Received: 30 November 2019 | Revised: 22 November 2020 | Accepted: 7 December 2020

DOI: 10.1002/wcc.698

OPINION

WIREs CLIMATE CHANGE WILEY

Modeling myths: On DICE and dynamic realism in integrated assessment models of climate change mitigation

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Funding information
Institute of New Economic Thinking, Grant/Award Number: Grant ID #INO19-00004; Rockefeller Foundation Economic Council for Planetary Health at Oxford Martin School; Climate Works, Grant/Award Numbers: 19-1466, R48555/CN009

Edited by Julie Rozenberg, Domain Editor, and Mike Hulme, Editor-in-Chief

Abstract

We analyze how stylized Integrated Assessment Models (IAMs), and specifically the widely-used Dynamic Integrated Climate-Economy model (DICE), represent the cost of emissions abatement. Many assume temporal independence—that abatement costs in one period are not affected by prior abatement. We contrast this with three dimensions of dynamic realism in emitting systems: (i) inertia, (ii) induced innovation, and (iii) path dependence. We review key evidence from the last quarter century on each of these three components. Studies of stock lifetime, dynamics of diffusion and past transitions suggest typical transition timescales of at least 20–40 years for the bulk emitting systems. The evidence that substantial innovation is induced by both prices and market deployment is unambiguous. Finally, both data and a rapidly growing literature demonstrate substantial path dependence in general, and specifically "carbon lock-in and lock-out." Some stylized models in the past decade have incorporated technology learning, and others have considered inertia, but the combination of these factors is important and not yet evident. More complex hybrid IAMs with technology-rich energy-system models incorporate these factors, but their complexity has limited the wider understanding and influence of their underlying insights. Few if any global models fully represent path dependence. We conclude with likely implications drawing upon the empirical and modeling evidence accumulated, including results from extending DICE with a highly stylized representation of such dynamic factors. This suggests that dynamic *inter*dependencies could multiply several-fold the optimal level of initial abatement expenditure. This is because early abatement then also directly facilitates subsequent emission savings. The diversity of dynamic linkages across sectors and technologies also implies more nuanced policy than a single global carbon price. Thus, the issues explored in this review can radically change the general policy conclusions drawn from models, which, like DICE, neglect dynamic realism.

This article is categorized under:

Climate Economics > Aggregation Techniques for Impacts and Mitigation Costs

KEYWORDS
climate change, DICE, induced innovation, integrated assessment models, path dependence, pollution abatement control expenditure

1 | INTRODUCTION

Ever since William Nordhaus (1992) published the first attempt at integrated global cost-benefit assessment of climate change with his DICE model, much economic debate has centered on how to represent the damages and the corresponding "social cost of carbon," and find the "least-cost" emissions pathway.

Twenty-five years ago, Grubb et al. (1995) argued that an important issue for such assessment could be the dynamic characteristics of energy systems. They suggested that energy systems had potential to adapt to emission constraints, but in ways constrained by their very long-lived and path-dependent nature. A quarter of a century on, we review the accumulated evidence and modeling developments concerning these issues and their implications for assessing the global costs, benefits, and optimal trajectories of climate change mitigation—the main objective of DICE and other "aggregate cost-benefit analysis" (Weyant, 2017) models (hereafter, termed "DICE and related stylized models").

Our point is simple. Across the now huge and diverse literature on DICE and related stylized models, the vast majority share one common structural assumption: that the cost of cutting emissions in a given period is unrelated to the previous pathway, and does not affect the subsequent prospects. This we term an assumption of *temporal independence*. Our review explores three main characteristics of "dynamic realism" (inertia, induced innovation, and path dependence) which demonstrate this to be a "myth"—a common and convenient assumption which is contradicted by the evidence.

1.1 | The significance of DICE

Global cost-benefit assessment of climate change policy has been a natural focus for climate economists. Nordhaus' DICE model was the first to do this, adding modules on climate science and damages to the standard (Ramsey) model of economic growth—work expanding over the years and culminating in his award of the Nobel Prize. DICE has become the iconic stylized model and typical reference point for such analyses—including those from many of its vocal critics. One economics colleague (pers. comm) remarked that "everything in economics in regard to climate change is based on DICE"—because economics is about balancing costs and benefits, and DICE provides a standard framework for doing that.

In IPCC mitigation assessments and associated socio-economic scenarios (e.g., IPCC, 2014 Ch. 6) DICE has been largely superseded by far more sophisticated models (see Section 7), due to its lack of technology and sector detail. In principle also, the world has accepted the case for a risk management approach based on the UNFCCC commitment to "avoid dangerous interference" in the world's climate system, interpreted in the Paris Agreement's goal to keep global temperature change to "well below 2°C above preindustrial levels and pursue efforts... to 1.5°C".

As indicated below, this contrasts with the sanguine conclusions when DICE is run with Nordhaus' default assumptions—which generate moderate initial action leading to 3–4°C global warming. The modest damage assumptions in DICE and similar models have been widely criticized (e.g., Moore and Diaz (2015), Glanemann et al. (2020), and Botzen and van den Bergh (2012)). Made widely and freely available (Nordhaus & Sztorc, 2013), DICE remains a common tool for exploration, with 380 citations of the newest version (Nordhaus, 2017) since January 2017.[1] Some show that DICE can generate "optimal" trajectories compatible with the Paris Agreement when including strongly nonlinear climate damages, climate risks, and endogenous drivers of economic growth (Dietz & Stern, 2015; Hänsel et al., 2020); other updates on the climate module, damage function, and discounting include Faulwasser et al. (2018) and Hafeez et al. (2017). Other developments include studies of regions, inequalities and more, using regionalized versions.

Beyond academia, DICE was the main US-based model used by the US government (Inter-Agency Working Group, 2016) to estimate the "social cost of carbon" (SCC)—the value of avoiding 1 tonne of CO_2 emissions. Its simplicity also makes DICE (or variants thereof [Tsigaris & Wood, 2016]) appealing for teaching, widely used for introducing climate change to economics courses and beyond. DICE also served as inspiration for new simple IAMs (Pottier et al., 2015; van der Ploeg & Rezai, 2019).

Such stylized models reflect and reinforce a common conclusion in global climate change economics that the best response is a global, uniform, gradually rising carbon price reflecting the magnitude of climate damages (or the shadow cost of an agreed goal). Probing that conclusion requires attention to the assumed dynamics not just of impacts, but of emissions abatement cost.

1.2 | Structure of the article

In Section 2, we first clarify the underlying temporal structure of DICE (and related stylized IAMs), and its resulting time profile of "optimal" policy. In Sections 3–5, respectively we outline accumulated evidence on each of technical inertia, induced innovation, and path dependence, concluding that the past 25 years have added a huge weight of empirical data to the contention that these are all important factors. Drawing upon the distinction in Weyant (2017), we then review dynamic characteristics in DICE and other stylized aggregate benefit–cost models (Section 6), and briefly consider more complex, "detailed process" IAMs developed over the past 25 years (Section 7). In Section 8, we illustrate the importance of dynamic realism using a simple extension to DICE. From this exploration of evidence and modeling developments, we conclude that—compared to the imponderable debates about monetizing climate damages and the "social cost of carbon"—representing dynamic realism in stylized IAMs is just as important, is more empirically tractable, and deserves far more attention.

2 | ON DYNAMIC REALISM AND TEMPORAL INDEPENDENCE IN DICE AND RELATED MODELS

DICE and other stylized models aim to calculate an optimal long-term balance of costs and benefits in climate policy. This involves projecting emissions in the absence of policy and the cost of reducing emissions, so as to balance against the estimated damages from climate change.

Figure 1 shows results from the most recent version of DICE (Nordhaus, 2017). Nordhaus' standard assumptions produce an optimal emissions path, which (after an initial drop) rises till 2050; emissions then decrease, at accelerating pace, to zero in 2130. Abatement expenditure rises gradually until that point, to a peak of 0.8% of GDP. Global warming reaches 3°C in 2100, but climate damages are then just 2% of GDP (or 3% without any emissions abatement)—trivial compared to assumed seven-fold GDP growth 2015–2100 (Panels c,d).

As noted, the main criticisms of DICE have focused on the assumed structure and valuation of climate damages. A recent WIRES review (Pezzey, 2019), echoing Weitzman's "dismal theorem" (Weitzman, 2009), suggests that the attempt to reach a globally objective single monetized estimate of the overall damages may be futile, given the challenges in estimating, monetizing and aggregating the wide range of expected impacts, and including uncertainty and risk. Figure 1 also shows that assuming larger damages (as argued in most of the literature noted), for example, 5×DICE's default damage function or the Weitzman (2012) representation (which resembles DICE for warming below 2.5°C but increases more sharply thereafter), leads to higher abatement.

However, these do not change the overall pattern, of abatement and expenditure increasing steadily, until zero emissions are reached.

This overall pattern is largely determined by the assumed structure of abatement costs. DICE and most related stylized models represent abatement as incurring a cost defined by the degree of emission reduction relative to a "no policy" baseline (reference trajectory). In its most general form:

$$\text{Cost at time t of reducing emissions at t by } \mu, C(t) = c_A(t).f(\mu(t)) \tag{1}$$

where $\mu(t)$ is the fraction of CO_2 emissions (of a no-policy baseline) prevented by policy, and abatement cost depends purely on the abatement fraction μ, scaled by $c_A(t)$. All such models assume $f(\mu(t))$ to be a monotonously rising cost function (the bigger the cutback at time t, the higher the cost); DICE uses a power law, $f(\mu(t)) = \mu(t)^\theta$, with the scaling factor declining *exogenously* over time.[2]

The fact that unit abatement costs decline autonomously over time makes it economically preferable to defer abatement to take advantage of falling costs, which along with rising impacts explains the pattern observed in Figure 1.

This general approach—a predefined "abatement cost curve" $\mu(t)$ which gets cheaper over time —seems almost taken for granted in many stylized IAMs. However, strikingly, this assumes that the cost of cutting emissions at any time is *independent of previous emission levels*. Abatement costs at time t reflect neither history, or inertia. Equation 1

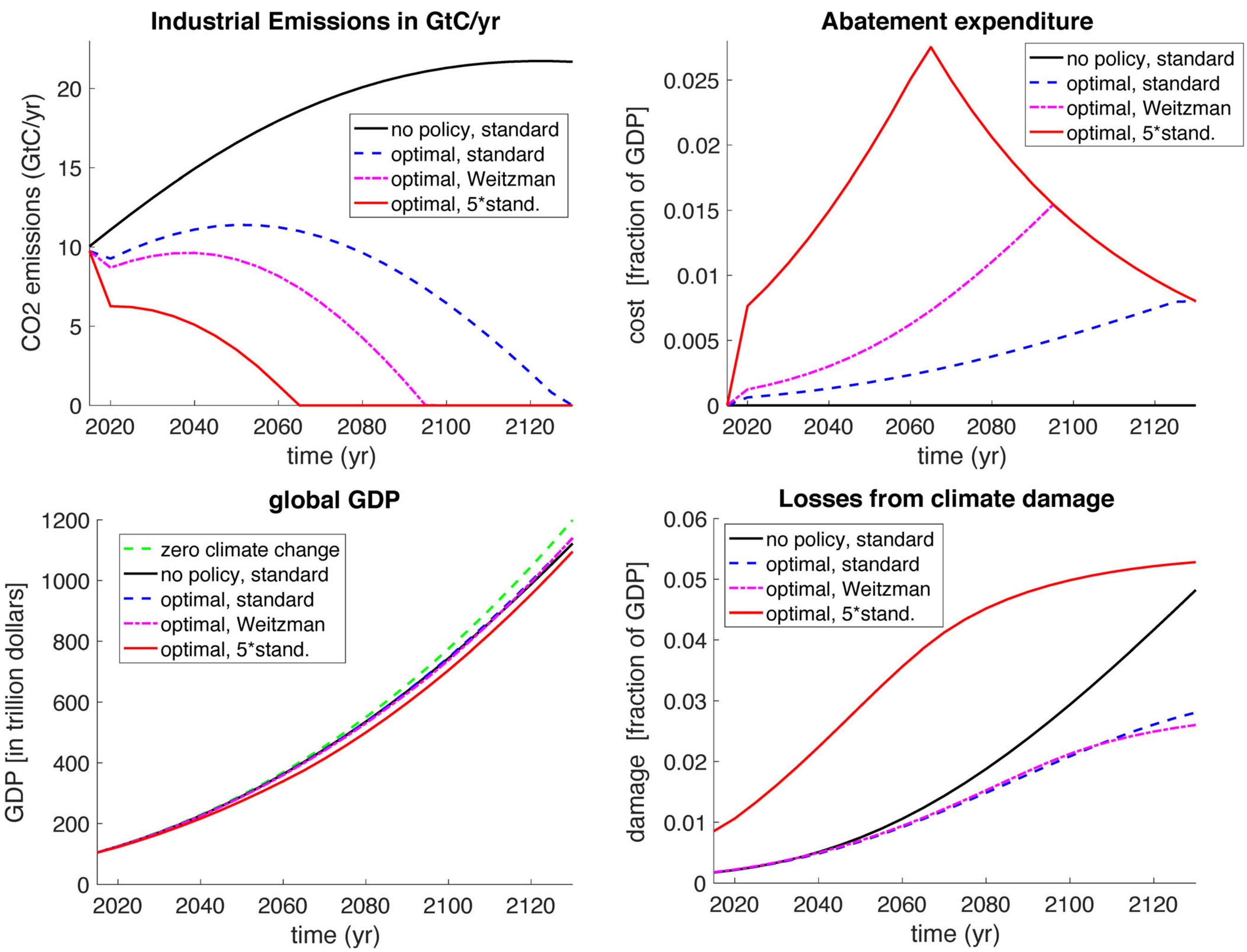


FIGURE 1 Optimal trajectory of CO_2 emissions, abatement expenditure, GDP, and climate damages from DICE 2016 with three damage functions (standard, 5*standard, and Weitzman)

supposes that radical cutbacks could occur in any period regardless of earlier (in)action. The abatement cost curves in each period are both *temporally independent*, and *rigid*: they cannot be influenced by the previous abatement path.

