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# Advanced Technologies in Energy-Economy Models for Climate Change Assessment

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This reprint is intended to communicate research results and improve public understanding of global environment and energy challenges, thereby contributing to informed debate about climate change and the economic and social implications of policy alternatives.

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*Joint Program Co-Directors*

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# Advanced technologies in energy-economy models for climate change assessment

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ABSTRACT

Considerations regarding the roles of advanced technologies are crucial in energy-economic modeling, as these technologies, while usually not yet commercially viable, could substitute for fossil energy when favorable policies are in place. To improve the representation of the penetration of advanced technologies in energy-economic models, we present a formulation that is parameterized based on observations, while capturing elements of rent and real adjustment cost increases if high demand due to a large policy shock suddenly appears. The formulation is applied to a global computable general equilibrium model to explore the role of low-carbon alternatives in the electric power sector. While other modeling approaches often adopt specific constraints on expansion, our approach is based on the assumption and observation that these constraints are not absolute, and how fast advanced technologies will expand is endogenous to economic incentives. The policy simulations, while not intended to represent realistic price paths, are designed to illustrate the response of our technology diffusion approach under sudden increased demand for advanced technologies.



## 1. Introduction

It has long been recognized that study of energy futures as they relate to greenhouse gas emissions requires a consideration of advanced technologies that could substitute for fossil energy. Absent substitutes, standard production functions where all inputs are necessary would make it impossible to eliminate carbon emissions from the economy, which is essentially required to stabilize $CO_2$ concentrations. Simulating the transition to low-carbon substitutes turns out to be challenging, as these low-carbon alternatives have not been widely adopted and so evidence for how quickly they can be adopted at large scale must come mostly from small samples or analogous technologies. At the same time, the speed of being able to transform the energy system to reduce GHG emissions is an important determinant of climate mitigation costs.

In this study, we aim to improve the representation of technology diffusion in integrated assessment models and ground the parameterization in empirical foundations. We develop an approach to model the penetration process of a low-carbon substitute within a global energy-economic computable general equilibrium (CGE) model. Our approach, embedded within the CGE framework, allows simulation of multiple dynamics related to new technology diffusion, including sunk investments in existing technology, monopoly rents associated with the new technology, adjustment costs related to expanding the new technology, short- and long-run pricing of output of the new technology, and the rate of diffusion of the new technology and how it is influenced by economic factors. We provide a brief background of relevant literature in Section 2, followed in Section 3 by a discussion of the theoretical background for a variety of factors that can affect technology diffusion. Section 4 describes our approach for representing technology diffusion, the estimation of parameters, and how it is embedded within a CGE framework. Section 5 demonstrates the new approach, focusing on the diffusion of low-carbon electricity generation technologies, and explores several sensitivities, including the impact of different parameterizations, costs of technologies, knowledge depreciation rates, and elasticities of substitution. In Section 6, we offer some conclusions.

## 2. Background

To represent a low-carbon substitute, Nordhaus (1979) introduced the concept of a backstop technology, available at a fixed marginal cost that was a perfect substitute for fossil energy. While improvement in the use of fossil energy could reduce emissions at least per unit of GDP, ultimately the backstop could be adopted as the cost of fossil fuels rose due to depletion, or if environmental taxes or limits were placed on fuel use. Edmonds and Reilly (1985) expanded on this idea by elaborating different energy services (e.g. transportation, industry, residential), different fuels and electricity, and various alternatives (solar, biofuels, nuclear, wind, etc.) that differentially competed to supply these energy services, and where each "backstop" might itself face resource limits or resource gradations that could lead to increased cost with expansion. More recently, effort has been made to elaborate the

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role of advanced technologies within energy-economic modeling frameworks. This marries together standard economic modeling (based on expenditure data that allows disparate goods to be added together) with an economic representation of technology options that do not yet exist at significant levels in the economy (based on engineering cost and efficiency data).

