framework and describe the diffusion formulations that we implement. We analyze historical data in Section 3 to estimate parameters for our formulations. Section 4 contains a description of the scenarios we run in MESSAGE. In Section 5, we present scenario results and discuss their implications for the diffusion of low-carbon generation technologies. We conclude in Section 6 with a summary of our most salient findings.

2. Technology diffusion formulations

This study utilizes the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE). We first introduce this model and its standard representation of technology diffusion, and then describe the progressively more detailed endogenous diffusion formulations that we implement within its broader framework.

2.1. MESSAGE

MESSAGE is a technology-detailed, least-cost optimization model of the global energy system (Riahi et al., 2007). Several versions of MESSAGE are available, each of which is tailored to research focusing on a different aspect of the linked energy, economic, and environmental systems. The version of MESSAGE selected for this study is a reduced-form version of the model implemented in GAMS and originally designed for analyses examining the roles of uncertainty and foresight (Krey and Riahi, 2013). It has 10-year time steps, a 2100 time horizon, four regions (Fig. 1), and 11 electricity generation technologies (Table 1). In addition, oil refining, liquid fuel production from coal, gas and biomass as well as hydrogen electrolysis are represented in the model to cover a wide range of primary to final energy supply routes. Energy end-use is modeled in a stylized fashion with three demand categories included: stationary electric demand, stationary thermal demand, and transport fuel demand. Energy savings are incorporated via so-called conservation cost curves that have been derived from the 11-region version of MESSAGE (Rogelj et al., 2013). The model is linear and deterministic. Throughout the remainder of this paper, MESSAGE shall refer to this particular version of the model. It is appropriate because its GAMS framework enables structural modifications and because its limited sets of regions and technologies focus attention on diffusion patterns without unnecessary complexity.

In MESSAGE, new technologies become available to each region in an exogenously specified period. For some advanced low-carbon technologies, certain regions gain access before others to reflect the fact that certain regions are more likely to be early adopters. For example, in MESSAGE scenarios such as the one developed for the Global Energy Assessment (Riahi et al., 2012), the assumption is made that the coal CCS and gas CCS technologies are available to OECD as well as China as of 2020 but to the other regions as of 2030 because, from today's perspective, OECD is most likely to be the innovating core region for these technologies.

MESSAGE limits diffusion rates by imposing soft constraints on the annual percentage growth of generation for each technology in each region (Keppo and Strubegger, 2010). The constraints are "soft" in that they can be exceeded, but doing so entails significant additional costs. For example, in each region, coal generation is allowed to expand up to 10% annually before additional costs must be incurred to scale up any faster.

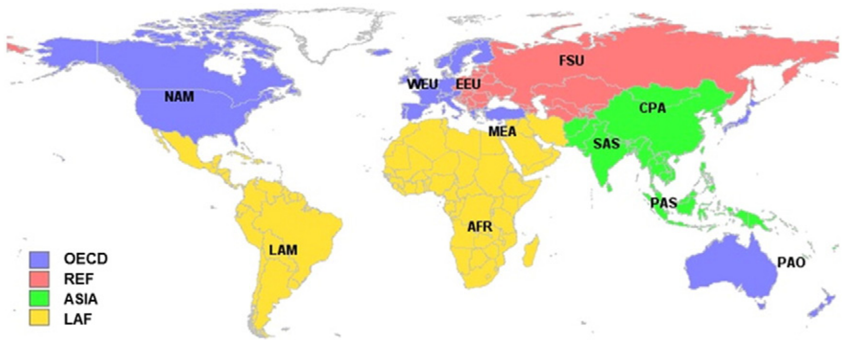

Fig. 1. Aggregation of the MESSAGE regions into four larger regions (OECD = Organization for Economic Cooperation and Development as of 1990, REF = reforming economies of Eastern Europe and the former Soviet Union, ASIA = developing Asia, LAF = Latin America, Africa, and the Middle East) (Nakićenović and Swart, 2000).

The assumptions and constraints that MESSAGE employs to control technology diffusion are fairly typical of energy system optimization models. We will later refer to our scenario featuring the unmodified version of MESSAGE with its standard representation of technology diffusion as the reference scenario. Its results will serve as benchmarks that allow us to assess the implications of the empirically motivated endogenous diffusion formulations we develop below.

2.2. Knowledge stock constraints on capacity expansion

MESSAGE imposes constraints on annual electricity generation expansion, but it is more consistent with the diffusion literature for such constraints to be applied to capacity expansion. Consider the example of nuclear power in the IEA countries. Although generation is still significant, most operating plants were built several decades ago and cumulative R&D expenditures have been declining since the early 1980s (IEA, 2014). Even with conservative assumptions about knowledge depreciation, the nuclear knowledge stock is lower today than it was at its 1980s peak (Grubler and Nemet, 2012). This important information is lost when constraints are applied to generation. Knowledge, expertise, and engineering capacity—the factors that limit the rate of technology diffusion—are embodied in the physical capital itself, not in generation levels. Therefore, constraining capacity growth is a superior alternative to constraining generation growth. We replace the MESSAGE generation expansion constraints with capacity expansion constraints and specify the additional costs incurred for exceeding soft growth limits based on investment cost instead of levelized cost. Mathematical expressions for these constraints appear later in this subsection.

The amount of new capacity installed in a given period is constrained in our model by a region-and-technology-specific knowledge stock. It embodies the knowledge, expertise, and engineering capacity required to add new plants. The knowledge stock is assumed to be a function of prior capacity additions. This simplification ignores other factors that are relevant to installing capacity, such as R&D spending, capital constraints, and infrastructure bottlenecks. Generally speaking, the more capacity that has previously been added, the more new capacity can be installed. This acceleration of the allowed capacity addition during the technology expansion phase resembles the convex portion of the S-shaped logistic growth function frequently used to describe technology diffusion. The flattening out of the diffusion trajectory will be enforced by market saturation effects, but by that point, the knowledge stock constraint on capacity addition will no longer be binding.