As we show in this review, this is unrealistic. It takes time, effort, and cost to change complex systems and to write-off, retrofit or replace existing capital stock. The cost of cutbacks depends on the inherited infrastructure, technologies and industries that have been built up over previous decades; it depends upon the prior efforts and inherited level of emissions. Indeed, the assumed "baseline" trajectory inevitably reflects the history of accumulated assets, infrastructure, industries, institutions, and indeed social norms. These simple observations reflect the core components of temporal *inter*dependence: namely *inertia*, and *induced learning*, which combine with other effects to generate *path dependence*. These three concepts are interrelated but analytically distinct, and we now outline our improved understanding on each in turn.

3 | CAPITAL INERTIA: INFRASTRUCTURE, TECHNOLOGY LIFETIMES, AND DIFFUSION

Change takes time and can be costly. The simplest form of inertia arises from the lifetime of capital stock, and particularly infrastructure. Power stations may last some decades, while roads, buildings, and urban forms last even longer. Electricity and rail networks have typically taken 25–50 years for their phases of major growth; transport networks, even longer (Grübler et al., 1999).

The IPCC (2007) observed that timescales "appear to be very long for most greenhouse-gas emitting sectors." Concerns about "carbon lock-in" were raised by Unruh (2000), with specific estimates of the "committed emissions" from capital stock (Davis et al., 2010). Erickson et al. (2015) identified the typical 40-year lifetime of coal plants as a dominant factor; Davis and Socolow (2014) estimated that the then-existing stock of power plants would emit about 300 $GtCO_2$, with a range 98–578 $GtCO_2$ for a 20–60 years range of operating lives. Lower utilization or premature scrapping imply loss of planned returns on investment, risking "stranded assets" (Kefford et al., 2018; Mercure et al., 2018).

Buildings and transport infrastructure have even longer lifetimes, but with more complex implications. Residential building investments coalesce around an average (first moment) lifetime of 50 years, with huge variety among components ranging from light bulbs to the foundations (Mequignon et al., 2013), while transport infrastructure can persist for centuries but emissions depend on the technologies that use it.

Introducing new technologies also takes time: The intertwined nature of technologies, infrastructure, finance, and regulation constrain rates of growth. Figure 2 shows typical timescales of market penetration *in initial markets*. Nuclear power took about 20 years from 10% to 90% penetration in leading countries; coal, about 30, after a slower formative phase. Modern wind turbines took 15 years from the mid-1990s to mature deployment in the initial market of Denmark, but global diffusion is clearly much slower. Consumer goods vary from very fast (e.g., lightbulbs), to the slow adoption of technologies that depended on consumer wealth, fuel infrastructure, and networks (e.g., cars in the US).

Of course, transitions have occurred more rapidly. French nuclear took just 10 years to go from 1% to 25% of the energy mix. UK coal generation collapsed from 35% in 2013 to under 5% just 5 years later. Solar PV capacity has shot from 15 to 500 GW globally within a decade, but as yet is still barely c. 2% of global electricity.

Even with high duress, energy systems can take decades to adapt. At the macro level, Bashmakov et al. (2020 in review) estimate that energy system adjustments in OECD countries took 25–33 years to work through after the 1970s oil shocks, and that involved little fundamental changes to fuels outside electricity. Jarvis (2018) takes long-run energy growth rates around 2.5% as reflecting a more fundamental investment time constant of around 40 years. The timescale for major transitions thus appears to be 20–40 years. Models with no inertia clearly omit an important characteristic of global energy systems.

Inertia combined with uncertainty provide clear justification for precautionary action, a central point of Ha-Duong et al. (1997). Twenty years on, having barely heeded such risks, we face the likely need for rapid transition—which would clearly be easier had the world not added almost 50% to the global stock of CO_2-emitting capital in the meantime. In *The Climate Casino*, Nordhaus (2013) himself underlined that uncertainty increases the case for precautionary abatement, but the extent of the damage done depends very much on the assumed inertia. Taking account of likely

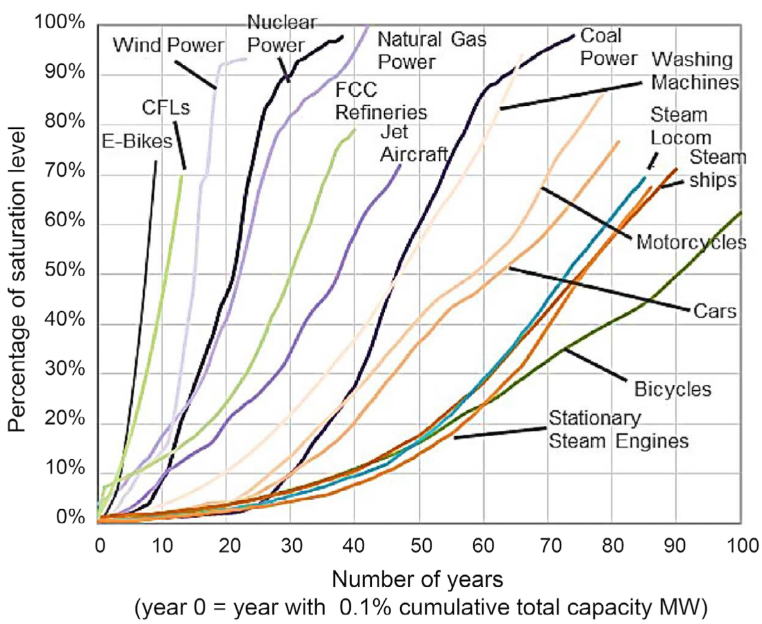


FIGURE 2 Shape and rate of diffusion of technologies in their initial markets. (From Bento and Wilson (2016)). The graph shows rising market shares in the initial markets, from the point when each technology passed a threshold of 0.1% of its eventual maximum installed capacity in that initial (geographic) market[11]

capital retirement over the next few decades years, the default "optimum" trajectory in DICE (Figure 1(a)) would involve constructing a huge amount of new carbon-intensive capital—a risky strategy (e.g., Vogt-Schilb et al., 2018), see Section 6.

As reviewed in Section 7, more complex IAMs do model capital lifetimes and diffusion, and correspondingly emphasize more the urgency of action. Of course, carbon-intensive capital can be retired prematurely, and growth rates of clean technologies can be accelerated. However, either may increase costs. For stylized IAMs, Grubb et al. (1995) were the first to reflect this by adding a second cost term related to the *rate of change* of abatement,

$$\text{Abatement cost as fraction of GDP}, C_{AB}(t) = c_A(t).\mu(t)^{\theta A} + c_B(t).\left(\frac{d\mu(t)}{dt}\right)^{\theta B} \tag{2}$$

The notation $C_{AB}(t)$ emphasizes that cost now includes a standard (A), and a transitional (B) element, a simple modification to reflect the first and most obvious dimension of dynamic realism.

4 | INDUCED LEARNING AND COST REDUCTION

The second issue concerns innovation: specifically, whether technology costs are assumed to be *exogenous*—specified externally by modeling assumptions—or *induced* by the cumulative impact of policy, investment, and market growth within a model. This reflects a long-standing issue in climate economics again going back about 25 years, drawing on earlier economic theory spanning (Hicks, 1932; Nordhaus, 1969; Romer, 1990; Schumpeter, 1934) and many others.

A major review of innovation modeling (Gillingham et al., 2008) concluded a decade ago that "our ability to conceptually model technical change has outstripped our ability to validate models empirically." Here, we summarize some evidence accumulated over the past 20 years (see also Grubb et al., 2021).

4.1 | Evidence on market-induced innovation

Innovation is not random but involves investment. Some of that may be "'exogenous,' for example, public R&D or 'spilling over'" from other sectors into deployed energy technologies. But the direction and scale of innovation is also substantially "endogenous"—influenced by relative prices, demand and expectations, as originally proposed by (Hicks, 1932). The 1970s oil price shocks stimulated private energy R&D (Lichtenberg, 1986), reflected in numerous studies of patents (Popp, 2002). Across 30 articles, Popp et al. (2010) and Popp (2019) found that a 10% increase in energy prices increased energy-related patenting by 3–6%—a "patenting elasticity" of 0.3–0.6 (also see Verdolini & Galeotti, 2011). For low carbon and energy efficient technologies specifically, elasticity averaged 0.86, and exceeded 1 for solar PV (Kruse & Wetzel, 2016, Vincenzi and Ozabaci (2017)), as also found for vehicles (Aghion et al. (2016)). Carbon prices also enhance low carbon patenting (Calel & Dechezleprêtre, 2016).

The influence of price goes beyond patenting. Rising electricity and gas prices induced efficiency improvement in end-use equipment (Newell et al., 1999) and vehicle fuel use (Knittel, 2011), and preceded lower solar module prices in major countries (Taghizadeh-Hesary et al., 2019). Similarly, carbon pricing is associated with lower wind and solar costs (Kim et al., 2017).

"Learning rates" document cost reductions associated with a doubling of capacity ("Wrights law"). While correlation is not causation (e.g., (Nordhaus, 2014)), many studies show that growing markets and deployment drive (renewable) innovation and cost reduction (Bettencourt et al. (2013), Kavlak et al. (2018), Nemet (2019)), and a major systematic review (Grubb & Wieners, 2020) documents both the evidence and causal mechanisms. The key mechanisms of cost reduction include learning-by-doing and learning-by-using, but also simple economies of scale, from unit size to bigger factories and the industry overall, along with the development of global supply chains, and growing confidence which reduces the perceived risks and hence cost of finance. Weiss et al. (2010, p. 411) found an average learning rate of 18% across 15 demand-side technologies. Reviews by Rubin et al. (2015), Samadi (2018), and Farmer and Lafond (2016) find learning rates for renewable technologies to be uniformly positive; in particular, they are remarkably high (close to 20%) and stable for solar. The evidence is unequivocal that deploying clean energy at scale helps to make it cheaper.

4.2 | The innovation gap in model projections

The assumptions of optimizing models with cost structures like Equation (1) require projections decades ahead, and we have been running such models for almost 30 years. It is time to compare their past projections with observed outcomes. Figure 3(a) shows that even since 2010, the global average cost of solar PV has fallen by a *factor of 5*, and onshore wind energy by about 30%. Even offshore wind, long considered an exceptionally challenging and expensive technology, has seen a rapid expansion. Deployment-related policies culminated with contract prices a third of the cost only 5 years previously (Jennings et al., 2020), resulting in "zero subsidy" auctions (BEIS, 2019; GWEC, 2019).

Figure 3(b) compares the PV trend to past model projections. The *average global* cost of PV is *already* well below the projections for 2030 made in 2011/12 by a wide range of institutions, including in the IPCC Renewables Assessment (Edenhofer et al., 2011). Models predicated on projections about technology costs over the century have thus become outdated within 5 years.

Three points flow from this. First, results from models with "rigid" abatement cost assumptions—projected independently of the scale of effort—may be rapidly rendered obsolete by innovation. Second, the impact can be radical, not marginal—though it involved large transitional investment, the *global average* costs of wind and solar are now comparable to the cheapest coal plants (bottom of the blue band in Figure 3(a1,a2)), and still declining. Competitive tenders during 2019 broke multiple consecutive tariff records, with costs well below the cost of fossil fuel generation even from existing coal plants, let alone the cost of building new ones,[3] leading the IEA (World Energy Outlook, 2020) to describe solar PV now as the cheapest electricity in history.

Third, this reflects the finding summarized above that costs are not exogenous but *depend on actions*, and in particular, deployment. The cost reductions reflect learning and development of the industry and its supply chains at scale. Moreover, PV cost variations between countries reflect not just the solar resource, but the maturity and scale of the local PV businesses. We are in the midst of a dynamic process in which the global average cost will continue to decline as renewables expand globally. Nor is this unique. For light duty transport, electric vehicles are cheaper to run than gasoline, and given battery costs are falling even faster than PV, may be cheaper to buy as well within a few years as the market grows (Bloomberg New Energy Finance, 2019).[4]

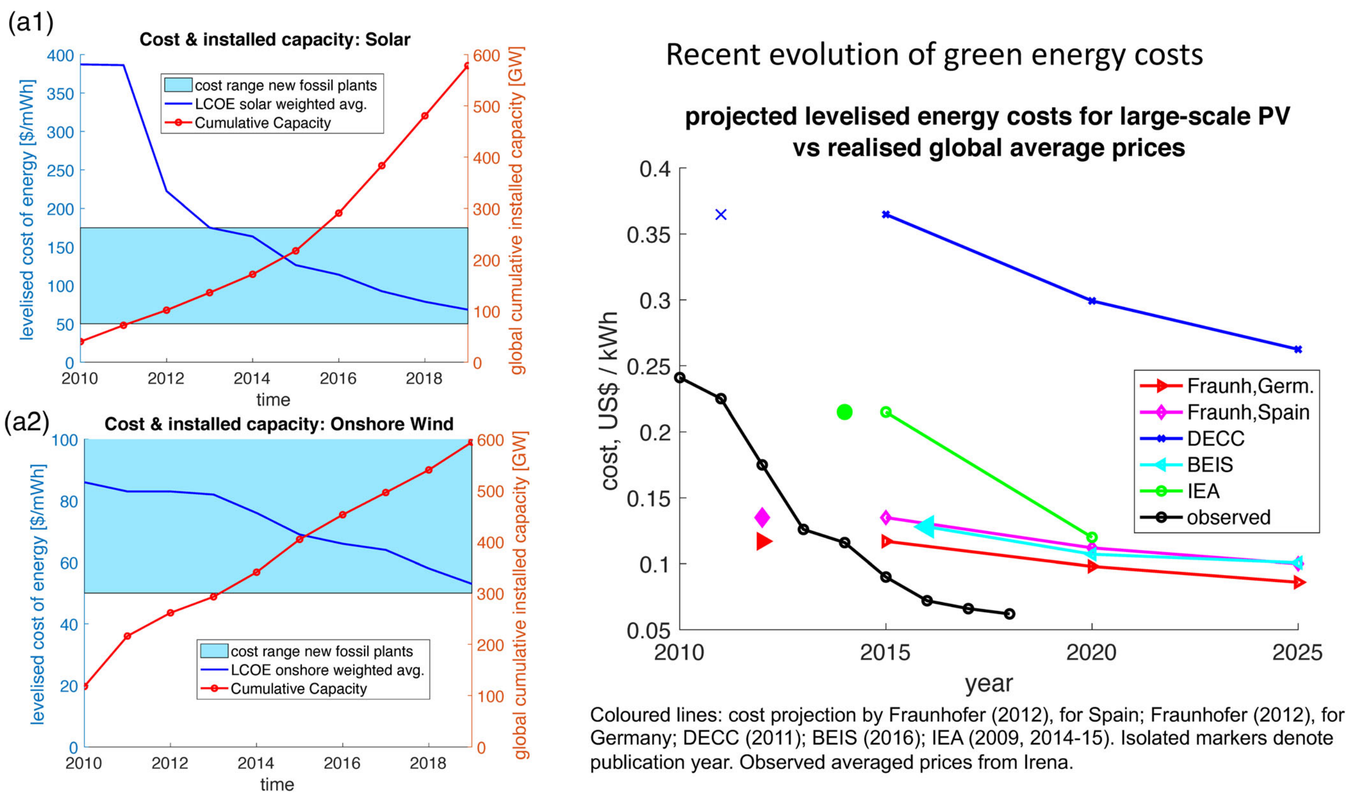


FIGURE 3 Cost trends in solar (a1) and wind (a2) electricity compared to cost ranges for new coal plants, (from IRENA, 2020) and (b) PV costs compared to projections

Only a decade ago, decarbonizing the electricity and transport sectors—which comprise over half of global CO_2 emissions—was projected to be difficult and expensive. The variability of wind and solar output may constrain contributions but only at high penetrations (Heptonstall & Gross, 2020)—renewables already supply half of Danish electricity for example,—while falling storage costs, interconnections and other flexibilities expand the scope further (Kroposki et al., 2017). The fact remains that extensive decarbonisation has already been rendered cheaper than historically assumed in most model projections—in many cases, for decades to come—and the costs continue to decline with deployment.