A key challenge in modeling an advanced technology is to capture the penetration dynamics. Models have taken different approaches. For instance, Iyer et al. (2015) controls the diffusion of low-carbon technologies by imposing fixed annual growth rates of deployment. Keppo and Strubegger (2010) incorporates a series of dynamic constraints that link outputs to previous levels, and these constraints can set upper bounds for activities to expand and lower bounds for them to decline. Leimbach et al. (2010) considers decreasing costs for the deployment of advanced technologies, while imposing additional costs for the nuclear capacity exceeding a certain level. McFarland et al. (2004) and Paltsev et al. (2005) both implement a quasi-fixed factor with an exponential growth to control for the growth of an advanced technology. Wilson et al. (2013) argues that the logistic function is a good candidate for modeling the expansion of an advanced technology, and estimates the historical scaling of example technologies and industries to provide a "reality check" on scenario projections of low-carbon technologies.

Each of the above approaches is designed to produce a gradual expansion path that is more or less in line with past experience. However, in general, they are not derived directly from theoretical frameworks nor do they represent multiple underlying processes that combine to give rise to a characteristic technology diffusion pattern. A common element of all of these approaches is to slow new technology diffusion to reflect "observed" diffusion patterns often described as an "S-shape" with a slow start-up, then rapid spread, and then saturation of the relevant market. However, fixed limits on expansion or a simple logistics curve function of time does not incorporate key economic elements. Of particular importance, if demand for the new technology is very strong, then bottlenecks in expanding may be overcome, but at increasing cost. On the other hand, if the technology is only marginally economic, the existence of sunk costs in the existing technology may allow it to price at less than long-run marginal cost and slow new technology entry.

We aim to address this issue by deriving a formulation of technology expansion based on theoretical foundations, and using empirical evidence from the expansion of several technologies in the past to parameterize the setting.

## 3. Theoretical considerations for the dynamics of adoption

Modeling of technology for climate change has drawn on basic observations from the more general literature on technology adoption. One is that technologies tend to be adopted over some period of time, often characterized by an S-shaped relationship between market share and time where initial adoption is slow, then speeds up, and finally slows as the market nears saturation. Among the earliest papers to study this process was that of Griliches (1957) who studied the adoption of hybrid corn, which competed against the traditional non-hybridized seed. Another key observation was that costs of a new technology often appear to fall after initial introduction (e.g. Wright, 1936). Arrow (1962) offered the idea that this was a process of "learning-by-doing."

A variety of possible explanations for gradual adoption and falling costs have been offered that have led to different adoption model formulations (e.g. Geroski, 2000). The S-shaped penetration of hybrid corn seemed best explained by there being a few early adopters willing to try new things, then as word of their success spread, many others adopted. But penetration slowed again as adoption reached high levels, with some farmers outside the mainstream. This model of adoption is similar to that of the spread of an epidemic, and so some technology adoption models have borrowed from that literature.

With other goods, especially consumer goods, the applicability of the new technology may vary by consumer or application. Electric vehicles may be good for short trips but less suitable for consumers who would at times like to drive long distances, and so the cost advantage for some consumers would need to be larger than for others, or further advance in the technology may be needed to expand the market. This has led to estimation of technology diffusion using a probit model, where the likelihood of adoption depends on characteristics of the potential adopter. The exact nature of the penetration of the new technology would depend on the distribution of differences among consumers, and on how changes in conditions make the technology more attractive to more consumers.

Another strong theme in economics is that there are adjustment costs associated with a sudden increase in demand (e.g. Lucas, 1967; Gould, 1968) even in conventional sectors, and this would certainly play an important role in a new technology sector where conditions suddenly change to create demand for a technology where before there was little or none. Rapid demand for new technology, creating adjustment costs that are gradually overcome, could cause high prices and slow diffusion early, and then falling prices and faster diffusion later. The vintaging of capital and the existence of sunk capital costs in the old technology would also suggest that, faced with competition from a new technology, the old technology would continue to operate as long as variable costs were met, at least until the sunk costs depreciated. The decay of sunk investments would tend to retain a gradually decreasing share of the market in the old technology.