Table 1
Electricity generation technologies in the MESSAGE model (CCS: with carbon capture and storage; PV: photovoltaic electricity generation).

Coal	Gas	Nuclear	Hydro	Biomass	Oil
Coal CCS	Gas CCS	Wind	Solar PV	Biomass CCS	

There is ample evidence to suggest that knowledge, like other forms of capital, depreciates with time. Previous capacity additions do not contribute equally to the current knowledge stock. In particular, capacity installed recently contributes more to the knowledge stock than capacity installed in the distant past because recent capacity additions likely featured current workers, the latest production methods and designs, and so forth. Several studies based on R&D spending and patent citations have estimated knowledge depreciation rates for energy technologies. Wantanabe et al. (Wantanabe et al., 2002) found that knowledge in the Japanese solar PV industry depreciates at a rate of 30% per year. Nemet (Nemet, 2009) identified a 10% knowledge depreciation rate in the American wind turbine industry. In general, energy technologies are characterized by knowledge depreciation rates in the 10–40% range, with the French breeder reactor program establishing the high end of this spectrum (Grubler and Nemet, 2012).

Mathematically, let X, R, and T respectively represent the sets of technologies, regions, and time periods included in the model. The sets X and R are defined by Table 1 and Fig. 1, respectively, and $T = \{0, 1, 2, 3 \ldots\}$. Let $K_t^{r,x}$ denote the knowledge stock for technology x in region r in period t. Denote the capacity installed in period t as $C_t^{r,x}$. Let d represent the knowledge depreciation rate. The initial period is denoted t_0 and Δ is the period length. With these conventions, the knowledge stock is defined according to Eq. (1). The discount factor is defined such that capacity added in the immediately preceding period contributes to the knowledge stock undiscounted.

$$K_t^{r,x} = \sum_{\tau=0}^{t-1} C_\tau^{r,x} (1-d)^{\Delta(t-1-\tau)} \qquad \forall r \in R, x \in X, t \in T \tag{1}$$

We assume that the soft upper bound on new capacity installation is linear with respect to the knowledge stock. For each unit of knowledge stock, g units of new capacity can be installed annually. This linear relationship may seem somewhat ad hoc but is supported by the historical data analysis presented in Section 3. Innovative regions capable of pioneering a new technology are assigned a positive start-up value s^r (annual capacity units) which allows them to deploy a small amount of capacity when knowledge stock is zero. The start-up value enables adoption to begin, after which the knowledge stock dominates in setting the constraint on new capacity. Eq. (2) is the soft constraint on capacity expansion.

$$C_t^{r,x} \leq K_t^{r,x}\left[(1+g)^{\Delta}-1\right] + \frac{s^r\left[(1+g)^{\Delta}-1\right]}{g} + Soft\ Terms \quad \forall r \in R, x \in X, t \in T \tag{2}$$

The coefficients refer to the fact that $C_t^{r,x}$ is the new capacity added in a period lasting Δ years while g and s^r refer to annual capacity installations. New capacity added in the first year of the period contributes to the knowledge stock available for adding capacity in the second year, meaning that the maximum possible capacity installation in each year grows by a factor of $(1 + g)$ annually throughout the period. The coefficients of Eq. (2) reflect the sums of these geometric series. In the transparent case of $\Delta = 1$ year, the constraint reduces to Eq. (3). Here it is clear that the soft constraint on new capacity is linear with respect to the knowledge stock with a start-up value that is either zero or positive.

$$C_t^{r,x} \leq gK_t^{r,x} + s^r + Soft\ Terms \quad \forall r \in R, x \in X, t \in T \tag{3}$$

Knowledge depreciation over the duration of a single period is ignored in this formulation. Energy plant construction times are significant relative to the period length in this study and, given the temporal resolution of the model (10-year time steps), the particular year within a period when new capacity is added is trivial. The formulation constrains the amount of capacity that can be added in one period based on the knowledge stock available at the beginning of that period.

The soft terms of the constraint allow the upper bound on new capacity addition to be relaxed, but at significant and marginally increasing cost. The optimizing agent can choose to make these components of Eq. (2) positive, but doing so would add cost to the objective function. Therefore, the agent faces a choice between restricting capacity growth to the level implied by the knowledge stock and start-up value, or relaxing this upper bound for additional cost. In our specification, capacity units installed beyond the soft upper bound are subject to a cost penalty equal to 50% of the normal plant investment cost. Beyond a doubling of the soft upper bound, additional capacity units are exorbitantly expensive. This possibility is incorporated to ensure model feasibility, but the optimizing agent should only elect to exercise this option in an environment of unusually severe constraints or extreme parameter values.

The endogenous diffusion formulation as developed up to this point, with knowledge stock constraints on capacity expansion, will later be featured in our scenario denoted KS.

2.3. Spatial diffusion via knowledge spillovers

The knowledge stock formulation constrains capacity expansion in each region independently, but it does not generate a diffusion trajectory that begins in an innovative core and extends to rim and periphery. This is accomplished by selecting a core region through the assignment of start-up values and incorporating knowledge spillovers that allow technology transfer to other regions.