4.3 | Implications for modeling

While stylized optimizing models summarize abatement costs with a function (Equation (1)), technology-rich models build “marginal abatement cost curves” (MACC) from the bottom-up, projecting costs for different specific technologies and sectors. Figure 4(a) shows how the DICE projected cost curve for 2030 has varied over successive model vintages, while Figure 4(b) shows one famous (and hotly debated) projected MACC for 2030, by McKinsey in 2009. The central parts of the cost curve are dominated by low carbon electricity generation options.

Observations include:

- The cost curves in DICE for 2030 have varied substantially between successive model vintages. The projected cost of cutting emissions by 10 $GtCO_2$ fell by two-thirds, before *rising* again in the 2016 version (in curious contrast to the evidence reviewed above);
- The DICE curves seem more expensive than the ones by McKinsey. In Equation (1), this would mean that $c_A(t)$ is too high (or the curve insufficiently nonlinear),[5] partly because DICE omits some options and assumes that any “negative cost” possibilities appear automatically in the baseline.
- Many of the sector options in corresponding parts of the McKinsey curve are ones in which the costs have fallen dramatically over the past few years.

With hindsight, both bottom-up and top-down approaches clearly underestimated the potential for innovation, and both have been eclipsed by the trends shown above (Figure 3). Many models—both stylized and complex—have thus been outdated by reality, unless they modeled processes of induced innovation. The future cost of abatement depends on cumulative action. The implication is not so much that c_A in Equation (1) has been too big in most models, but that the structural form is too simplistic: It lacks dynamics.

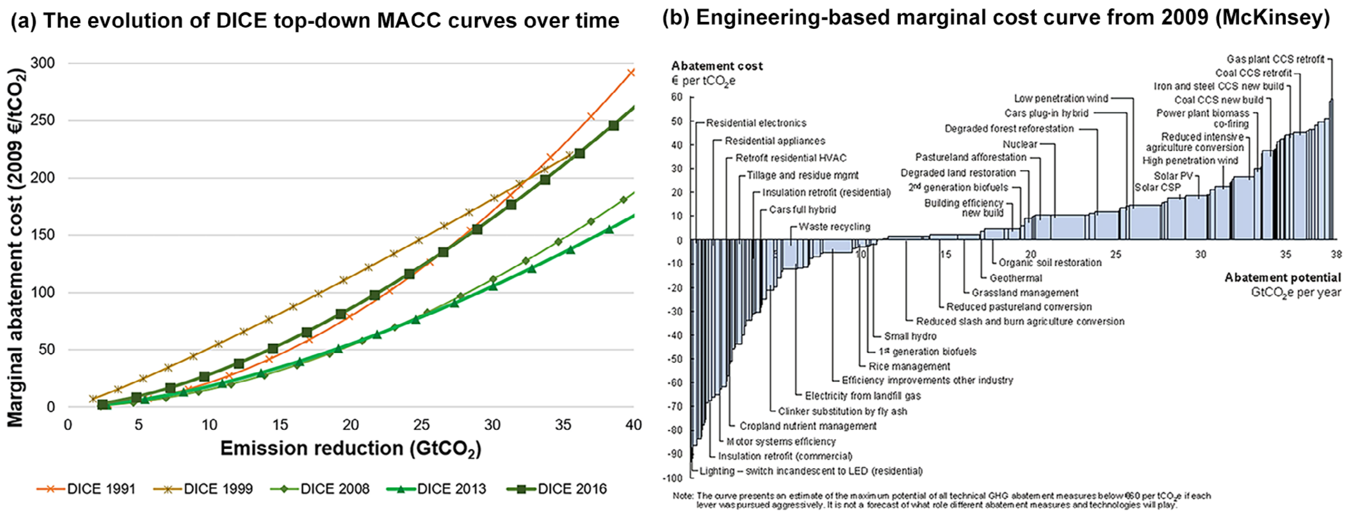
Indeed, the initial policy-driven strategic deployment of the technologies noted above *was* expensive: renewables deployment in the German *Energiewende*, which substantially drove the renewables revolution, cost over a hundred billion dollars. But it was a transitional, not an enduring cost: Rather than “prematurely” deploying a high-cost element of the abatement cost curve, it fundamentally changed the curve itself.[6] From the stylized perspective of Equation (2), it seems that DICE and similar models misallocated abatement costs, assigning them to the rigid (c_A) cost term, while for a large part they were (initially high) transitional investments.

5 | PATH DEPENDENCE

At any given point in time, the state of an economy reflects its previous evolution. An economy inherits, and bequests, a given set of infrastructure, technologies, industries, institutions, and social norms. For climate change, this concept points to “carbon lock-in” (Unruh, 2000; Unruh, 2002): Once established, a system of carbon-based, interlocked technologies and institutions is hard to replace. Lehmann et al. (2012) identified the corresponding risk of “lock-out” of renewable systems without strong policies to shift the trajectory of electricity technologies and systems.

5.1 | Path dependence—the economic concepts

Path dependence obviously entails induced innovation and inertia. Inertia expresses a transitional cost of moving away from a given path. Innovation, through economies of scale and learning-by-doing, makes an established path more attractive. Fouquet and Aghion (2019) identify at least three more relevant economic processes:



Note: Direct comparison is complicated by many factors including different discount rates, currencies and base years, source coverage, inclusion of 'negative costs' in the McKinsey curve, and other factors.

FIGURE 4 Top-down and bottom-up marginal abatement cost curves (MACC)

- *Knowledge spillovers*—innovations to build upon prior, related innovations in cumulative ways
- *Network effects*— attractiveness of a technology depends upon interrelated networks of other users or suppliers
- *Complementarities*—when technologies have complementary roles, such as renewables and storage

A review of carbon lock-in (Seto et al., 2016) identified a dozen contributions to lock-in, including institutional and behavioral ones (Table 1).

Path dependence implies that past choices create a new default trajectory, and that there may be many such possible paths. It features not only in theories of evolutionary economics since Arthur (1989), but also more mainstream economics on "sunspot equilibria" (e.g., Azariadis and Guesnerie (1986), Farmer (1993), and Benhabib and Farmer (1999)), in which different equilibrium paths are shaped partly by expectations and the intervention of random events.

5.2 | Path dependence—evidence in energy systems

For energy, the theories of path dependence are complemented by the observed trends of the past quarter century. A simplistic interpretation of the idea of a "least-cost, optimum pathway" would imply that countries at a similar stage of economic development would have similar levels of per-capita energy consumption. In fact, among developed countries with similar per-capita income differ by almost a factor of 3 in their primary per-capita energy consumption (Figure 5(a)). Effects of geography and trade can only account for a modest part of these differences. Per-capita CO2 emissions vary even more (Figure 5(b)), though this is also influenced by the endowment of hydro and other noncarbon energy sources.

Even more striking, there has been no sign of convergence. If carbon really were a generally valuable input to economic development, one might expect countries to use more, and converge at least somewhat in their carbon intensity, over time. In fact, per-capita CO_2 emissions have been stable or declining in most OECD countries, but show no convergence: Europe and Japan have remained at less than half the levels in North America for decades. This is consistent with theories of path dependence, in which the institutions, infrastructures, and vested interests in fossil-fuel-intensive countries tend to self-perpetuate, while lower carbon economies may be more able to further decarbonize.

Econometrics literature supports this observation. An extensive series of studies culminated in the finding by Parker and Liddle (2017) that "For the 33 countries analyzed… regression test provided no evidence of convergence within our sample," but rather "a clustering algorithm identified four convergence clubs for economy-wide energy productivity and six for manufacturing. The clubs did not show any clear reason for groupings, such as geography…."

This offers a different perspective from the structures of DICE and many other IAMs, most of which start from an assumption that there is a unique, least-cost pathway for the global energy system, that can serve as a reference.

TABLE 1 Summary of three types of carbon lock-in and their key characteristics

Lock-in type	Key characteristics
Infrastructural and technological	• Technological and economic forces lead to inertia • Long lead times, large investments, sunk costs, and long-lived effects • Initial choices account for private but not social costs and benefits • Random, unintentional events affect final outcomes (e.g., QWERTY)
Institutional	• Powerful economic, social, and political actors seek to reinforce status quo that favors their interests • Institutions are designed to stabilize and lock in • Beneficial and intended outcome for some actors • Not random chance but intentional choice (e.g., support for renewable energy in Germany)
Behavioral	• Lock-in through individual decision making (e.g., psychological processes) • Single, calculated choices become a long string of noncalculated and self-reinforcing habits • Lock-in through social structure (e.g., norms and social processes) • Interrupting habits is difficult but possible (e.g., family size, thermostat setting)

Note: Source: Seto et al. (2016).

This issue has remained problematic—not least in communication (Schenk & Lensink, 2007)—ever since the IPCC's Special Report on Emission Scenarios (Rogelj et al., 2000) concluded that we could not plausibly reduce the future to just one projected, least-cost path amended by costly abatement. Analysis needs to consider multiple different kinds of futures as reference paths. This includes the scope for emerging economies to orient along different paths, based on the newfound cost-effectiveness of renewables and smart systems in electricity, transport, and buildings energy use.

From this view, assumptions of temporal independence (Equation 1) are again invalidated. Not only does history matter and abatement potentially endure, it may also create positive international spill overs. Far from being neglected, these dynamic realities should be at the core of more realistic modeling.

6 | DYNAMIC REALISM IN IAMs: (A) STYLISED MODELS AND CONCEPTUAL DEVELOPMENTS

Against this background, we now consider the main development of efforts to include dynamic realism in Integrated Assessment Models (IAMs). In the Appendix (Table A1), we list 28 global IAMs, with brief notes on their coverage of the three components discussed in this article. This section considers "stylized IAMs" (such as DICE), which correspond closely to the class of "aggregate cost-benefit analysis (CBA) IAMs" distinguished in (Weyant, 2017). Section 7 addresses "complex" or detailed-process IAMs, which have high sectoral detail and are often calibrated to extensive datasets, including hybrid models derived from linking the stylized with detailed-process IAMs. Complex IAMs typically focus on providing a feasible (usually optimized, "cost-effective") trajectory toward a predefined goal (such as global warming level).

6.1 | The role of stylized IAMs

Three pioneer models developed in the 1990s were DICE (Nordhaus, 1992), PAGE (Hope et al., 1993), and FUND (Tol, 1997), which sought to quantify optimal responses to climate change. In 2010, 2013, and 2016, the US government Inter-Agency Working Group adopted these three cost-benefit IAMs to analyses the SCC.

The DICE-based studies outlined in Sections 1 and 2 illustrate the use of such models as a platform for exploring multiple issues and uncertainties. As noted, the dominant focus has been upon factors influencing the SCC, through assumptions particularly around damages and discounting (including regional/equity weighting). As such, the models are tools for important economic debates (though results are generally interpreted in terms of a global carbon tax, which is practically problematic and ethically complex). In recent years, these stylized models have been used to review broader issues, for example the assumptions which could underpin Paris goals, and emission pathways toward them