Finally, with new technology we might expect firms with intellectual property rights (IPR) to monopoly price. With conventional downward sloping demand, the potential market for the new technology would be initially limited (absent perfect discrimination among consumers) until patents or intellectual property rights expire. Those lower down the demand curve, for whom the new technology was only worth a bit more than the old technology, would be unwilling to pay the monopoly price and continue to use the old technology. Monopoly pricing alone could explain falling prices and a gradually expanding market share. This is essentially the same logic as that behind the probit model, as the downward sloping demand curve exists because of differences among consumers in their willingness to pay for the new technology. The main difference is that it offers a very specific reason for why the price is initially high and then falls.

In summary, there are many processes at work that would cause or contribute to the gradual spread of a new technology and explain a higher initial cost (or price) of the new technology. Ideally, all of these processes would be separately identified and modeled. However, a general challenge is understanding and separating causes, even for historical technologies that have been successful. The simplest idea, that of a learning curve, relies on cost and cumulative output. Cost itself can be hard to measure. It is far easier to observe the selling price, which may include monopoly rents, inducements aimed at expanding the market to gain economies of scale, and/or various government subsidies that may reduce the private cost. Also, learning curves alone do not necessarily explain gradual market penetration or cost reduction (Nemet, 2006). One would need to combine a learning curve with diverse potential consumers, some of whom are willing to pay a high price initially. Or one would need an additional assumption that learning takes time, as well as cumulative experience, otherwise forward-looking firms would have an incentive to generate cumulative experience instantly to bring the cost down, cross-subsidizing early sales with the expectation of later profits.

Our goal is to unify and capture some of these key processes within a CGE model with a representation of technology diffusion that is grounded in theory, economics and observation. The technology options we represent first and foremost are alternative technologies in the electricity sector. Here the output for baseload technologies is indistinguishable—electricity is electricity, and so adoption theories based on differences among consumers are less compelling. The issue of adjustment costs, scaling up the capability to meet demand for new plants, is more compelling for these technologies, and well-established as an economic principle, and so we focus on a method that incorporates adjustment costs.

## 4. An approach for representing adoption in a CGE framework

We seek a relatively simple formulation of technology diffusion that can be parameterized based on observations, while capturing elements of rent and real cost increases if high demand suddenly appears (e.g. due to a big policy shock) as well as the role of sunk capital costs. We also look to make the process consistent with a general equilibrium framework, and apply our formulation to the MIT Economic Projection and Policy Analysis (EPPA) model, which will be briefly discussed in Section 4.3.

### 4.1. Overview of approach for technology diffusion

Our modeling of technology diffusion presumes there is a pre-existing technology-specific resource available in limited supply that is required (a necessary input in the production function) to produce the new technology, and expands based on the amount of previous investment in the resource. There is a unique resource for each technology. This technology-specific factor (TSF), as with all factors of production, is owned by the representative household. It is a latent resource until there is demand for output from the new technology. Actual investment in a physical plant and the training of engineers capable of building and operating the technology only occurs once economic demand (i.e. willingness to pay above the cost of production) appears. Demand for output from the technology such that price is above the full cost of production generates a scarcity rent on the TSF—or sometimes referred to as "quasi-rents" because it is associated with a short-term scarcity. In a general equilibrium setting, this assures that all conditions of equilibrium are met—price is equal to marginal cost inclusive of the rent and total factor payments including the rent equal income for the representative household.

The nature of the production function is an important consideration. First, consider a fixed-share production function (Leontief) between the TSF and other inputs. In that case, the amount of the TSF would prescribe exactly the level of output in any period, by the amount of the factor and the factor share required to produce the good. Greater demand would simply result in a higher rent on the TSF. The cost to the economy of the constraint would be less consumption of the good than would be desired if the price were equal to the marginal cost of production, less the scarcity rent. In this case, there are no adjustment costs.

Now consider a production function where we allow substitution of capital, labor and other inputs for the TSF. This substitution allows expansion of production beyond what would otherwise be prescribed by the available TSF, but at an added real cost, using more of other inputs. This is the adjustment cost component of our formulation. Intuitively, trying to speed up production leads to waste, requires hiring workers with less training, etc. Hence, in this formulation, sudden demand for the advanced technology will cause its price to rise, partly due to rents on the TSF and partly due to higher real costs. In general, rents to the TSF can include specific monopoly rents associated with a license or patent, but can also include bidding up wages of technical specialists needed to produce the technology, or due to the existence of bottlenecks to expansion such as difficulty in siting plants or overcoming regulatory hurdles. Since the rent goes to the representative consumer, as does all factor returns, there is no reason to separately identify rents associated with monopoly pricing from those created by skilled labor shortages or other expansion costs.