We let OECD be the core region. Given how large and varied the other regions are, a distinction between rim and periphery would be arbitrary for the simple model setup in this study, so we refer to all other regions collectively as the rim. While the technological and innovative primacy of the OECD economies is subject to debate, especially when looking ahead several decades, there is great reason to believe these countries will pioneer the emerging low-carbon electricity technologies featured in the reduced-form MESSAGE model. The OECD countries accounted for 90% of global wind power capacity in 1990 and still accounted for 81% in 2008 (Wilson, 2013). The United States, Europe, Australia, New Zealand, Canada, and South Korea are collectively home to 48 of the 62 large-scale integrated CCS pilot projects underway in the world (Global CCS Institute, 2013). More generally, empirical research demonstrates that a small subset of OECD nations drive a substantial fraction of technological progress around the world (Eaton and Kortum, 1999; Verspagen, 1997). However, dependent on the overall scenario storyline (e.g., (Nakićenović and Swart, 2000; O'Neill et al., 2014)) or specific technologies considered (e.g., biomass-based liquid transport fuels), this assumption can be changed easily in the model.

Regardless, for the purpose of this study, OECD is assumed to be the core region and it is assigned a start-up value $s^{OECD} > 0$ while the other regions are assigned start-up values $s^r = 0 (r \neq \text{OECD})$. Absent a spillover of knowledge from the core, the other regions cannot begin to adopt a new technology. This framework exogenously demands that OECD be the first adopter of all technologies.

The diffusion of a technology from core to rim is governed by a knowledge spillover mechanism. Essentially, capacity units installed in the core contribute at least partially to the knowledge stocks of other regions. Mathematically, the spillover is incorporated into the expression for the knowledge stock. Eq. (4) builds on the foundation of Eq. (2), but includes the spillover mechanism.

$$K_t^{r,x} = \sum_{\tau=0}^{t-1}\left[C_\tau^{r,x} + \sigma_\tau^r C_\tau^{OECD,x}\right](1-d)^{\Delta(t-1-\tau)} \quad \forall r \in R, x \in X, t \in T \tag{4}$$

The rim regions now receive a knowledge spillover from the core in which a unit of capacity added in the core is some fraction σ_t^r as potent as a domestic unit of capacity for augmenting the domestic knowledge stock. Clearly, $\sigma_t^{OECD} = 0$ $\forall\ t \in T$ to avoid double counting; in other words, there is no spillover from OECD to itself. The spillover coefficient varies across the rim regions and evolves over time because larger energy systems should be able to absorb a greater absolute quantity of knowledge generated elsewhere. A unique spillover coefficient corresponds to each region and period because the energy system size varies regionally and temporally.

In summary, the OECD region is exogenously chosen to be the core. Other regions may only begin to adopt a new technology once knowledge generated through experience in the core spills over. Within each region, capacity expansion is limited by an accumulating and depreciating knowledge stock, which is based on the history of prior capacity additions. Having incorporated spatial technology diffusion via knowledge spillovers, the diffusion formulation as developed up to this point will later be included in the scenario denoted KS + SP.

2.4. Cross-technology spillovers

Until now, our diffusion formulation has assumed that knowledge stocks associated with different technologies evolve independently. In reality, when two technologies share common components, installing capacity of one technology should contribute to the knowledge stock for the other. This is similar to the central claim of the component-based learning curve approach, in which the overall cost of a technology is the sum of the costs of its individual components. The cost of each component evolves according to its own cumulative capacity and learning rate, where cumulative capacity reflects the inclusion of the component in units of all technologies that feature it (Yeh and Rubin, 2012).

De Feber et al. define a cluster of technologies as a “group of technologies sharing a common essential component” (De Feber et al., 2002). The reduced MESSAGE model has just 11 electricity generation technologies, most of which have little in common with the others, but the three forms of CCS-coupled generation comprise one obvious technology cluster. The common essential components are the CO_2 capture and CO_2 compression systems. Since each CCS technology features these components, adding capacity of one of these technologies should contribute to the knowledge stocks for all three. In this subsection we incorporate cross-technology spillovers for CCS-coupled generation into our technology diffusion formulation.

We update the expression for the knowledge stock in Eq. (4) to allow for cross-technology spillovers, yielding Eq. (5). The coefficient $\alpha^{x,x'}$ determines the amount of technology x knowledge stock gained per unit of technology x' capacity added.

$$K_t^{r,x} = \sum_{\tau=0}^{t-1} \sum_{x' \in X} \alpha^{x,x'} \left[C_\tau^{r,x'} + \sigma_\tau^r C_\tau^{OECD,x'} \right] (1-d)^{\Delta(t-1-\tau)} \qquad \forall r \in R, x \in X, t \in T \tag{5}$$

Most elements of the cross-technology spillover coefficient matrix are zero. The exceptions are the diagonal elements $\alpha^{x,x} = 1 \ \forall \ x \in X$ and the elements representing cross-technology spillovers between pairs of CCS-coupled generation options. We will instantiate the latter such that $\alpha^{x,x'}$ equals the fraction of technology x investment cost attributed to components which are also included in technology x', where x and x' are generation technologies with CCS. We return to these parameters in the scenario description of Section 4.

Our full endogenous diffusion formulation with knowledge stock constraints on capacity expansion, spatial diffusion through knowledge spillovers, and cross-technology spillovers will later be featured in our scenario denoted KS + SP + CT.

3. Historical data analysis

Our endogenous diffusion formulations include several parameters that can be estimated using historical data. These parameters are the amount of new capacity that can be added annually per unit of available knowledge stock (g), the start-up value that enables initial deployment of a technology by the core region (s^{OECD}), and the spillover coefficients (σ_t^r).