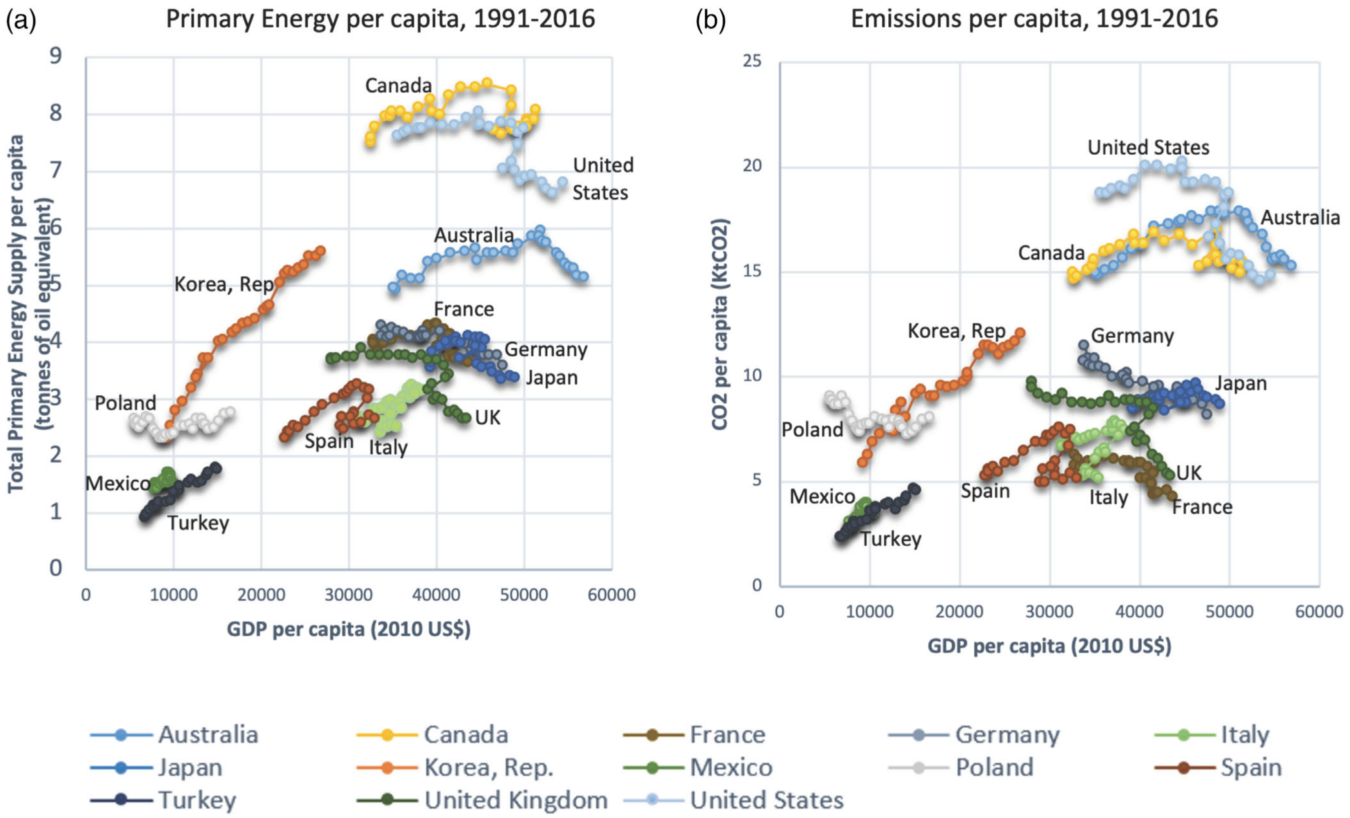


FIGURE 5 Primary energy and CO_2 emissions per capita plotted against per-capita income, for the 13 richest (GDP) OECD countries

(Glanemann et al., 2020; Hänsel et al., 2020). Others take advantage of the model's simplicity and analyze the impact of probabilistic assumptions around climate damages (Daniel et al., 2019) or the conceptual reaction toward climate inflection points (Lemoine & Rudik, 2017).

In contrast, attention to the dynamic characteristics of emitting systems in DICE and related models has been limited, although some stylized approaches have been developed.

Reasons for this situation could include the appeal of relatively simple frameworks. It may also reflect a common misunderstanding. DICE and related models are characterized as Computable General Equilibrium models, a name that reflects origins in the basic theories of that name taught as fundamental in economics classes. In much of the IAM community this has commonly been interpreted as implying also optimal path solutions over time and space. However, as noted in Grubb and Wieners (2020), this is not at all implied by the fundamental axioms of General Equilibrium theory, which the "Sonnenschein–Mantel–Debreu" critique demonstrated decades ago to be incredibly *un*restrictive (as reviewed in Rizvi, 2006). Core GE theory is about balancing aggregate supply and demand in economies through markets and pricing, and in no way implies such equilibria to be either overall least-cost, forward-looking, or dynamically stable.

6.2 | Induced innovation in stylized models

The topic of induced innovation has attracted long-standing attention. In modeling terminology, the high-level distinction is between exogenous and endogenous treatments of technology change. Reviews by Gillingham et al. (2008) and by Wei et al. (2015) note several approaches to modeling endogenous change, typified as R&D/learning-by-searching; price-induced; and learning-by-doing.

Of the three cost-benefit IAMs used in the US Inter-Agency Review, DICE and the PAGE-02 model (Hope, 2006, used also in the Stern review) neglected all three components of dynamic realism, though the subsequent version, PAGE-09 (Hope, 2012) has some learning. FUND 3.9 (Anthoff & Tol, 2013) models Learning-by-doing as a knowledge stock that increases (sub-linearly) with cumulative abatement expenditure, reducing abatement cost.

Even some new stylized IAMs (e.g., Dietz and Venmans (2019) and van der Ploeg and Rezai (2019)), while shedding useful light on established debates around the shape of abatement cost curves and rates of (exogenous) cost reduction, do not incorporate the dynamic realities considered in this article.[7]

Goulder and Mathai (2000) showed that in a cost–benefit setting, while R&D-type "learning-by-searching" would reduce initial abatement (to wait for cheaper technologies), the impact of learning-by-doing (and hence price-induced innovation) on abatement is analytically ambiguous: the overall benefits of accelerated abatement or higher carbon prices may or may not outweigh the gain (in discounted costs) of waiting for such improvements—though their empirical illustration suggests it does.

To address induced innovation in DICE, R&DICE (Nordhaus, 2002a) replaces the "abatement" of the standard DICE by R&D-induced reduction of the carbon intensity coefficient, and finds slower emission reductions than DICE. In ENTICE (Popp, 2004), fossil fuels can be substituted by a knowledge stock which is built up through R&D expenditure. In neither model does learning directly depend on emission reduction, and both assume diminishing returns to energy-related research and (as opposed to Buonanno et al., 2003) "crowding out" of more growth-inducing R&D. Consequently energy-related R&D incurs substantial opportunity costs with modest gains in terms of future emission reduction.

In these models, abatement increases energy costs relative to an emissions-intensive baseline, which is implicitly assumed to be least-cost and optimal without climate change. By construction this does not allow for the possibility that low carbon technologies might become cheaper than fossil-based ones once the (costly) transition is completed. As opposed to DICE and PAGE, FUND3.9 can, at least in principle, reach such a state, but it is unclear whether this state is reached in any of its actual applications (within relevant modeled time horizons).

The ground-breaking model by Acemoglu et al. (2012) explicitly distinguished low and high carbon technologies (as opposed to general abatement costs) in a long-run growth model. By switching R&D and direct investment from high to low carbon technologies, with knowledge accumulation, this generated scenarios in which low-carbon energy could, through such investment, rapidly displace the fossil fuel system once it became cheap enough.

From a different angle, this was challenged by Pottier et al. (2014) as an "incorporeal" vision—an economy still based on sequential equilibria with little inertia, so that successful learning in low carbon technologies meant an implausibly rapid, painless displacement of fossil fuels. The combination of Acemoglu with this critique suggests the central importance of combining learning with inertia.

6.3 | Inertia and path dependence in stylized models

Inertia may be captured by including an abatement cost term which depends on the rate of change of abatement. The approach was first implemented by Grubb et al. (1995) in their DIAM (Dynamics of Inertia and Adaptability) model, and used to study also timing in the face of uncertain stabilization targets (Ha-Duong et al., 1997). Pottier et al. (2015) added a similar inertial term to their RESPONSE model. FUND3.9 lets part of the abatement effort cause a lasting (as opposed to temporary) emission reduction. However, the share of lasting emission reduction decreases with abatement efforts, a choice which is not empirically based but helps to align results with the behavior of other models.

All these models take a single global carbon price as the efficient mechanism because they equalize marginal abatement costs at any point in time. By contrast, Vogt-Schilb and Hallegatte (2014) explored the implications when different options have different inertia. Their model showed that adopting the cheapest abatement first could exacerbate a carbon intensive-lock-in and make long-term targets more expensive to reach. Their subsequent model of sectors with different capital and lifetime structures showed that carbon budgets are delivered most efficiently if initial abatement efforts (marginal prices) are larger in sectors with higher inertia (Vogt-Schilb et al., 2018). Otherwise, there seems to have been little attention to the issue in stylized IAMs. Moreover, as far as we could ascertain, none of the stylized models allow for explicit path dependence in the abatement trajectory, though some (notably Acemoglu et al. (2012)) do so for innovation as a cumulative process.[8]

To summarize Sections 6.1–6.3, treatment of dynamic realism in standard stylized IAMs is patchy at best, but dedicated (stylized) models illustrated the potential importance of learning (Goulder & Mathai, 2000), the possibility of a cheap low-carbon future (Acemoglu et al., 2012), and the need to swiftly address sectors with high inertia (Vogt-Schilb et al., 2018). All these are beyond the standard results of DICE-like models.

7 | HYBRID AND OTHER COMPLEX IAMs

Here we give a brief overview of temporal interdependence in complex IAMs, drawing on model intercomparison studies such as Köhler et al. (2006), Edenhofer et al. (2006), and the EMF 27 project (Krey et al., 2014; Weyant & Kriegler, 2014). See Table A1 for model-specific information.

7.1 | Endogenous innovation in complex/hybrid models

In the 1990s, few models (IMAGE (Rotmans, 1990), ICAM (Dowlatabadi, 1998)) incorporated endogenous technical change, initially in terms of price-induced energy efficiency improvements (Hassler and Krusell (2012)). Path-breaking studies using ERIS, MARKAL, and MESSAGE introduced learning-by-doing at scale in global modeling, suggesting it could radically change views of future possibilities (Seebregts et al., 1999). Latter works also found that high and low carbon futures might have similar costs (Grübler et al., 1999). A meta-analysis (Barker et al. (2006)) confirmed that induced technological change generally amplifies the benefits of abatement. "Learning" through international knowledge spill-overs can also affect policy: Paroussos et al. (2019) built on GEM-E3 to show that this could allow economically positive formation of "climate clubs" arising from the innovation benefits of participation.

By the time of the IPCC's Fifth Assessment Report (IPCC, 2014), hybrid models with detailed energy sectors featured far more than stylized IAMs. Although many of these models (e.g., TIAM-ETL) can incorporate induced innovation, several often skip this facility because it hugely increases the computational complexity and sensitivities to assumptions. Most models in the IPCC Assessments were actually run without induced innovation.[9] One comparison found that different representations of endogenous technological change in IAMs may still result in similar future energy structures (Bosetti et al., 2015), though the robustness of this finding may be challenged for example, by the dramatic fall in renewables costs since observed (section 4).

7.2 | Inertia

At the macro level, capital stock accumulation is standard in CGE models, but does not in itself constrain rates of abatement. Inertia enters models more directly in terms of the technology lifetime in technology-rich models (see Table A1). Other models like the GEM-E3 introduce the concept of durable and nondurable goods to reflect some lock-in effects (Capros et al., 2013).

The RECIPE project (Luderer et al., 2012) found a wide diversity of responses in comparing just three models. Notably, compared to REMIND and WITCH, IMACLIM-R—which has high inertia derived from its representation of urban and transport systems in particular—required large abatement expenditure (consumption loss of about 5%) in the first few decades, but consumption subsequently *increases* (and carbon prices fall) thanks to the improved infrastructure.

The more extensive AMPERE programs (Kriegler, Riahi, et al., 2015) used a dozen different models to explore implications of delayed (Riahi et al., 2015; Bertram et al., 2015) or initially partial (Kriegler, Riahi, Bauer, et al., 2015a) action and introduced diagnostic indicators to explore the model behavior, helping to illuminate (though not explicitly) the different dynamic characteristics, finding considerable difference among models' abatement cost (Kriegler, Petermann, 2015b). Subsequent studies have added further to concerns about the cost of delayed action (Winning et al., 2019), and its implications for potentially risky reliance on CDR technologies (Rogelj et al., 2019).

7.3 | Path dependence and other dimensions

Few if any models represent path dependence beyond the capital inertia and induced learning, to take account of institutional, social, and behavioral inertia, a limitation acknowledged in some of the leading studies.[10] The data and improved understanding of "carbon lock-in," complemented by the mainstream economic insights about path dependence associated with expectations (e.g., "self-fulfilling prophesies," Section 5), suggest a scale of path dependence that has yet to be adequately addressed in global IAMs. Probably the closest to this are simulation (rather than optimizing) models, the most detailed linking an econometric model (E3ME) with technology innovation (FTT) and climate (GENIE) modules (Mercure et al., 2018).

Also, abatement cost is substantially influenced determined by the underlying socioeconomic development pathway, policy effectiveness, and assumptions around hard-to-abate sectors, rather than climate target stringency (Mercure et al., 2019; van Vuuren et al., 2020). The emerging field of agent-based climate-economy models (Farmer et al., 2015) may handle nonequilibrium effects, learning (by firms, voters, policy makers,…), and bounded rationality in a more natural way (e.g., Hoekstra et al., 2017; Lamperti et al., 2018; Rengs et al., 2020; Wolf et al., 2013).

7.4 | Interpretation, complexity, and influence

Despite ongoing efforts, it remains a challenge to construct models that capture enough complexity to be reflect dynamic realities, while producing transparent insights that can be easily interpreted and communicated. Broadly, the more stylized models are easy to compute and well-behaved, generating a global least-cost optimal pathway and simple narrative from a limited set of assumptions. Yet, we have charted serious limitations in their treatment of abatement dynamics.

Conversely, hybrid IAMs have made great strides, but tend to be complex in their specification, operation, and data requirements, and can be sensitive to assumptions. As a result, the insights can be hard to communicate and fall prey to charges of being "black boxes." The IPCC has increasingly found itself under pressure to increase their transparency, but this can result in vast datasets and extensive descriptions; our Table A1 only scratches the surface of one small aspect of such models.

Moreover, the results can seem potentially quite indeterminate or unstable. This is less satisfactory to modelers, harder to communicate, and harder to implement computationally (e.g., whether a result is a local or global least cost). In researching this article, we came across references to such features as "problems" which needed to be "solved." Given our empirical findings, it is not scientific to force such models to be more conventional by excluding dynamic realities. The fact that such models can generate widely diverse behaviors, with results sensitive to assumptions, is telling us something important.

8 | THE IMPACT OF DYNAMIC FACTORS ON OPTIMAL PATHWAYS

To compare the optimal policy under temporal independence versus interdependence in one single, established IAM, we integrate the stylized approach from Equation (2) into DICE itself (see Supporting Information for details).