Over time, we allow the technology-specific factor to expand as a function of the previous period's investment level, with the idea that as capacity expands to produce more of the technology, the constraints on expansion ease. This lowers the price by reducing the scarcity rent and also reduces the incentive to substitute other inputs for the TSF—so both the real cost of production and the rent will tend to fall. The expectation is that expansion of the TSF will be such that once the technology is well known, workers are trained, patents expire, and capacity to expand production is well-matched to the growth in demand and depreciation of existing capacity, then no one can command monopoly rents and the production cost and price approaches its long run cost.

This is not the classic learning-by-doing story, but in many ways it operates in a similar fashion. In learning-by-doing, the technology has an initial cost and the cost falls with cumulative experience. There is no process that creates monopoly or scarcity rents. In our formulation, the dependence of growth of the TSF on previous investment levels creates a similar dependence of the cost (and price) on previous capacity, but we are also incorporating rents and real adjustment costs. In our formulation, the expanding work force is learning, and hence the higher initial and then falling costs is a learning phenomenon in our formulation, though somewhat different than in the classic learning-by-doing story.

In principle, we could introduce a further learning-by-doing function where the long-run cost of production also fell as a function of previous or cumulative production. However, as discussed above it would appear difficult in practice to separate even costs from rents, and then further identify cost reductions due to learning from early cost add-ons associated with adjustment costs.

Another element of our approach is that we depreciate the TSF each period. With growth in demand for the good, there will be additions to the amount of TSF in excess of depreciation. By depreciating the TSF, we allow for a situation where demand for the technology potentially disappears for some time and then reappears. Nuclear power is an example of a technology that expanded rapidly, but then demand collapsed and much of the capacity to build plants depreciated away. Without depreciation of the TSF, production from the technology could restart at a very high level in later periods. With depreciation, production capability must be built back up. To continue to allow restart of the technology in later periods, we set the amount of the TSF in any period equal to the greater of the depreciated level plus new additions in that period or the initial endowment. Our base assumption is that the TSF depreciates at 5% per year, the same rate we assume for capital depreciation. Grubler and Nemet (2012) provide a literature review of knowledge depreciation rates. The TSF would not be generally considered "basic" knowledge as we assume the underlying technology is mature. The Grubler and Nemet review includes research and development, more of a basic knowledge, but they also include knowledge gained from learning by doing and the depreciation of human capital via loss of trained staff as in, for example, the nuclear industry. This latter component is exactly the type of depreciation we are attempting to capture. They find a wide range of knowledge depreciation rates, and in Section 5.6 we conduct a sensitivity analysis over the range.

We combine this new approach of a technology-specific factor, parameterized based on empirical data, with our established approach to vintaging capital. Vintage capital is technology/sector specific, available in a fixed supply in a given period, determined by investment in previous periods (Chen et al., 2017; Paltsev et al., 2005; Babiker et al., 2001). As a result of its fixed supply in any period, the rental price/return on capital in the period is determined endogenously depending on demand for output from that vintage. Consider imposition of an unexpected carbon price and a variety of vintages of fossil power plants in the electricity sector, where power plant efficiency and performance has generally been improving over time. The carbon price creates demand for low-carbon technology and/or lower-carbon vintages at the expense of high-carbon technology/vintages. The rental price of different vintages will reflect this demand. The rental price for the older, dirtier vintages of coal power plants may fall to zero, in which case the vintage may go unused or only partly used. This follows observations that often the oldest, dirtiest power plants have low capacity factors. It is less expensive and easier to meet environmental requirements with newer, more efficient fossil power plant vintages or completely new technologies (e.g. wind, solar, advanced nuclear), but the older plants are kept on line for periods of peak demand or outages to the newer capacity, and so they run at low capacity. In this sense, depreciation is endogenous because the old vintage becomes increasingly obsolete given new relative prices that include pollution charges, and may not be used at all even though they formally remain available. The gradual depreciation of old capacity will by itself tend to result in gradual penetration of a new technology, unless the emissions constraint is very stringent. With a high carbon price it is possible that several or all vintages could be essentially retired immediately. However, with multiple vintages having different efficiencies subject to gradual depreciation, it would take an extreme policy to create a sudden switch. The "premature" retirement results in an economic cost through a combination of more investment required in the new technology and less output from the sector.