We estimate these parameters by analyzing historical data on additions of coal, gas, nuclear, hydro, and wind electricity capacity in the OECD region. Data on coal, gas, and nuclear come from the Scaling Dynamics of Energy Technologies (SD-ET) database compiled at IIASA (Wilson, 2009). Wilson (Wilson, 2013) personally provided additional data on hydro and wind. For each technology, a time series of annual capacity additions is used to construct a time series of the knowledge stock according to Eq. (1). A scatter plot is constructed with knowledge stock on the horizontal axis and new capacity addition on the vertical axis, each point corresponding to a year in the time series. Envisioning vectors drawn from the origin to each point, the points whose vectors have the greatest slopes correspond to the years when capacity was expanding as fast as possible given the available knowledge stock. These points define a capacity expansion frontier. They are isolated and a least squares regression is implemented to fit a line to this set of points. This line indicates how the maximum possible new capacity addition varies with the knowledge stock. Its slope is an estimate of the parameter g and its vertical intercept is an estimate of the parameter s^{OECD}. This parameter estimation method is illustrated in Fig. 2, which presents data for coal power plants. The graph on the left includes all data points while the graph on the right shows the isolated capacity expansion frontier which is used in our model to constrain the maximum scale-up rate. This estimation method is repeated for all five technologies analyzed. Parameter estimates resulting from this exercise are reported in Table 2.

The only spillover coefficient we estimate directly from the data is σ_{2000}^{ASIA}. The ASIA region is chosen because the REF and LAF regions are institutionally very different today than they were for most of the 20th century covered by the time series data. There is little reason to think, for example, that the ability of the Soviet Union to appropriate foreign knowledge in 1965 is representative of the capacity of the REF region to absorb knowledge spillovers in the present. Once σ_{2000}^{ASIA} is estimated from the data, all other spillover coefficients are simply this value weighted by the size of the energy system relative to the size of the ASIA energy system in the base year, where size is measured in terms of total primary energy consumption. This is a simplifying approximation for other variables that might better reflect absorptive capacity, such as energy R&D spending.

For each of the five technologies studied, a scatter plot is constructed in the style of Fig. 2 featuring data for both OECD and ASIA. The knowledge stocks are computed using Eq. (1), so the spillover to ASIA is not captured in the knowledge stock values. Across technologies, we find that the capacity expansion frontier is generally steeper for ASIA than for OECD. This can be explained by the fact that the ASIA knowledge stock as computed using Eq. (1) does not account for knowledge that spilled over from OECD. Alternatively using Eq. (4) to calculate the ASIA knowledge stock and gradually increasing the spillover coefficient from zero would raise the knowledge stock values

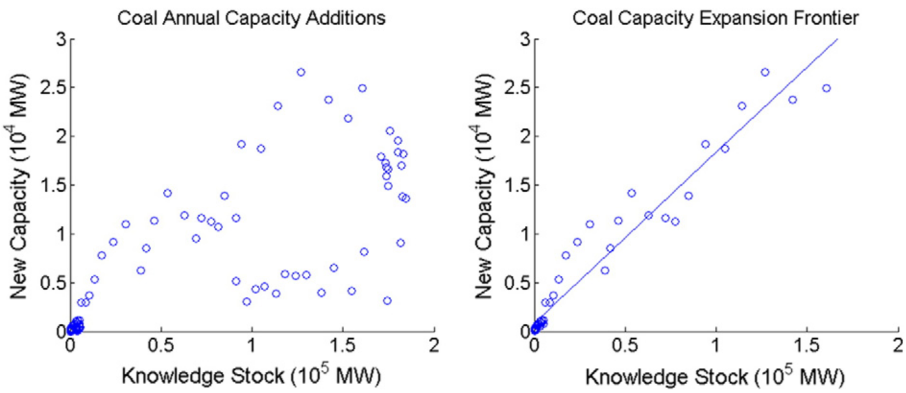

Fig. 2. Annual coal capacity additions in OECD are plotted against corresponding knowledge stocks. The slope and vertical intercept of the capacity expansion frontier serve as estimates of $\boldsymbol{g}$ (new capacity allowed per unit knowledge stock) and $\boldsymbol{s^{OECD}}$ (OECD start-up value), respectively.

and effectively shift all the ASIA data points to the right. Increasing the spillover coefficient until the slope of the ASIA capacity expansion frontier matches the slope of the OECD frontier identifies the spillover coefficient value that explains the divergent growth rates. In this way, we generate a σ_{2000}^{ASIA} estimate from the data on each technology. The capacity expansion frontiers prior to the incorporation of the spillover effect are depicted in Fig. 3, and σ_{2000}^{ASIA} is estimated to exactly account for the difference in their slopes.

The historical data analysis yields several interesting observations. The g parameter estimates for coal, gas, and hydro are fairly similar while the estimates for nuclear and wind are considerably higher. This is likely because the early expansion of coal, gas, and hydro required the simultaneous development of electricity transmission and distribution infrastructure as well as growth in end-use demand. Nuclear and wind entered the electricity supply mix later when the necessary infrastructure and demand were already in place, resulting in faster market penetration. It is difficult to detect any coherent spillover effect associated with nuclear. This is not surprising given the important role that political and national security factors play in the adoption of nuclear power.

4. Scenario analysis

We investigate the implications of our endogenous diffusion formulations for the market adoption of low-carbon technologies by running four MESSAGE climate policy scenarios. These scenarios correspond to the four diffusion formulations developed in Section 2 above. The reference scenario uses MESSAGE in its original form, with exogenous constraints on generation expansion. Replacing this formulation with knowledge stock constraints on capacity growth gives us the scenario-denoted KS. In the KS + SP scenario, new technologies diffuse spatially from core to rim via knowledge spillovers. The addition of technology spillovers across the CCS-coupled generation options yields the final scenario, KS + SP + CT.