Thus, like Pottier et al. (2015), we add an inertial term depending on the *rate* of abatement (c_B in Equation (2)), but simultaneously, we reduce the "rigid" cost term (c_A) to account for the fact that at least part of the abatement costs are transitional rather than lasting. As in Grubb et al. (2018), we express Equation (2) in terms of the "pliability" p and a characteristic transition timescale $\hat{t}$:

$$\boldsymbol{C}_{\mathrm{AB}}(t,\mu,\dot{\mu}) = \mathrm{c}_{\mathrm{AB}}(t)\left[(1-p).\mu(t)^{\theta} + p.\frac{\hat{t}^{\theta}}{\theta+1}\dot{\mu}(t)^{\theta}\right] \tag{3}$$

A system with no pliability ($p = 0$) has full temporal independence, and is just the DICE model, with no induced technology learning. A fully pliable system ($p = 1$) is fully path-dependent; the abatement costs reflect the investment required to overcome inertia and to induce innovation sufficient to make low-carbon technologies as cheap as fossil fuels. 50% pliability corresponds to the "half-and-half" case in Grubb et al. (1995). We term this model DICE-PACE—DICE with Pliable Abatement Cost Elements.

Results are shown in Figure 6. While inertia precludes the initial jump of abatement observed in models with temporal independence (e.g., the pure DICE ($p = 0$) formulation), positive pliability implies a smoother path of mitigation toward deeper emission reductions. This reflects the behavior observed in the more complex IAMs with learning-by-doing as observed in Section 7.

The second panel shows that this is achieved by greater up-front investment and a radically different investment profile. The DICE model with $p = 0$ initially invests a mere 0.055% of GDP in mitigation, a figure which rises toward

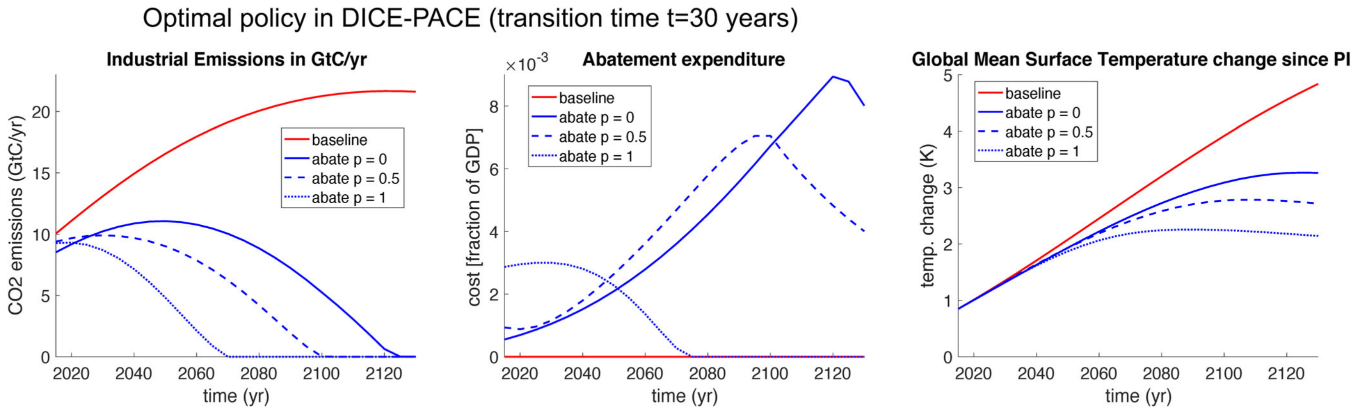


FIGURE 6 DICE-PACE result for transition time of 30 years

1% over a century. With $p = 1$, the initial effort is increased more than five-fold, to about 0.3% GDP. Even with the very modest damage assumptions, global warming stays below 2.3°C. In a sensitivity run with trebled damage (based on Howard & Sterner, 2017), global warming stays below 2°C for $p = 1$ and the initial effort is 1% of GDP (see SOM), similar to typical estimates from more complex energy system models of the investment requirements for delivering the Paris goals, but declining steadily.

The underlying reason for these results is simple. With temporal *inter*dependence, every early abatement effort reduces the costs of ambitious abatement levels later (the inertial costs being already paid). With high pliability, the future stream of emission savings induced by early action is several times larger than the initial cuts themselves. This is hardly rocket science, but is impossible in models which assume temporal independence.

So, if the system is substantially pliable, such expenditure has only to be sustained at the initial level for few decades, to drive the low-carbon innovation, overcome inertia and break the path-dependency upon fossil fuels. After that, the effort required declines as the world adapts to a low-carbon economy. The outcome with pliable mitigation costs is both lower mitigation costs, and far lower climate damages. As outlined in the SOM, the effect of pliability on optimal policy is of similar magnitude to the effect of damage uncertainty.

Despite its simplicity, DICE-PACE echoes the findings of some of the far more complex models, for example the IMACLIM studies in which the inertia of systems combined with learning leads to high initial investment followed by declining costs (Section 7.2).

The DICE-PACE exercise illustrates that correctly representing temporal interdependence profoundly influences the policy recommendations of IAMs, and that it can be (qualitatively) included even in stylized IAMs such as DICE. One open question remains: How pliable is the real world? The evidence reviewed across Sections 3–5 seems to suggest pliability in the upper range of 0.5–1, but we advance this as a contention for further research.

9 | CONCLUSIONS

We have reviewed some lessons from quarter of a century of evidence and, briefly, model developments, concerning the dynamic characteristics of mitigation costs. We conclude that these lessons deserve just as much future attention in stylized cost-benefit models as that previously devoted to climate damages, for the implications for policy are just as large (and more tractable).

The traditional stylized structure assumes a fixed and predefined (exogenous) abatement cost curve at all points in time: thus, within the model they are *temporally independent*. In sharp contrast, overwhelming empirical evidence shows that the global energy system has considerable inertia, involves technologies which respond both to market incentives and scale, and has significant path dependence. Correspondingly, we have observed two important conceptual advances in "stylized" economic models. One is recognition (following Acemoglu et al. (2012)) that abatement is not an independent cost factor, but rather represents the difference between two cost streams of high and low carbon investment respectively; superior learning in the latter can lead the whole system to switch. The other advance is recognition that inertia can fundamentally change the dynamics of optimal abatement (Vogt-

Schilb et al., 2018). The interaction of these two factors is likely to be important, but has yet to be adequately combined in stylized models.

More complex IAMs incorporating sectoral representations capture more of these features and can display quite different behaviors from DICE. However, their complexity has impeded more widespread understanding of the fundamental insights, and indeed, has in some leading models led these features to be turned off in applied scenario studies. Also, no mainstream IAM explicitly captures other features that contribute to the path dependencies observed in energy and other complex systems. A stylized but flexible representation of dynamic realities inserted into the DICE model illustrates the sensitivity of results to these assumptions. Greater emphasis upon dynamics—temporal *inter*dependence—results in much greater up-front investment in abatement, with a flatter subsequent trajectory, and steadily declining emissions rather than deferred abatement.

The implications concern not just the optimal effort, pathways, and outcomes. Obviously, the extent of dynamic linkages—and the corresponding potential for present actions to reduce future emissions—will vary for different technologies, sectors, and types of intervention. Lecocq and Shalizi (2014) demonstrate the need for targeted mitigation in long-lived infrastructure. Innovation itself may be induced more effectively by more targeted instruments than through a global carbon price (e.g., Rozenberg et al., 2020), and dynamic realities imply a more varied policy landscape as also emphasized by Vogt-Schilb et al. (2018). However, enhanced and sustained abatement is also implied by wider inertia and some degree of path dependence that is likely pervasive across many emitting systems.

The past 25 years have demonstrated dynamic realities of energy systems which differ substantially from the standard stylized approaches, including the archetypal DICE model. Temporal independence is a myth, and we have shown it to be one that matters. The observational evidence reviewed in Sections 3–5 implies that early decisive climate action is beneficial to gain time to overcome inertia, to generate and harvest accumulated knowledge, and avoid carbon lock-in. More sophisticated models corroborate this. This needs to be reflected also in DICE and related stylized IAMs, and the implications need to be more widely acknowledged in the economics and modeling of climate change abatement.

ACKNOWLEDGMENTS

The research was supported by INET under Grant ID #INO19-00004, with additional support for the DICE modeling work by ClimateWorks, Grant 19-1466, and the Rockefeller Foundation Economic Council, Grant No. R48555/CN009 Extension for Planetary Health at Oxford Martin School. The authors are grateful to Ilias Tsagas at Greenwich University for compiling the data and graph of Figure 3(b) on projected and realized PV costs; to Dan Chester at Lancaster University for additional insights into inertia; to Ben Hinder for producing Figure 5; and to Pablo Salas at Cambridge University, as well to anonymous referees who stimulated us to review much more extensively in particular the developments in more complex Integrated Assessment Models.

CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

AUTHOR CONTRIBUTIONS

Michael Grubb: Conceptualization; data curation; formal analysis; investigation; methodology; validation; visualization; writing-original draft; writing-review and editing. **Claudia Wieners:** Formal analysis; investigation; methodology; software; visualization; writing-original draft; writing-review and editing. **Pu Yang:** Data curation; methodology; software; visualization; writing-review and editing.

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ENDNOTES

[1] According to google search on July 25th, 2020.

[2] The DICE model uses the terms $\theta_1(t)$ and θ_2 respectively for c_A (t) and the exponent $^{\theta}$; $\theta_1(t)$ comprises two components, $C_0(t)\sigma(t)$, where C_0 is an exogenous cost factor declining by 0.5% per year (representing technological improvement), and $\sigma(t)$ is the "no policy" projected CO2 per unit of GDP, initially declining with 1.5% per year.

[3] PV auction prices struck in the US (Los Angeles @ 2 c/kWh), Brazil (1.75 c/kWh), and Portugal (1.6 c/kWh) (PV Magazine (2019a,2019c). Critiques and data on the systematic failures in PV cost and deployment forecasting include Hoekstra et al. (2017) and the site https://rameznaam.com/2020/05/14/solars-future-is-insanely-cheap-2020/.

[4] "Battery prices keep falling. As a result, we expect price parity between EVs and internal combustion vehicles (ICE) by the mid-2020s in most segments, though there is wide variation between geographies and vehicle segments."

[5] The evidence of Figures 3 and 4 is that $c_A(t) \, . \, \mu(t)^{\theta A}$ may be close to zero for at least the first portions of the cost curve, or even negative for low μ, which is the implication if zero carbon sources become cheaper than fossil fuels.

[6] Modeling in Newbery (2018) concludes that if PV learning curves are taken at face value, the German programme, which many economists criticized for cutting emissions at far greater expense than needed, was in fact globally cost-effective precisely because of the innovation it induced. Many countries have yet to make the investments required to bring down the local costs of PV or electric vehicles (including charging infrastructure) at scale.

[7] At least in their default settings: The stylised model by van der Ploeg and Rezai (2019) does consider some of the relevant effects but only in the Appendix, not in the standard version.

[8] It is now well established that patents are path-dependent—companies build upon previous research and innovate most in areas of established comparative advantage. Also of course, all styled models have some form of cumulative economic growth (usually based on the standard Ramsay model of economic growth). However, this is very different from path-dependence in the abatement trajectory.

[9] A clear example comes from the lead author's own Institute, which runs the global technology-rich TIAM model. One article (Anandarajah, McDowall, & Ekins, 2013) explored the impact of including learning-by-doing in this model (TIAM-Energy Technology Learning). However, it was so computationally complex to run, unstable and uncertain to parametise, that the TIAM-ETL has not been used since.

[10] As part of the AMPERE studies on the cost of delay, Bertram et al. (2015) note being "well aware that the models are only able to capture the restricted aspect of carbon lock-in associated with physical capital and emissions, while institutional and other aspects of this phenomenon (Unruh, 2000) are not modeled and hence, not the subject of this study."

[11] "The spatial scale of analysis always corresponds to the initial markets of first commercial application for each technology in which the formative phases marked the emergence of a new innovation system. As examples, wind power is analyzed in Denmark, cars in the US, e-bikes in China" (Bento & Wilson, 2016, p. 7).

FURTHER READING

*BEIS. (2016). Electricity generation costs, Available from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/566567/BEIS_Electricity_Generation_Cost_Report.pdf

*DECC. (2011). Review of the generation costs and deployment potential of renewable electricity technologies in the UK, Available from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/147863/3237-cons-ro-banding-arup-report.pdf

*Fraunhofer ISE. (2012). Levelized cost of electricity renewable energies, Available from https://www.ise.fraunhofer.de/content/dam/ise/en/documents/publications/studies/EN2012_ISE_Studie_Stromgestehungskosten_Erneuerbare%20Energien_eng-version_17-01-2013_final.pdf

*IEA. (2010). Projected costs of generating electricity, 2010 Edition, Available from https://www.oecd-nea.org/ndd/pubs/2010/6819-projected-costs.pdf

*IEA. (2015). Projected costs of generating electricity, 2015 Edition. Available from https://www.oecd-nea.org/ndd/pubs/2010/6819-projected-costs.pdf

*IRENA. (2019). Renewable energy auctions: Status and trends beyond price. Available from https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Jun/IRENA_Auctions_beyond_price_2019_findings.pdf

*PV Magazine. (2019b). German PV tender brings average solar price of €0.049/kWh. Available from https://www.pv-magazine.com/2019/10/21/german-pv-tender-brings-average-solar-price-of-e0-049-kwh/

*Renewable Energy Cost references for Figure 3.

REFERENCES

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *The American Economic Review*, *102*, 131–166. https://doi.org/10.1257/aer.102.1.131

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, *124*, 1–51. https://doi.org/10.1086/684581

Akimoto, K., Sano, F., Homma, T., Oda, J., Nagashima, M., & Kii, M. (2010). Estimates of GHG emission reduction potential by country, sector, and cost. *Energy Policy*, *38*(7), 3384–3393.

Anandarajah, G., McDowall, W., Ekins, P. (2013). Decarbonising road transport with hydrogen and electricity: Long term global technology learning scenarios, *International Journal of Hydrogen Energy*, *38*: 8, doi.org/10.1016/j.ijhydene.2012.12.110

Anthoff, D., & Tol, R. S. J. (2013). The climate framework for uncertainty, negotiation and distribution (fund), tables, version 3.7. Available from Www.Fund-Model.Org

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The Econometrics Journal*, *99*, 116. https://doi.org/10.2307/2234208

Azariadis, C., & Guesnerie, R. (1986). Sunspots and cycles. *The Review of Economic Studies*, *53*, 725. https://doi.org/10.2307/2297716

Bashmakov, I., Grubb, M., Drummond, P., Lowe, R., & Myshak, A. (2020). "Minus 1" and energy costs constants: empirical evidence, theory and policy implications. *in review with Journal of Cleaner Production Letters*.