### 4.2. Implementation within a CES-based general equilibrium structure

The CES production function is well-known and widely used in economics. To briefly review, the general expression for a two-input CES production function with inputs of capital (K) and labor (L), is:

$$X_{KL} = \left[\theta K^{\gamma} + (1-\theta)L^{\gamma}\right]^{\frac{1}{\gamma}} \tag{1}$$

where $X_{KL}$ is an output of a K-L service, θ is the share of capital, $(1-\theta)$ is the share of labor, and $\gamma$ determines $\sigma$, the elasticity of substitution among inputs, where $\sigma = 1/(1-\gamma)$. An equivalent formulation is to replace $\gamma$ with $\sigma/(\sigma-1)$. This expression can be generalized to more than two inputs with a share parameter for each input, that together sum to 1.0, however the structure requires an identical $\sigma$ across all input pairs. This restriction can be relaxed by creating input bundles, presaged by the definitions in Eq. (1). To produce a good from this capital and labor service we likely need at least some other input, such as energy ($E$). We create another CES production function that uses $X_{KL}$ and $E$ to produce output of good $Y$

$$Y = \left[\theta_E(E)^{\gamma_E} + (1-\theta_E)(X_{KL})^{\gamma_E}\right]^{1/\gamma_E} \tag{2}$$

While the same structure, here we are free to choose values for $\gamma_E$ different from $\gamma$ in Eq. (1). Special cases of the CES function are when $\gamma = 1$, $\gamma = 0$, and $\gamma = -\infty$. When $\gamma = 1$ then the output is the simple sum of the two inputs, implying that they are perfect substitutes for each other—one can get proportionally more output if you increase either input by itself. The case of $\gamma = -\infty$ collapses to a case where the elasticity is zero:

$$Y = \min\{\theta_E E, (1-\theta_E)X_{KL}\} \tag{3}$$

often referred to as a Leontief production function. In this case, expanding one input without expanding the others gets no increase in output unless there is an excess of the other input in the first place. With $\gamma$=0 we get the Cobb-Douglas production function:

$$Y = E^{\theta_E}X^{1-\theta_E} \tag{4}$$

where the elasticity of substitution between inputs is 1.

#### 4.2.1. Technology-specific factor

Of importance to the discussion above, we can formulate a technology-specific factor, $TSF_{S,\,T}$, defined for each technology ($S$) over time ($T$), as an input into a CES production function. We can then specify the share of TSF, $\theta_{TSF,\,S}$, required to produce a unit of output from technology $S$, and endow the economy with an initial amount of the technology-specific resource, $inishTSF_{S,\,R}$, defined for technology $S$ and region $R$. If the production function is the special Leontief case of the CES as in (3), then the first year production level will be determined. If, for example, the $\theta_{TSF} = 0.01$ (here suppressing the technology subscript) and we endow the economy with \$1 of TSF, and denote this endowment by *inishTSF*, then, if there is demand for output from the technology, we will be limited to at most \$100 of output (other inputs are used economy-wide and can be bid away from other sectors and so are essentially not limited). A non-zero elasticity allows more rapid expansion depending on the endogenous rental price on *inishTSF*. Fig. 1 illustrates the technology-specific resource as it enters the production nest structure of an advanced electricity generation technology in EPPA, using a carbon capture and storage (CCS) technology as an example. For all advance generation technologies, the TSF enters at the top-level nest of the production function.

*TSF* accumulates and depreciates, with a lower limit of the initial endowment:

$$TSF_{t+1} = \max\{[TSF_t(1-\delta_{TSF}) + INVTSF_t], inishTSF\} \tag{5}$$

where *INVTSF* is investment in *TSF* and δ is the depreciation rate. This follows a standard capital accumulation model, with the exception that there is a minimum level, otherwise *TSF* could fall to zero and production would never restart. As long as there is *TSF* in the economy, it provides a source of expertise for creating more capacity.