In all scenarios, we apply the same diagnostic carbon price schedule featured in (Kriegler et al., 2015b) in which the tax begins at \$18.50/tCO_2 in 2020 and rises 4% annually thereafter.[2] This tax profile is applied in all scenarios to generate conditions under which the optimizing agent will elect to adopt advanced low-carbon electricity technologies to a significant degree, allowing us to observe their diffusion patterns. The knowledge depreciation rate d is assumed to be 10% per year for all technologies in all regions, a conservative depreciation assumption.

Values for the parameters of our endogenous diffusion formulations are based on the historical data analysis of the preceding section. We set g equal to 0.25 and s^{OECD} equal to 674 MW, their mean estimates across the five technologies studied. We set σ_{2000}^{ASIA} equal to 0.03. Table 3 summarizes and distinguishes the scenarios on the basis of these diffusion parameters.

Referring to Subsection 2.4, for the KS + SP + CT scenario with cross-technology spillovers, the parameters governing spillovers across CCS technologies need to be instantiated using data that decompose CCS plant investment costs into components. One such decomposition was conducted by Rubin et al. (Rubin et al., 2007). Different CCS plant types have two components in common: the CO_2 capture and CO_2 compression systems. Therefore, based on our formulation, the cross-technology spillover coefficient from one CCS technology to another equals the share of these two components in the recipient technology's total investment cost. We take the data on pulverized coal with CCS and natural gas combined cycle

Table 2
Parameter estimates based on historical data for each studied technology. Recall that $\boldsymbol{g}$ is the amount of new capacity that can be added annually per unit knowledge stock, $\boldsymbol{s^{OECD}}$ is the start-up value that enables initial deployment by OECD when knowledge stock is zero, and $\boldsymbol{\sigma_{2000}^{ASIA}}$ is the spillover coefficient to ASIA in the base year.

Technology	g	s^{OECD} (MW)	σ_{2000}^{ASIA}
Coal	0.175	848	0.02
Gas	0.217	29	0.02
Nuclear	0.300	1029	N/A
Hydro	0.170	859	0
Wind	0.401	603	0.03

[2] This carbon price schedule begins at \$12.50/tCO_2 in 2010 in Kriegler et al. (2015b). There is some ambiguity in the implementation of the carbon price trajectory due to different interpretations of reporting years across models. We impose the same price schedule as in (Kriegler et al., 2015b), beginning the pricing at a value of \$18.50/tCO_2 in the 2020 period, which stretches from 2011 to 2020.

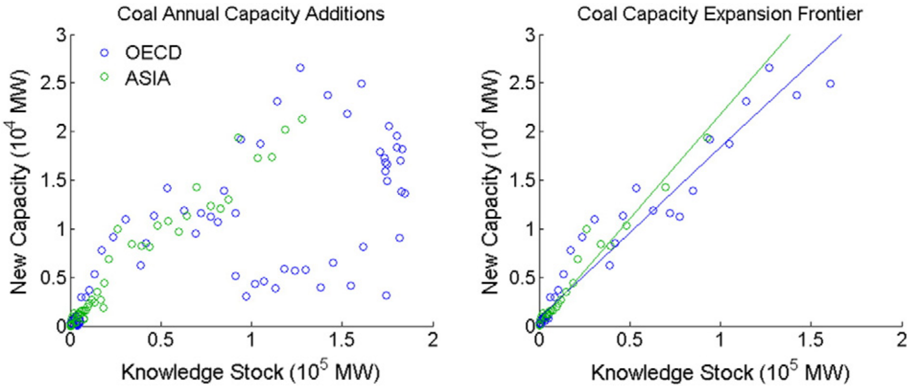

Fig. 3. Without accounting for knowledge spillovers, ASIA exhibits a steeper coal capacity expansion frontier than OECD. We estimate the spillover coefficient σ_{2000}^{ASIA} as the value that augments ASIA knowledge stocks such that the slopes of the OECD and ASIA capacity expansion frontiers are equal.

with CCS reported in Rubin et al. (2007) as representative of the coal CCS and gas CCS technologies, respectively, in our reduced-form MESSAGE model. Since analogous data for biomass CCS is unavailable, we instantiate spillover coefficients to this technology with the more conservative of the values estimated for coal CCS and gas CCS. The cross-technology spillover coefficients are reported in Table 4.

5. Results and discussion

5.1. Reference scenario

We begin our presentation and discussion of results by focusing on the reference scenario. This scenario features the standard technology diffusion formulation of MESSAGE, which is fairly representative of how most energy system optimization models constrain technology diffusion. Therefore, the reference scenario results provide a benchmark that will allow us to assess the implications of our progressively more detailed endogenous diffusion formulations. Fig. 4 shows how the optimal electricity capacity mix of each region evolves over time in the reference scenario.

All regions respond to the rising carbon price with a dramatic transition in the electricity sector from fossil fuel generation to low-carbon alternatives. They phase out virtually all fossil generation without CCS by 2060. However, the regions pursue very different technology strategies to reduce their emissions. OECD relies almost exclusively on wind and solar PV. ASIA deploys coal CCS in the middle of the century but turns to a combination of solar PV and nuclear as the carbon price escalates. The REF and LAF regions both transition to mixes of gas CCS, biomass CCS, wind, and solar PV, though in different proportions and at different times. Across the regions, the results imply that the role of fossil generation with CCS is to bridge the transition from current fossil generation without CCS to zero- and negative-emission technologies like nuclear, solar PV, wind, and biomass CCS. A plot analogous to Fig. 4 above, but with generation rather than capacity shares, is included in the supplementary material.

Table 3
Summary of endogenous diffusion formulation parameter values in each scenario.