Barker, T., Qureshi, M. S., & Köhler, J. (2006). *The costs of greenhouse gas mitigation with induced technological change: A meta-analysis of estimates in the literature*. (Tyndall Center Working Paper), pp. 1–63.

*BEIS. (2019). CfD allocation round 3 auction results. Available from https://www.gov.uk/government/publications/contracts-for-difference-cfd-allocation-round-3-results/contracts-for-difference-cfd-allocation-round-3-results

Benhabib, J., & Farmer, R. E. A. (1999). Chapter 6 Indeterminacy and sunspots in macroeconomics. In J. Taylor & M. Woodford (Eds.), *Handbook of Macroeconomics* (pp. 387–448). Elsevier.

Bento, N., & Wilson, C. (2016). Measuring the duration of formative phases for energy technologies. *Environmental Innovation and Sustainability Transitions*, *21*, 95–112. https://doi.org/10.1016/j.eist.2016.04.004

Bertram, C., Johnson, N., Luderer, G., Riahi, K., Isaac, M., & Eom, J. (2015). Carbon lock-in through capital stock inertia associated with weak near-term climate policies. *Technological Forecasting and Social Change*, *90*, 62–72. https://doi.org/10.1016/j.techfore.2013.10.001

Bettencourt, L. M. A., Trancik, J. E., & Kaur, J. (2013). Determinants of the pace of global innovation in energy technologies. *PLoS One*, *8*, e67864. https://doi.org/10.1371/journal.pone.0067864

Bloomberg New Energy Finance. (2019). New energy outlook 2019.

Bosetti, V., Carraro, C., Galeotti, M., Massetti, E., and Tavoni, M. (2006). WITCH: A World Induced Technical Change Hybrid model. Energy J., Hybrid Modeling, Special Issue #2: https://doi.org/10.5547/ISSN0195-6574-EJ-VolSI2006-NoSI2-2

Bosetti, V., Marangoni, G., Borgonovo, E., Diaz Anadon, L., Barron, R., McJeon, H. C., Politis, S., & Friley, P. (2015). Sensitivity to energy technology costs: A multi-model comparison analysis. *Energy Policy*, *80*, 244–263. https://doi.org/10.1016/j.enpol.2014.12.012

Botzen, W. J., & van den Bergh, J. C. J. M. (2012). How sensitive is Nordhaus to Weitzman? Climate policy in DICE with an alternative damage function. *Economics Letters*, *117*, 372–374. https://doi.org/10.1016/j.econlet.2012.05.032

Buonanno, P., Carraro, C., & Galeotti, M. (2003). Endogenous induced technical change and the costs of Kyoto. *Resource and Energy Economics*, *25*, 11–34. https://doi.org/10.1016/S0928-7655(02)00015-5

Calel, R., & Dechezleprêtre, A. (2016). Environmental policy and directed technological change: Evidence from the european carbon market. *The Review of Economics and Statistics*, *98*, 173–191. https://doi.org/10.1162/REST_a_00470

Capros, P., Van Regemorter, D., Paroussos, L., Karkatsoulis, P., Fragkiadakis, C., Tsani, S., Charalampidis, I., Revesz, T., Perry, M. and Abrell, J., 2013. GEM-E3 model documentation. *JRC Scientific and Policy Reports*, *26034*.

Chateau, J., Dellink, R., & Lanzi, E. (2014). *An overview of the OECD ENV-linkages model: Version 3*.

Crassous, R., Hourcade, J. C., & Sassi, O. (2006). Endogenous structural change and climate targets modeling experiments with imaclim-R. *The Energy Journal*. SI2006. https://doi.org/10.5547/issn0195-6574-ej-volsi2006-nosi1-13

Daniel, K. D., Litterman, R. B., & Wagner, G. (2019). Declining CO2 price paths. *Proceedings of the National Academy of Sciences of the United States of America*, *116*, 20886–20891. https://doi.org/10.1073/pnas.1817444116

Davis, S. J., Caldeira, K., & Matthews, H. D. (2010). Future CO2 emissions and climate change from existing energy infrastructure. *Science*, *329*, 1330–1333. https://doi.org/10.1126/science.1188566

Davis, S. J., & Socolow, R. H. (2014). Commitment accounting of CO2 emissions. *Environmental Research Letters*, *9*. https://doi.org/10.1088/1748-9326/9/8/084018

Dietz, S., & Stern, N. (2015). Endogenous growth, convexity of damage and climate risk: How Nordhaus' framework supports deep cuts in carbon emissions. *The Econometrics Journal*, *125*, 574–620. https://doi.org/10.1111/ecoj.12188

Dietz, S., & Venmans, F. (2019). Cumulative carbon emissions and economic policy: In search of general principles. *Journal of Environmental Economics and Management*, *96*, 108–129. https://doi.org/10.1016/J.JEEM.2019.04.003

Dowlatabadi, H. (1998). Sensitivity of climate change mitigation estimates to assumptions about technical change. *Energy Economics*, *20*, 473–493. https://doi.org/10.1016/s0140-9883(98)00009-7

Edenhofer, O., & Coauthors. (2011). *IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation*. Cambridge UK: CUP.

Edenhofer, O., Lessman, K., Kemfert, C., Grubb, M., & Köhler, J. (2006). Induced technological change: Exploring its implications for the economics of atmospheric stabilization: Synthesis report from the innovation modeling comparison project. *The Energy Journal*, *27*. https://doi.org/10.5547/issn0195-6574-ej-volsi2006-nosi1-3 SI2006.

Erickson, P., Kartha, S., Lazarus, M., & Tempest, K. (2015). Assessing carbon lock-in. *Environmental Research Letters*, *10*(8), 084023.

Farmer, J. D., Hepburn, C., Mealy, P., & Teytelboym, A. (2015). A third wave in the economics of climate change. *Environmental and Resource Economics*, *62*, 329–357. https://doi.org/10.1007/s10640-015-9965-2

Farmer, J. D., & Lafond, F. (2016). How predictable is technological progress? *Research Policy*, *45*, 647–665. https://doi.org/10.1016/j.respol.2015.11.001

Farmer, R. E. A. (1993). *The macroeconomics of self-fulfilling prophecies* (1st ed.). Cambridge MA: MIT Press.

Faulwasser, T., Nydestedt, R., Kellett, C. M., & Weller, S. R. (2018). Towards a FAIR-DICE IAM: Combining DICE and FAIR models ☐. *IFAC-PapersOnLine*, *51*, 126–131. https://doi.org/10.1016/j.ifacol.2018.06.222

Fisher-Vanden, K., Schu, K., Sue Wing, I., & Calvin, K. (2012). Decomposing the impact of alternative technology sets on future carbon emissions growth. *Energy Economics*, *34*, S359–S365. https://doi.org/10.1016/j.eneco.2012.07.021

Fouquet, R., and Aghion, P. (2019). *Path dependence, innovation and the economics of climate change*. in Handbook on Green Growth, R. Fouquet, Ed., Edward Elgar, 67–83.

Fujii, Y., & Komiyama, R. (2015). Long-term energy and environmental strategies. In *Reflections on the Fukushima Daiichi nuclear accident: Toward social-scientific literacy and engineering resilience*.

Fujimori, S., Hasegawa, T., Masui, T., Takahashi, K., Herran, D. S., Dai, H., Hijioka, Y., & Kainuma, M. (2017). SSP3: AIM implementation of shared socioeconomic pathways. *Global Environmental Change*, *42*, 268–283. https://doi.org/10.1016/j.gloenvcha.2016.06.009

Gillingham, K., Newell, R. G., & Pizer, W. A. (2008). Modeling endogenous technological change for climate policy analysis. *Energy Economics*, *30*, 2734–2753. https://doi.org/10.1016/j.eneco.2008.03.001

Glanemann, N., Willner, S. N., & Levermann, A. (2020). Paris climate agreement passes the cost-benefit test. *Nature Communications*, *11*, 110. https://doi.org/10.1038/s41467-019-13961-1

*Global Wind Energy Council (GWEC). (2019). Global wind report 2018. Available from https://gwec.net/wp-content/uploads/2019/04/GWEC-Global-Wind-Report-2018.pdf

Goulder, L. H., & Mathai, K. (2000). Optimal CO2 abatement in the presence of induced technological change. *Journal of Environmental Economics and Management*, *39*, 1–38. https://doi.org/10.1006/jeem.1999.1089

Gritsevskyi, A., & Nakićenovi, N. (2000). Modeling uncertainty of induced technological change. *Energy Policy*, *28*, 907–921. https://doi.org/10.1016/S0301-4215(00)00082-3

Grubb, M., Chapuis, T., & Duong, M. H. (1995). The economics of changing course. Implications of adaptability and inertia for optimal climate policy. *Energy Policy*, *23*, 417–432. https://doi.org/10.1016/0301-4215(95)90167-6

Grubb, M., Mercure, J.-F., Salas, P., Lange, R.-J., & Sognnaes, I. (2018). Systems innovation, inertia and pliability: A mathematical exploration with implications for climate change abatement. Available from https://www.eprg.group.cam.ac.uk/eprg-working-paper-1808/.

Grubb, M., and Wieners, C. (2020). Modeling Myths: On the Need for Dynamic Realism in DICE and other Equilibrium Models of Global Climate Mitigation. Working Paper, Institute of New Economic Thinking. https://doi.org/10.36687/inetwp112. Accessed 12 Dec 2020

Grubb, M., Drummond, P., Poncia, A., McDowall, W., Popp, D., Samadi, S., Penasco, C., Gillingham, K., Smulders, S., Glachant, M., Pavan, G., Hassel, G., Mizuno, E., Rubin, E., Dechezlepraitre, A. (2021). Induced innovation in energy technologies and systems: a review of evidence and potential implications for CO2 mitigation. *Environmental Research Letters*. https://doi.org/10.1088/1748-9326/abde07

Grübler, A., Nakićenović, N., & Victor, D. G. (1999). Dynamics of energy technologies and global change. *Energy Policy*, *27*, 247–280. https://doi.org/10.1016/S0301-4215(98)00067-6

Ha-Duong, M., Grubb, M. J., & Hourcade, J.-C. (1997). Influence of socioeconomic inertia and uncertainty on optimal CO2-emission abatement. *Nature*, *390*, 270–273. https://doi.org/10.1038/36825

Hafeez, S., Weller, S. R., & Kellett, C. M. (2017). *Transient Climate Response in the DICE Integrated Assessment Model of Climate-economy*. 2016 Australian Control Conference, AuCC 2016, Engineers Australia, pp. 282–287.

Hänsel, M. C., Drupp, M. A., Johansson, D. J. A., Nesje, F., Azar, C., Freeman, M. C., Groom, B., & Sterner, T. (2020). Climate economics support for the UN climate targets. *Nature Climate Change*, *10*, 781–789. https://doi.org/10.1038/s41558-020-0833-x

Hassler, J., & Krusell, P. (2012). Economics and climate change: Integrated assessment in a multi-region world. *Journal of the European Economic Association*, *10*, 974–1000. https://doi.org/10.1111/j.1542-4774.2012.01082.x

Heptonstall, P. J., & Gross, R. J. K. (2020). A systematic review of the costs and impacts of integrating variable renewables into power grids. *Nature Energy*. https://doi.org/10.1038/s41560-020-00695-4.

Hicks, J. (1932). *A theory of wages*. MacMillan.

Hoekstra, A., Steinbuch, M., & Verbong, G. (2017). Creating agent-based energy transition management models that can uncover profitable pathways to climate change mitigation. *Complexity*, *2017*. https://doi.org/10.1155/2017/1967645

Hope, C. (2006). The marginal impact of CO2 from PAGE2002: An integrated assessment model incorporating the IPCC's five reasons for concern. *Integrated Assessment Journal*, *6*, 19–56.

Hope, C. (2012). The social cost of Co2 from the Page09 model. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1973863

Hope, C., Anderson, J., & Wenman, P. (1993). Policy analysis of the greenhouse effect. An application of the PAGE model. *Energy Policy*, *21*, 327–338. https://doi.org/10.1016/0301-4215(93)90253-C

Hope, C. The Social Cost of Co2 from the Page09 Model (2011). Economics Discussion Paper No. 2011-39, Available at SSRN: https://ssrn.com/abstract=1973863 or https://doi.org/10.2139/ssrn.1973863

Howard, P. H., & Sterner, T. (2017). Few and not so far between: A meta-analysis of climate damage estimates. *Environmental and Resource Economics*, *68*, 197–225. https://doi.org/10.1007/s10640-017-0166-z

Inter-Agency Working Group. (2016). Technical support document: Technical update of the social cost of carbon for regulatory impact analysis under executive order 12866.

IPCC. (2007). *Climate change 2007 synthesis report*.

IPCC (2011). In O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, & C. von Stechow (Eds.), *IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation*. Cambridge, United Kingdom: Cambridge University Press.

IPCC. (2014). *Climate change 2014: Mitigation of climate change*. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

IRENA. (2020). *Renewable energy statistics 2020*.

Janse, J. H., et al. (2015). GLOBIO-aquatic, a global model of human impact on the biodiversity of inland aquatic ecosystems. *Environmental Science & Policy*, *48*, 99–114. https://doi.org/10.1016/j.envsci.2014.12.007

Jarvis, A. (2018). Energy Returns and The Long-run Growth of Global Industrial Society. *Ecol. Econ.*, *146*, 722–729. https://doi.org/10.1016/j.ecolecon.2017.11.005

Jennings, T., Tipper T., Andrews H., Daglish J., Drummond P., & Grubb M. (2020): Policy, innovation and cost reduction in UK offshore wind. https://www.carbontrust.com/resources/policy-innovation-and-cost-reduction-in-uk-offshore-wind (Accessed 14 September 2020).

Kavlak, G., McNerney, J., & Trancik, J. E. (2018). Evaluating the causes of cost reduction in photovoltaic modules. *Energy Policy*, *123*, 700–710. https://doi.org/10.1016/J.ENPOL.2018.08.015

Kefford, B. M., Ballinger, B., Schmeda-Lopez, D. R., Greig, C., & Smart, S. (2018). The early retirement challenge for fossil fuel power plants in deep decarbonisation scenarios. *Energy Policy*, *119*, 294–306. https://doi.org/10.1016/j.enpol.2018.04.018

Keramidas, K., Kitous, A., Despres, J., & Schmitz, A. (2017). *POLES-JRC model documentation*.