We do not have direct measures of *TSF* or *INVTSF*, but it is easy to observe the level of output of a technology as it expands in the market. Output can be considered an approximate scalar for the TSF input. If

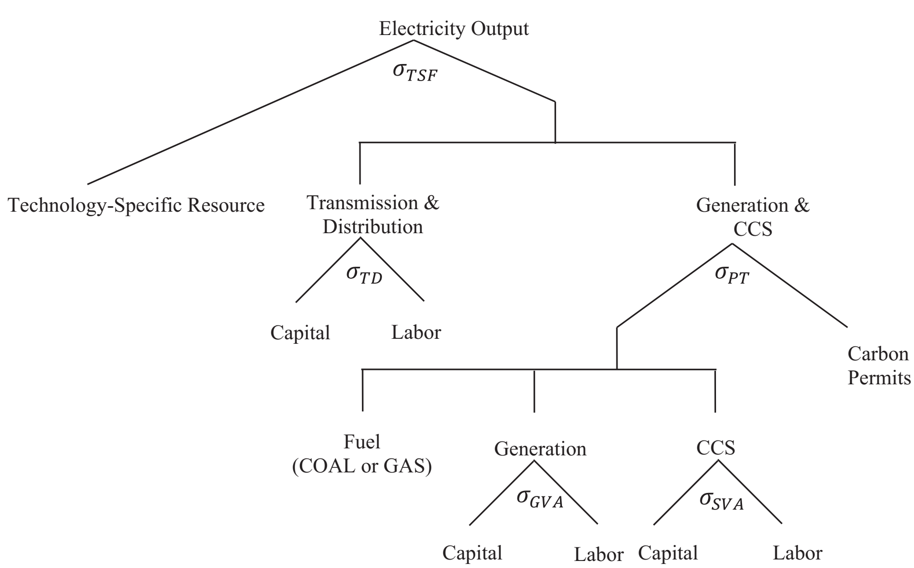


**Fig. 1.** Example of the technology-specific resource in production structure nest for advanced generation technologies.

**Table 1**
Regression information for different technology analogues.

| | Regression information | | | | | | |
|---|---|---|---|---|---|---|---|
| | Start year | End year | % in start | % in end | β1 | Intercept[h] | Standard error |
| **Nuclear US[a]** | **1970** | **1987** | **1.40%** | **17.70%** | **1.064*** | **21686*** | **0.042** |
| Nuclear US | 1970 | 1991 | 1.40% | 19.90% | 1.077* | 19987* | 0.029 |
| Nuclear US | 1970 | 1978 | 1.40% | 12.50% | 1.148* | 18,911 | 0.074 |
| Nuclear US | 1970 | 1975 | 1.40% | 9.00% | 1.496* | 2257 | 0.071 |
| **Nuclear France[b]** | **1966** | **1982** | **1.45%** | **38.68%** | **1.249*** | **1942** | **0.097** |
| Nuclear France | 1966 | 1996 | 1.45% | 69.72% | 1.230* | 3042 | 0.037 |
| Nuclear France | 1966 | 1986 | 1.45% | 77.06% | 1.083* | 7945* | 0.018 |
| Nuclear France | 1966 | 1971 | 1.45% | 5.99% | 1.484* | −37 | 0.233 |
| **Solar Germany[c]** | **2009** | **2014** | **1.18%** | **6.10%** | **1.087*** | **4662** | **0.089** |
| Solar Germany | 2009 | 2015 | 1.18% | 6.35% | 1.026* | 5368* | 0.073 |
| **Wind US[d]** | **2008** | **2013** | **1.34%** | **4.12%** | **1.105*** | **17508*** | **0.031** |
| Wind US | 2008 | 2016 | 1.34% | 5.54% | 1.058* | 20491* | 0.052 |
| **Wind China[e]** | **2010** | **2013** | **1.12%** | **2.73%** | **1.406*** | **7422** | **0.110** |
| Wind China | 2010 | 2016 | 1.12% | 4.03% | 1.161* | 1855 | 0.088 |
| **Shale gas US[f,g]** | **1999** | **2011** | **1.40%** | **30.09%** | **1.666*** | **−176** | **0.046** |
| Shale gas US | 1999 | 2012 | 1.40% | 36.81% | 1.388* | 93 | 0.067 |
| Shale gas US | 1999 | 2004 | 1.40% | 3.11% | 1.301* | −34 | 0.101 |