Scenario	g	s^{OECD} (MW)	s^r (r ≠ OECD)	σ_{2000}^{ASIA}
Reference	Standard MESSAGE with exogenous generation expansion constraints			
KS	0.25	674	674	0
KS + SP	0.25	674	0	0.03
KS + SP + CT	0.25	674	0	0.03

5.2. Implications of endogenous diffusion formulations

Figs. 5 and 6 illustrate how our progressively more detailed, endogenous diffusion formulations influence the market adoption of six low-carbon generation technologies. Fig. 5 contains results for the whole world while Fig. 6 decomposes results by region. The figures show how the installed capacities compare to those of the reference scenario, with positive numbers indicating an increase in installed capacity relative to the reference case and negative numbers indicating a decrease relative to the reference case. The discussion that follows highlights the major implications of our endogenous formulations for the diffusion of low-carbon technologies. Its intention is not to cover all scenario results comprehensively, but to focus on the most compelling findings. Capacity and generation share results for each scenario, in the style of Fig. 4 above, are included in the supplementary material.

Replacing the exogenous generation expansion constraints of the reference scenario with endogenous knowledge stock constraints on capacity growth (KS scenario) eliminates virtually all coal CCS deployment that occurs in the reference scenario, which is predominantly in ASIA. Adding the spillover mechanism (KS + SP scenario) and cross-technology spillovers (KS + SP + CT scenario) to the formulation barely influences this result. Unlike nuclear, solar PV, and wind, coal CCS has not yet reached commercial scale and its associated knowledge

Table 4
Cross-technology spillover coefficient values for CCS-coupled generation technologies used in the KS + SP + CT scenario (Rubin et al., 2007).

$\alpha^{Bio\ CCS,}_{Coal\ CCS}$	$\alpha^{Bio\ CCS,}_{Gas\ CCS}$	$\alpha^{Coal\ CCS,}_{Bio\ CCS}$	$\alpha^{Coal\ CCS,}_{Gas\ CCS}$	$\alpha^{Gas\ CCS,}_{Bio\ CCS}$	$\alpha^{Gas\ CCS,}_{Coal\ CCS}$
0.22	0.22	0.22	0.22	0.28	0.28

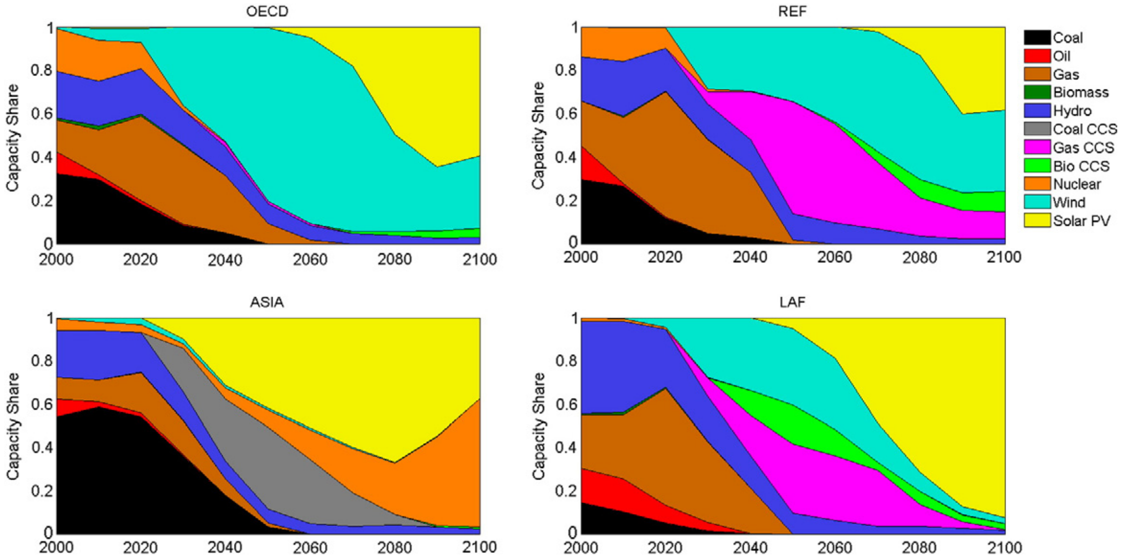

Fig. 4. Evolution of the optimal electricity capacity mix by region in the reference scenario.

stock is minimal. With knowledge stock constraints on capacity expansion, it would require either significant time or additional expenditure to bring this technology to scale, and given that it is only competitive within a particular range of carbon prices,[3] it does not diffuse to a great extent. These findings suggest that energy system optimization models which employ exogenous constraints on the rate of generation expansion may overstate the role that coal CCS could play in reducing electric sector emissions.

Our endogenous diffusion formulations have the opposite effect on nuclear deployment, which is far higher under all three endogenous formulations than in the reference case. The vast majority of additional nuclear capacity is added in ASIA, suggesting that it substitutes for eliminated coal CCS capacity. While CCS-coupled generation technologies are still in the development and demonstration phases, nuclear power is a mature technology that has diffused for over half a century. Its associated knowledge stock is comparatively high, particularly in ASIA where a lot of nuclear capacity has been installed recently and continues to be added. With an endogenous diffusion formulation featuring knowledge stock constraints on capacity growth, nuclear continues to diffuse in ASIA at the expense of coal CCS, a less mature technology that could only be deployed in smaller quantities or at great expense for the near future. This suggests that our formulations endogenously respect technology lock-in, which is a major feature of historical energy transitions that is not represented by standard diffusion formulations. Of course, the expansion of nuclear in ASIA could be halted if a major adopter (e.g., China) suffers a nuclear catastrophe, a possibility which is not captured by the deterministic structure of MESSAGE.