Kim, K., Heo, E., & Kim, Y. (2017). Dynamic policy impacts on a technological-change system of renewable energy: An empirical analysis. *Environmental and Resource Economics*, *66*, 205–236. https://doi.org/10.1007/s10640-015-9946-5

Knittel, C. R. (2011). Automobiles on steroids: Product attribute trade-offs and technological progress in the automobile sector. *The American Economic Review*, *101*, 3368–3399. https://doi.org/10.1257/aer.101.7.3368

Köhler, J., Grubb, M., Popp, D., & Edenhofer, O. (2006). The transition to endogenous technical change in climate-economy models: A technical overview to the innovation modeling comparison project. *The Energy Journal*. *27*, 17–55. https://doi.org/10.5547/issn0195-6574-ej-volsi2006-nosi1-2

Krey, V., Luderer, G., Clarke, L., & Kriegler, E. (2014). Getting from here to there - energy technology transformation pathways in the EMF27 scenarios. *Climatic Change*, *123*, 369–382. https://doi.org/10.1007/s10584-013-0947-5

Kriegler, E., Riahi, K., Bosetti, V., Capros, P., Petermann, N., van Vuuren, D. P., Weyant, J. P., & Edenhofer, O. (2015). Introduction to the AMPERE model intercomparison studies on the economics of climate stabilization. *Technological Forecasting and Social Change*, *90*, 1–7. https://doi.org/10.1016/j.techfore.2014.10.012

Kriegler, E., Riahi, K., Bauer, N., Schwanitz, V. J., Petermann, N., Bosetti, V., Marcucci, A., Otto, S., Paroussos, L., Rao, S., Arroyo Currás, T., Ashina, S., Bollen, J., Eom, J., Hamdi-Cherif, M., Longden, T., Kitous, A., Méjean, A., Sano, F., … Edenhofer, O. (2015a). Making or breaking climate targets: The AMPERE study on staged accession scenarios for climate policy. *Technological Forecasting and Social Change*, *90*, 24–44.

Kriegler, E., Petermann, N., Krey, V., Schwanitz, V. J., Luderer, G., Ashina, S., Bosetti, V., Eom, J., Kitous, A., Méjean, A., Paroussos, L., Sano, F., Turton, H., Wilson, C., & Van Vuuren, D. P. (2015b). Diagnostic indicators for integrated assessment models of climate policy. *Technological Forecasting and Social Change*, *90*, 45–61.

Kriegler, E., Bauer, N., Popp, A., Humpenöder, F., Leimbach, M., Strefler, J., Baumstark, L., Bodirsky, B. L., Hilaire, J., Klein, D., Mouratiadou, I., Weindl, I., Bertram, C., Dietrich, J.-P., Luderer, G., Pehl, M., Pietzcker, R., Piontek, F., Lotze-Campen, H., … Edenhofer, O. (2017). Fossil-fueled development (SSP5): an energy and resource intensive scenario for the 21st century. *Global environmental change*, *42*, 297–315.

Kroposki, B., Johnson, B., Zhang, Y., Gevorgian, V., Denholm, P., Hodge, B. M., & Hannegan, B. (2017). Achieving a 100% renewable grid: Operating electric power systems with extremely high levels of variable renewable energy. *IEEE Power & Energy Magazine*, *15*, 61–73. https://doi.org/10.1109/MPE.2016.2637122

Kruse, J., & Wetzel, H. (2016). *Innovation in clean coal technologies: Empirical evidence from firm-level patent data*. (EWI Working Paper, No. 16/01).

Kurosawa, A. (2006). Multigas mitigation: An economic analysis using GRAPE model. *The Energy Journal*. *3*, 275–288. SI2006. https://doi.org/10.5547/issn0195-6574-ej-volsi2006-nosi3-13

Kypreos, S. (2007). A MERGE model with endogenous technological change and the cost of carbon stabilization. *Energy Policy*, *35*, 5327–5336. https://doi.org/10.1016/j.enpol.2006.01.029

Labriet, M., Kanudia, A., & Loulou, R. (2012). Climate mitigation under an uncertain technology future: A TIAM-world analysis. *Energy Economics*, *34*, S366–S377. https://doi.org/10.1016/j.eneco.2012.02.016

Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., & Sapio, A. (2018). Faraway, so close: Coupled climate and economic dynamics in an agent-based integrated assessment model. *Ecological Economics*, *150*, 315–339. https://doi.org/10.1016/j.ecolecon.2018.03.023

Lecocq, F., & Shalizi, Z. (2014). The economics of targeted mitigation in infrastructure. *Climate Policy*, *14*, 187–208. https://doi.org/10.1080/14693062.2014.861657

Lehmann, P., Creutzig, F., Ehlers, M. H., Friedrichsen, N., Heuson, C., Hirth, L., & Pietzcker, R. (2012). Carbon lock-out: Advancing renewable energy policy in Europe. *Energies*, *5*, 323–354. https://doi.org/10.3390/en5020323

Lemoine, D., & Rudik, I. (2017). Managing climate change under uncertainty: Recursive integrated assessment at an inflection point. *Annual Review of Resource Economics*, *9*, 117–142. https://doi.org/10.1146/annurev-resource-100516-053516

Lichtenberg, F. R. (1986). Energy prices and induced innovation. *Research Policy*, *15*, 67–75. https://doi.org/10.1016/0048-7333(86)90002-8

Luderer, G., Bosetti, V., Jakob, M., Leimbach, M., Steckel, J. C., Waisman, H., & Edenhofer, O. (2012). The economics of decarbonizing the energy system-results and insights from the RECIPE model intercomparison. *Climatic Change*, *114*, 9–37. https://doi.org/10.1007/s10584-011-0105-x

Markovic, F., Lazarou, S., & Dagoumas, A. (2018). Energy and climate policy consideration using the GCAM model: Assessing energy sources and technology options. *International Journal of Renewable Energy Research*, *8*, 2299–2309.

McKinsey&Co, 2009: Pathways to a low carbon economy: Version 2.0 of the Global Greenhouse Gas Abatement Cost Curve. https://www.mckinsey.com/~/media/mckinsey/dotcom/client_service/sustainability/costcurvepdfs/pathways_lowcarbon_economy_version2.ashx.

Mercure, J.-F., Knobloch, F., Pollitt, H., Paroussos, L., Scrieciu, S. S., & Lewney, R. (2019). Modelling innovation and the macroeconomics of low-carbon transitions: Theory, perspectives and practical use. *Climate Policy*, *19*, 1019–1037. https://doi.org/10.1080/14693062.2019.1617665

Mercure, J. F., Pollitt, H., Viñuales, J. E., Edwards, N. R., Holden, P. B., Chewpreecha, U., Salas, P., Sognnaes, I., Lam, A., & Knobloch, F. (2018). Macroeconomic impact of stranded fossil fuel assets. *Nature Climate Change*, *8*(7), 588–593.

Mequignon, M., Ait Haddou, H., Thellier, F., & Bonhomme, M. (2013). Greenhouse gases and building lifetimes. *Building and Environment*, *68*, 77–86. https://doi.org/10.1016/j.buildenv.2013.05.017

Moore, F. C., & Diaz, D. B. (2015). Temperature impacts on economic growth warrant stringent mitigation policy. *Nature Climate Change*, *5*, 127–131. https://doi.org/10.1038/nclimate2481

National Energy Board. (2016). Canada's energy future 2016 energy supply and demand projections to 2040.

Nemet, G. F. (2019). *How solar energy became cheap a model for low-carbon innovation*. Routledge.

Newbery, D. (2018). Evaluating the case for supporting renewable electricity. *Energy Policy*, *120*, 684–696. https://doi.org/10.1016/J.ENPOL.2018.05.029

Newell, R. G., Jaffe, A. B., & Stavins, R. N. (1999). The induced innovation hypothesis and energy-saving technological change. *Quarterly Journal of Economics*, *114*, 941–975. https://doi.org/10.1162/003355399556188

Nordhaus, W. (2013). *The climate casino: Risk, uncertainty, and economics for a warming world*. Yale University Press.

Nordhaus, W., & Sztorc, P. (2013) DICE 2013R: Introduction and user's manual. Available from http://www.econ.yale.edu/∼nordhaus/homepage/homepage/documents/DICE_Manual_100413r1.pdf.

Nordhaus, W. D. (1969). An economic theory of technological change. *The American Economic Review*, *59*(2), 18–28.

Nordhaus, W. D. (1992). An optimal transition path for controlling greenhouse gases. *Science (80-.)*. *258*(5086), 1315–1319. https://doi.org/10.1126/science.258.5086.1315

Nordhaus, W. D. (2002a). Modeling induced innovation in climate change policy. Chapter 8. In A. Grubler, N. Nakicenovic, & W. Nordhaus (Eds.), *Technological change and the environment* (pp. 259–290). Washington, DC: Resources for the Future Press.

Nordhaus, W. D. (2002b). *Induced technological change with applications to modeling of climate-change policies*.

Nordhaus, W. D. (2014). The perils of the learning model for modeling endogenous technological change. *The Energy Journal*, *35*(1). https://doi.org/10.5547/01956574.35.1.1

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences of the United States of America*, *114*, 1518–1523. https://doi.org/10.1073/pnas.1609244114

Parker, S., & Liddle, B. (2017). Economy-wide and manufacturing energy productivity transition paths and club convergence for OECD and non-OECD countries. *Energy Economics*, *62*, 338–346. https://doi.org/10.1016/j.eneco.2016.07.018

Paroussos, L., Mandel, A., Fragkiadakis, K., Fragkos, P., Hinkel, J., & Vrontisi, Z. (2019). Climate clubs and the macro-economic benefits of international cooperation on climate policy. *Nature Climate Change*, *9*, 542–546. https://doi.org/10.1038/s41558-019-0501-1

Pezzey, J. C. V. (2019). Why the social cost of carbon will always be disputed. *Wiley Interdisciplinary Reviews: Climate Change*, *10*, e558. https://doi.org/10.1002/wcc.558

Popp, D. (2002). Induced innovation and energy prices. *The American Economic Review*, *92*, 160–180.

Popp, D. (2004). ENTICE: Endogenous technological change in the DICE model of global warming. *Journal of Environmental Economics and Management*, *48*, 742–768. https://doi.org/10.1016/j.jeem.2003.09.002

Popp, D. (2019). Environmental policy and innovation: A decade of research. *International Review of Environmental and Resource Economics*, *13*, 265–337. https://doi.org/10.1561/101.00000111

Popp, D., Newell, R. G., & Jaffe, A. B. (2010). *Energy, the Environment, and Technological Change. Vol. 2 of Handbook of the Economics of Innovation, B.H. Halland and N* (pp. 873–937). Rosenberg: Eds., North-Holland.

Pottier, A., Espagne, E., Perrissin Fabert, B., & Dumas, P. (2015). The comparative impact of integrated assessment Models' structures on optimal mitigation policies. *Environmental Modeling and Assessment*, *20*, 453–473. https://doi.org/10.1007/s10666-015-9443-9

Pottier, A., Hourcade, J. C., & Espagne, E. (2014). Modelling the redirection of technical change: The pitfalls of incorporeal visions of the economy. *Energy Economics*, *42*, 213–218. https://doi.org/10.1016/j.eneco.2013.12.003

*PV Magazine. (2019a). Brazil A-4 auction signs 211 MW of solar for record-low price of $0.0175 kWh. Available from https://www.pv-magazine.com/2019/07/01/Brazil-a-4-auction-signs-211-mw-of-solar-for-record-low-price-of-0-0175-kwh/.

*PV Magazine. (2019c). Portuguese auction attracts world record bid of €14.8/MWh for solar. Available from https://www.pv-magazine.com/2019/07/31/portuguese-auction-attracts-world-record-bid-of-e14-8-mwh-for-solar/?utm_source=Bibblio&utm_campaign=Internal

Rengs, B., Scholz-Wäckerle, M., & van den Bergh, J. (2020). Evolutionary macroeconomic assessment of employment and innovation impacts of climate policy packages. *Journal of Economic Behavior and Organization*, *169*, 332–368. https://doi.org/10.1016/j.jebo.2019.11.025

Riahi, K., Kriegler, E., Johnson, N., Bertram, C., den Elzen, M., Eom, J., Schaeffer, M., Edmonds, J., Isaac, M., Krey, V., Longden, T., Luderer, G., Méjean, A., McCollum, D. L., Mima, S., Turton, H., van Vuuren, D. P., Wada, K., Bosetti, V., … Edenhofer, O. (2015). Locked into Copenhagen pledges—implications of short-term emission targets for the cost and feasibility of long-term climate goals. *Technological Forecasting and Social Change*, *90*, 8–23.

Rizvi, S. A. T. (2006). The Sonnenschein-mantel-Debreu results after thirty years. *History of Political Economy*, *38*, 228–245. https://doi.org/10.1215/00182702-2005-024

Rogelj, J., Forster, P. M., Kriegler, E., Smith, C. J., & Séférian, R. (2019). Estimating and tracking the remaining carbon budget for stringent climate targets. *Nature*, *571*, 335–342. https://doi.org/10.1038/s41586-019-1368-z

Rogelj, J., Meinshausen, M., Knutti, R., Farag, A. A., Abdrabbo, M. A. A., El-sharkawi, H. M., …, Intergovernmental panel on Climate Change. 2000. Special report on emission scenarios. *Nature Climate Change. Summary for Policymakers*. https://doi.org/10.1017/CBO9781107415416.005.