Biomass CCS diffusion is sensitive to the particular endogenous diffusion formulation applied. Moving from the reference case to knowledge stock constraints on capacity expansion (KS scenario) does not have a consistent or large effect, but requiring that new technologies diffuse spatially from core to rim via knowledge spillovers (KS + SP scenario) greatly attenuates biomass CCS diffusion in developing regions. REF and LAF include biomass CCS in their optimal technology portfolios in the reference scenario, but in the KS + SP scenario, OECD does not deploy biomass CCS early or significantly enough to enable subsequent global diffusion in this century. However, this drastic reduction in biomass CCS deployment does not occur if knowledge spills over across the CCS-coupled generation options (KS + SP + CT scenario). In this case, enough gas CCS deployment takes place in OECD over the next several decades to create a knowledge stock relevant to biomass CCS, which spills over to other regions. Biomass CCS is well-suited to some developing regions, but the results suggest that these regions would likely have to pioneer the technology themselves or be able to appropriate knowledge gained from experience with other forms of CCS generation if they plan to make biomass CCS a major component of emission reduction strategies.

In the reference scenario, ASIA is the first region to make solar PV a large component of the electricity mix, and the endogenous diffusion formulations further increase deployment of solar PV in ASIA. Although OECD was the earliest adopter of solar PV (almost invisible at the top left of Fig. 4), in recent years, solar PV deployment has been great enough to create a knowledge stock capable of stimulating widespread global diffusion without much additional deployment in the advanced economies that originally developed the technology. Note, however, that with spatial diffusion through knowledge spillovers (KS + SP and KS + SP + CT scenarios), OECD deploys more solar PV than in the case where all regions can pioneer new technologies independently (KS scenario). This occurs because MESSAGE is a global energy system optimization model, and even though the additional solar PV may not be locally optimal for OECD, it is evidently globally optimal because it enables faster diffusion in developing regions with

[3] Fossil CCS technologies typically require a high-enough carbon price to make them competitive with their fossil counterparts without CCS, yet at high carbon prices, residual (non-captured) emissions reduce their competitiveness with non-fossil technologies such as nuclear or renewable energy.

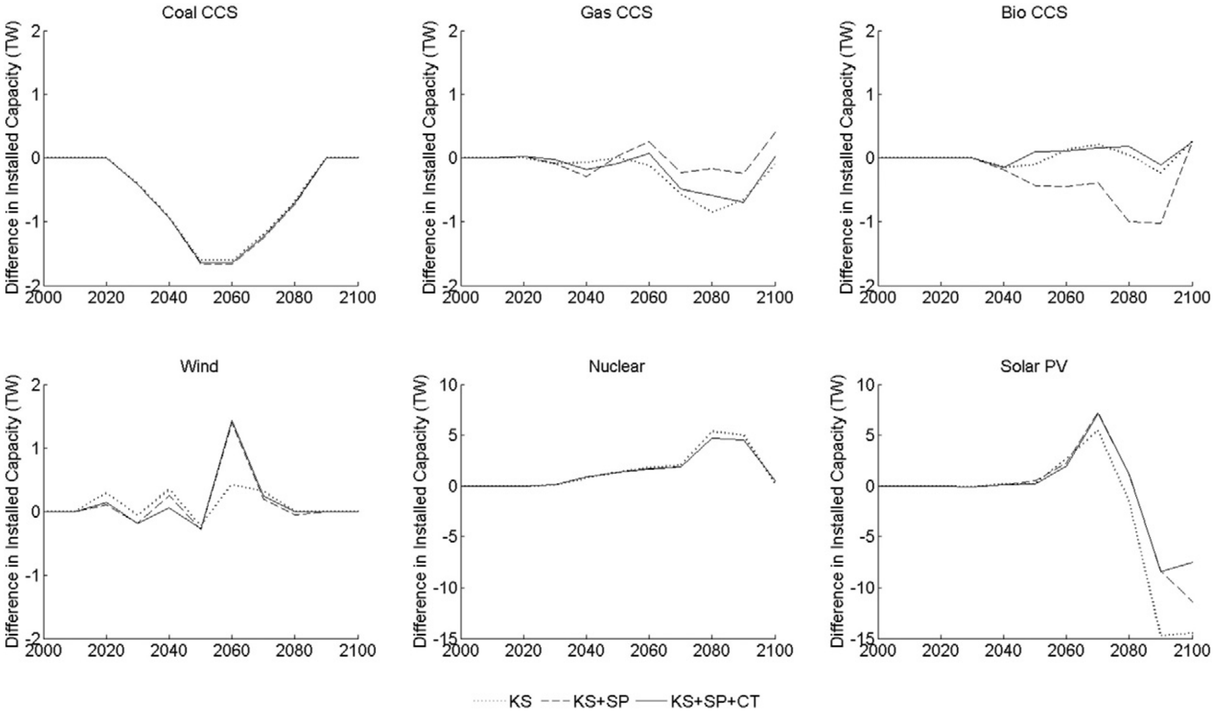

Fig. 5. Difference in global installed capacity relative to the reference scenario, by technology.

better resource potential that rely on spillovers from the core. It is important to note that, in scenarios where they are adopted heavily, solar PV and wind require simultaneous deployment of the electricity storage technology to relax the exogenous cap the model imposes on the intermittent generation share (20%). Whether these scenarios are plausible will therefore depend on continued reductions in electricity storage costs, which MESSAGE exogenously assumes.

Early gas CCS deployment in OECD is higher in the KS + SP scenario than in the KS scenario, and even higher in the KS + SP

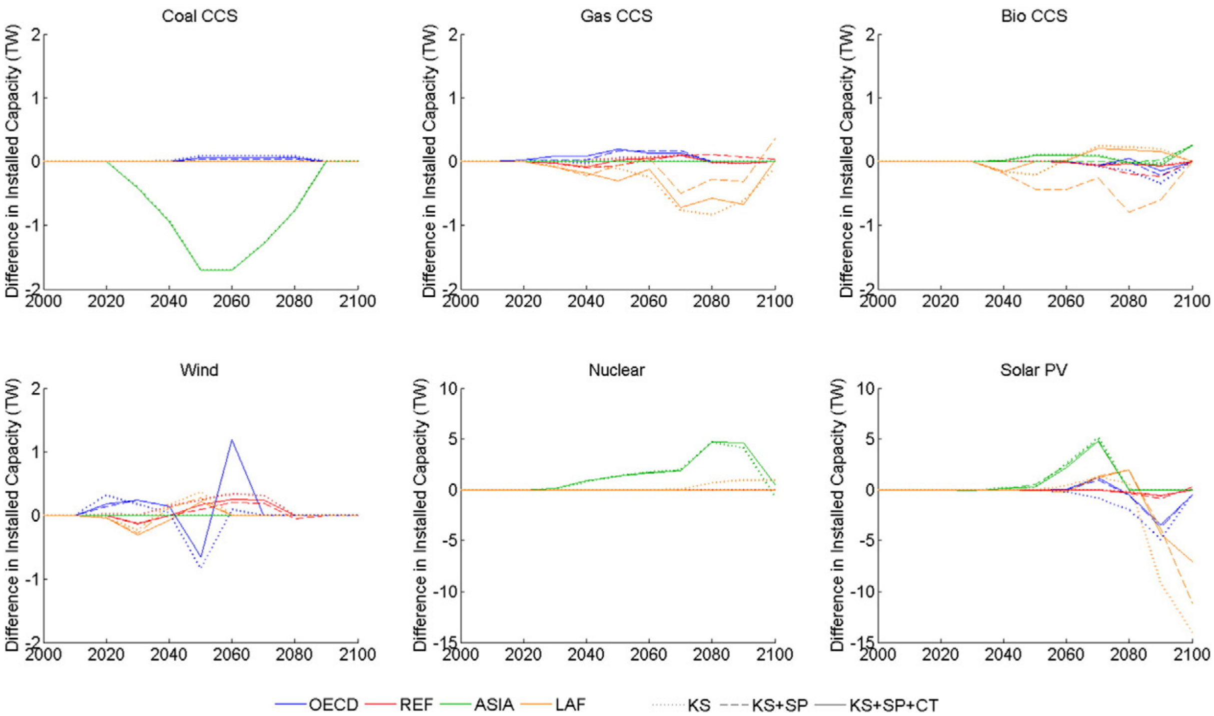

Fig. 6. Difference in regional installed capacity relative to the reference scenario, by technology.

+ CT scenario. This is more evidence that it can be globally optimal for the most advanced economies to deploy new technologies more than is locally optimal due to the spillover benefits that would accrue to other regions. It also implies that technologies become more attractive options if experience gained from installing capacity spills over to other, closely related technologies. The endogenous diffusion formulations reduce gas CCS diffusion in LAF, but to varying degrees. The LAF results seem to be driven by competition with other technologies that are more directly influenced by the different formulations.

6. Conclusions

This analysis presented above primarily serves as a proof of concept. We have demonstrated that implementing a more empirically consistent technology diffusion formulation than the crude, exogenous constraints typically featured in energy system optimization models is feasible, is not overly complicated, and has important implications for the market adoption of low-carbon electricity technologies. It is our hope that developers of IAMs used for technology assessments and policy evaluations will target technology diffusion constraints as an area for model improvement.

Our endogenous diffusion formulations incorporate capacity expansion constraints based on accumulating and depreciating knowledge stocks, spatial technology diffusion from core to rim via knowledge spillovers, and spillovers across closely related technologies. These are all features that characterize historical energy transitions but are neglected by the exogenous diffusion constraints imposed in traditional energy system optimization model formulations.

Four major insights emerge from our results. First, energy system optimization models with exogenous diffusion constraints may overstate the ability of nascent technologies to quickly penetrate markets and replace more mature technologies. This has been suspected previously (Bertram et al., 2015), and our results support this concern. The exogenous constraints do not respect the empirically observed lock-in phenomenon, whereby mature technologies have an advantage based not only on cost, but also on existing infrastructures and a sufficiently large and experienced capacity installation industry.

Second, new technologies which are attractive options in developing regions but not in advanced regions may struggle to diffuse if those developing regions lack the resources or institutions required to pioneer their development and commercialization. Biomass CCS is one such technology, but its diffusion could proceed if experience gained from deployment of other CCS-coupled generation options (e.g., gas CCS) facilitates biomass CCS adoption. This insight suggests that understanding cross-technology knowledge spillovers should be a high priority of future research, especially given the importance and optimism which recent energy technology assessments have attached to bioenergy with CCS (Kriegler et al., 2014; Bertram et al., 2015).

Third, some low-carbon technologies are now reaching a scale and associated knowledge stock large enough to enable widespread global diffusion even without much additional deployment in the advanced economies that originally developed them. Thus additional (and costly) market-pull subsidies for these technologies in the OECD under a global common goods (knowledge stock creation) perspective—as often advocated in renewable energy policy circles—may no longer be necessary. Our results indicate that solar PV likely falls in this category, but that CCS technologies clearly do not.

Lastly, it can be globally optimal for innovative economies to deploy advanced technologies more than what is locally optimal if this enables faster diffusion in less advanced regions that could benefit from the technology. Even if a national policy mandating or incentivizing adoption of low-carbon technologies fails the cost–benefit test when only domestic costs and benefits are considered, it could be justified from a global perspective due to benefits that spill over to other economies. Various international policy remedies might be able to address this potential market failure.

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