Rogelj, J., Meinshausen, M., & Knutti, R. (2012). Global warming under old and new scenarios using IPCC climate sensitivity range estimates. *Nature climate change*, *2*(4), 248–253.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*, S71–S102. https://doi.org/10.3386/w3210

Rotmans, J. (1990). IMAGE: An integrated model to assess the greenhouse effect. *Ecological Economics*, *7*, 262–263. https://doi.org/10.1016/0921-8009(93)90013-v

Rozenberg, J., Vogt-Schilb, A., & Hallegatte, S. (2020). Instrument choice and stranded assets in the transition to clean capital. *Journal of Environmental Economics and Management*, *100*, 102183. https://doi.org/10.1016/j.jeem.2018.10.005

Rubin, E. S., Azevedo, I. M. L., Jaramillo, P., & Yeh, S. (2015). A review of learning rates for electricity supply technologies. *Energy Policy*, *86*, 198–218. https://doi.org/10.1016/j.enpol.2015.06.011

Samadi, S. (2018). The experience curve theory and its application in the field of electricity generation technologies – A literature review. *Renewable and Sustainable Energy Reviews*, *82*, 2346–2364. https://doi.org/10.1016/j.rser.2017.08.077

Sands, R. D., Förster, H., Jones, C. A., & Schumacher, K. (2014). Bio-electricity and land use in the future agricultural resources model (FARM). *Climatic Change*, *123*, 719–730. https://doi.org/10.1007/s10584-013-0943-9

Schenk, N. J., & Lensink, S. M. (2007). Communicating uncertainty in the IPCC's greenhouse gas emissions scenarios. *Climatic Change*, *82*, 293–308. https://doi.org/10.1007/s10584-006-9194-3

Schumpeter, J. A. (1932). The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle (1912/1934). *Transaction Publishers.–1982.–January*, *1*(1982), 244.

Seebregts, A. J., Kram, T., Schaeffer, G. J., Stoffer, A., Kypreos, S., Barreto, L., Messner, S., & Schrattenholzer, L. (1999). *Endogenous technological change in energy system models*. IIASA: Paul Scherrer Institut.

Selvakkumaran, S., & Limmeechokchai, B. (2015). Low carbon society scenario analysis of transport sector of an emerging economy-the AIM/Enduse modelling approach. *Energy Policy*, *81*, 199–214. https://doi.org/10.1016/j.enpol.2014.10.005

Seto, K. C., Davis, S. J., Mitchell, R. B., Stokes, E. C., Unruh, G., & Ürge-Vorsatz, D. (2016). Carbon lock-in: Types, causes, and policy implications. *Annual Review of Environment and Resources*, *41*, 425–452. https://doi.org/10.1146/annurev-environ-110615-085934

Stehfest, E., van Vuuren, D., Bouwman, L., & Kram, T. (2014). Integrated assessment of global environmental change with IMAGE 3.0: Model description and policy applications. Netherlands Environmental Assessment Agency (PBL).

Taghizadeh-Hesary, F., Yoshino, N., & Inagaki, Y. (2019). Empirical analysis of factors influencing the price of solar modules. *International Journal of Energy Sector Management*, *13*, 77–97. https://doi.org/10.1108/IJESM-05-2018-0005

Tol, R. S. J. (1997). On the optimal control of carbon dioxide emissions: An application of FUND. *Environmental Modeling and Assessment*, *2*, 151–163.

Tsigaris, P., & Wood, J. (2016). A simple climate-Solow model for introducing the economics of climate change to undergraduate students. *International Review of Economics Education*, *23*, 65–81. https://doi.org/10.1016/j.iree.2016.06.002

Unruh, G. C. (2000). Understanding carbon lock-in. *Energy Policy*, *28*, 817–830. https://doi.org/10.1016/S0301-4215(00)00070-7

Unruh, G. C. (2002). Escaping carbon lock-in. *Energy Policy*, *30*, 317–325. https://doi.org/10.1016/S0301-4215(01)00098-2

van der Ploeg, F., & Rezai, A. (2019). Simple rules for climate policy and integrated assessment. *Environmental and Resource Economics*, *72*, 77–108. https://doi.org/10.1007/s10640-018-0280-6

van Vuuren, D. P., van der Wijst, K.-I., Marsman, S., van den Berg, M., Hof, A. F., & Jones, C. D. (2020). The costs of achieving climate targets and the sources of uncertainty. *Nature Climate Change*, *10*, 329–334. https://doi.org/10.1038/s41558-020-0732-1

Verdolini, E., & Galeotti, M. (2011). At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. *Journal of Environmental Economics and Management*, *61*, 119–134. https://doi.org/10.1016/j.jeem.2010.08.004

Vincenzi, M., & Ozabaci, D. (2017). The effect of public policies on inducing technological change in solar energy. *Journal of Agricultural and Resource Economics*, *46*, 44–72. https://doi.org/10.1017/age.2016.36

Vogt-Schilb, A., & Hallegatte, S. (2014). Marginal abatement cost curves and the optimal timing of mitigation measures. *Energy Policy*, *66*, 645–653. https://doi.org/10.1016/j.enpol.2013.11.045

Vogt-Schilb, A., Meunier, G., & Hallegatte, S. (2018). When starting with the most expensive option makes sense: Optimal timing, cost and sectoral allocation of abatement investment. *Journal of Environmental Economics and Management*, *88*, 210–233. https://doi.org/10.1016/J.JEEM.2017.12.001

Wei, Y. M., Mi, Z. F., & Huang, Z. (2015). Climate policy modeling: An online SCI-E and SSCI based literature review. *Omega*, *57*, 70–84. https://doi.org/10.1016/j.omega.2014.10.011

Wei, Y., Han, R., Liang, Q., Yu, B., Yao, Y., Xue, M., Zhang, K., Liu, L., Peng, J., Yang, P., Mi, Z., Du, Y., Wang, C., Chang, J., Yang, Q., Yang, Z., Shi, X., Xie, W., Liu, C., … Liao, H. (2018). An integrated assessment of INDCs under Shared Socioeconomic Pathways: an implementation of C3IAM. *Natural Hazards*, *92*(2), 585–618.

Weiss, M., Junginger, M., Patel, M. K., & Blok, K. (2010). A review of experience curve analyses for energy demand technologies. *Technological Forecasting and Social Change*, *77*, 411–428. https://doi.org/10.1016/J.TECHFORE.2009.10.009

Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The Review of Economics and Statistics*, *91*, 1–19. https://doi.org/10.1162/rest.91.1.1

Weitzman, M. L. (2012). GHG targets as insurance against catastrophic climate damages. *Journal of Public Economics Theory*, *14*, 221–244. https://doi.org/10.1111/j.1467-9779.2011.01539.x

Weyant, J. (2017). Some contributions of integrated assessment models of global climate change. *Review of Environmental Economics and Policy*, *11*, 115–137. https://doi.org/10.1093/reep/rew018

Weyant, J., & Kriegler, E. (2014). Preface and introduction to EMF 27. *Climatic Change*, *123*, 345–352. https://doi.org/10.1007/s10584-014-1102-7

Winning, M., Price, J., Ekins, P., Pye, S., Glynn, J., Watson, J., & McGlade, C. (2019). Nationally determined contributions under the Paris agreement and the costs of delayed action. *Climate Policy*, *19*, 947–958. https://doi.org/10.1080/14693062.2019.1615858

World Energy Outlook (2020) – Analysis - IEA. https://www.iea.org/reports/world-energy-outlook-2020 (Accessed November 10, 2020).

Wolf, S., Fürst, S., Mandel, A., Lass, W., Lincke, D., Pablo-Martí, F., & Jaeger, C. (2013). A multi-agent model of several economic regions. *Environmental Modelling & Software*, *44*, 25–43. https://doi.org/10.1016/j.envsoft.2012.12.012

Yamamoto, H., Sugiyama, M., & Tsutsui, J. (2014). Role of end-use technologies in long-term GHG reduction scenarios developed with the BET model. *Climatic Change*, *123*, 583–596. https://doi.org/10.1007/s10584-013-0938-6

Yang, P., Yao, Y., Mi, Z., Cao, Y., Liao, H., Yu, B., Liang, Q., Coffman, D., & Wei, Y. (2018). Social cost of carbon under shared socioeconomic pathways. *Global Environmental Change*, *53*, 225–232.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Grubb M, Wieners C, Yang P. Modeling myths: On DICE and dynamic realism in integrated assessment models of climate change mitigation. *WIREs Clim Change*. 2021;12:e698. https://doi.org/10.1002/wcc.698

APPENDIX: DYNAMIC CHARACTERISTICS IN INTEGRATED ASSESSMENT MODELS

The table in this Appendix tabulates, to the extent possible, how various global Integrated Assessment Models incorporate the three aspects of dynamic realities covered in this article. The first part of the table covers the main stylized "simple" IAMs, namely DICE, PAGE, FUND, and variants thereof. The second part covers complex IAMs, based mainly on the EMF 27 model comparison exercise (Krey et al., 2014; Table A1).

TABLE A1 Major integrated assessment models—key dynamic characteristics

Model	References	Intertemporal solution method	Inertia	Induced innovation	Additional sources of path dependence
Stylized global cost-benefit IAMs					
DICE	Nordhaus (1992, 2017)	Intertemporal optimization	None	None	None
R&DICE (DICE variant)	Nordhaus (2002b)	Intertemporal optimization	None	R&D builds up knowledge stock (diminishing returns to scale; crowding-out of growth-enhancing R&D)	None
ENTICE (DICE variant)	Popp (2004)	Intertemporal optimization	None	R&D builds up knowledge stock (diminishing returns to scale; crowding-out of growth-enhancing R&D)	None
RESPONSE (partly inspired by DICE)	Pottier et al. (2015)	Intertemporal optimization	A cost term depending on rate of change of abatement is *added* to the abatement cost	None	None
DICE-PACE (DICE variant)	This paper	Intertemporal optimization	A cost term depending on rate of change of abatement (partly) *replaces* enduring abatement cost	Only indirect insofar as costs is shared between two terms, one of which reflects abatement *rate* as a proxy for investments which reduce the long term costs	The pliability term reflects an aggregated proxy for path-dependent costs, but system only fully path-dependent for $p = 1$.
FUND	Anthoff and Tol (2013)	Policy testing	Carbon tax causes (costly) abatement; part of the effect is lasting, part is temporary	Learning-by-doing expands knowledge stock decreasing abatement cost	None
PAGE	Hope (2012)	Policy testing (under uncertainty)	None	Learning-by-doing expands knowledge stock decreasing abatement cost	None
Complex IAMs					
AIM-CGE	Fujimori et al. (2017)	Recursive dynamic	None	None	Initial technology share affecting future technological path by calibrating CES production function to base-year value shares
DNE21+	Fujii and Komiyama (2015)	Intertemporal optimization	Fixed lifetimes, early retirement allowed	None	None
IMACLIM-R	Crassous et al. (2006)	Recursive dynamic	Immobility of the installed capital across sectors	Learning by doing for energy; Price induced change and international spillovers of knowledge in the productive sector	Initial technology share affecting future technological path by logit share weights; rigidities in real wages, which may lead to partial utilization of production factors (labor and capital)

TABLE A1 (Continued)

Complex IAMs					
IMAGE	Stehfest et al. (2015)	Recursive dynamic	None	Learning by doing	Initial technology share affecting future technological path by logit share weights
MERGE	Kypreos (2007)	Intertemporal optimization	Fixed lifetimes for existing vintages (early retirement allowed), smooth depreciation for new vintages	Not included in EMF27, but can provide induced technology analysis by offline interactions (MERGE-ETL).	Initial technology share affecting expansion constraints and determine value share in each region's production function
MESSAGE	Gritsevskyi and Nakićenovi (2000)	Intertemporal optimization	Fixed lifetimes, early retirement allowed	Not included in EMF27, but can include ITC by offline iteration with learning curves to project their technology costs.	Initial technology share affecting future technological path by technology vintages
REMIND	Kriegler et al. (2017)	Intertemporal optimization	Fixed lifetimes, early retirement allowed	Learning curves for solar and wind energy as well as electric vehicles	Initial technology share affecting future technological path by calibrating CES production function to base-year value shares
WITCH	Bosetti et al. (2006)	Intertemporal optimization	None	Induced technology change for advanced, noncommercial technologies. Experience depends on cumulative deployment; innovation depends on R&D investments. Features international spillovers of knowledge	Initial technology share affecting future technological path by calibrating production function to match the productivities of the factors of production
GEM-E3	Capros et al. (2013)	Recursive dynamic	Consumption split between durable and nondurable goods	Learning by doing; Price induced change in energy consumption	Initial technology share affecting future technological path by calibrating CES production function to base-year value shares
POLES	Keramidas et al. (2017)	Recursive dynamic	Early retirement allowed in the power sector	Investment costs depend on cumulative installed capacity and cumulative R&D effort	Initial technology share affecting future technological path by logit share weights
GCAM	Markovic et al. (2018)	Partial equilibrium	Fixed lifetimes, early retirement allowed. Initial technology share reflected by logit share weights	None	Initial technology share affecting future technological path by logit share weights
AIM-Enduse	Selvakkumaran and Limmeechokchai (2015)	Recursive dynamic	Early retirement allowed	None	None
C^3IAM	Wei et al. (2018), Yang et al. (2018)	Intertemporal optimization	None	None	Initial technology share affecting future technological path by calibrating CES production function to base-year value shares

(Continues)

TABLE A1 (Continued)

Complex IAMs					
BET	Yamamoto et al. (2014)	Intertemporal optimization	Fixed lifetimes in the power sector; Technology expansion and contractions constraints	None	Initial technology share affecting future technological path by calibrating CES production function to base-year value shares
EC-IAM	National Energy Board (2016)	Intertemporal optimization	Capital vintage in the macroeconomy and certain electricity generation technology	None	Initial technology share affecting future technological path by expansion constraints and contractions constraints
E3ME-FTT-GENIE	Mercure et al. (2018)	Recursive dynamic	Fixed lifetimes. Technology availability is endogenously depending on market share	Technology level learning curves. Sectoral technology progress increase competitiveness with cumulative investment	Initial technology share affecting future technological path by expansion constraints
ENV-linkages	Chateau et al. (2014)	Recursive dynamic	New versus old vintages in all sectors with full malleability of new and limited possibilities to sell old capital	None	Initial technology share affecting future technological path by calibrating production function to match the productivities of the factors of production
FARM	Sands et al. (2014)	Recursive dynamic	None	None	Initial technology share affecting future technological path by calibrating CES production function to base-year value shares
GRAPE	Kurosawa (2006)	Intertemporal optimization	Fixed lifetimes in the energy sector	None	Initial technology share affecting future technological path by calibrating production function to match the productivities of the factors of production
Phoenix	Fisher-Vanden et al. (2012)	Recursive dynamic	None	None	Initial technology share affecting future technological path by calibrating CES production function to base-year value shares
TIAM-WORLD	Labriet et al. (2012)	Intertemporal optimization	Fixed lifetime, early retirement allowed	For investment costs only. No endogenous technological learning	Flexible link between base year and future years capacities with growth constraints for several key technologies