Data from: [a] EIA (2014a); [b] IEA (2014); [c,d,e] EIA (2019); [f] EIA (2014b).
* Statistically significant with a $p$-value < 0.05.
[g] Note that after EIA AEO 2014 (with last data year of 2012), shale gas reporting began to include gas from tight oil plays.
[h] Note that the intercept falls out of the TSF equations and is therefore not relevant for our modeling.

the production function is Leontief, then it is an exact scalar. We can then estimate a relationship for output based on output in the previous period, and accounting for depreciation. We estimate this relationship as linear[1]

$$OUT_{t+1} = \beta_1 OUT_t - OUT_t\ (\delta_0) \tag{6}$$

where *OUT* is technology output, and $\delta_0$ is the depreciation rate of the capacity to produce *OUT*. We then recognize that the added production capacity in $t$ is

$$INVOUT_t = OUT_t - OUT_{t-1}(1-\delta_0) \tag{7}$$

where *INVOUT* is investment in the capability to produce *OUT*, and was needed to meet the difference between output in two periods, accounting for the depreciated capacity to produce *OUT*. Then by defining a value for $\theta_{TSF}$ in our production process,

$$INVTSF_{t+1} = \theta_{TSF}\ INVOUT_{t+1} \tag{8}$$

Then, by combining Eqs. (6), (7) and (8), we arrive at the necessary equation for *INVTSF*, which is needed in Eq. (5). We now have a relationship between output in previous periods, our TSF input share and estimated βs that produces the new investment in TSF and the new stock of TSF.

### 4.2.2. Estimating parameters for technology-specific factor

The challenge of estimating Eq. (6) is that the new technologies we wish to model have not yet entered the market. A reasonable solution is to identify analogue technologies, of similar nature, that have penetrated in the past. We apply our approach to technologies in the electric sector that are fairly capital intensive and so, for example, the diffusion of hybrid corn would seem inappropriate for our purposes. Further, our interest in adjustment costs of expanding suggests we need an analogue technology constrained by supply, not by demand, so as to give insight into the upper bounds of the rate of expansion.

We consider several candidate energy technologies that have expanded rapidly within large jurisdictions. We focus on what were considered, for at least some period of time, a sample of energy technology success stories: nuclear power in the U.S. and France, modern wind turbines in the U.S. and China, shale gas in the U.S. and solar PVs in Germany. We use output data, mainly from the U.S. Energy Information Administration (EIA) and the International Energy Agency (IEA), for each to estimate Eq. (6). We do not imagine our approach is necessarily applicable to very early stages of deployment that are better characterized as the last D (development) in RD&D where early stage learning may play a dominant role. Rather, our goal is to focus on expansion of commercially-ready technologies to relatively large scale when demand conditions suddenly favor them, as would be the case if a significant carbon tax was fairly suddenly imposed. As a result, we use data on expansion only after the technology achieved 1.0–1.5% of the relevant market as the starting point for each regression. End points for the regression were chosen based on when expansion appeared to slow down, with sensitivity to the end point explored, or based on the last year of data available. For all regressions, $\beta_1$ is statistically significant ($p$-value < 0.05). Information about the regressions is given in Table 1, with the main regressions in bold, followed by alternate time windows. The TSF parameter value ($\beta_1$) for the main regressions ranges from 1.064 to 1.666, with the values for alternate time windows falling within that range (with the exception of the longer time window for solar in Germany, which is lower than the range).

We use the expansion of nuclear power in the U.S. for our base parameterization (see Fig. 2). While it was expanding, nuclear was generally seen as the next generation technology, poised to take over most of the base load generation. We use data on the annual output (in million kilowatt hours) of nuclear electricity in the U.S. (EIA, 2014a) to estimate

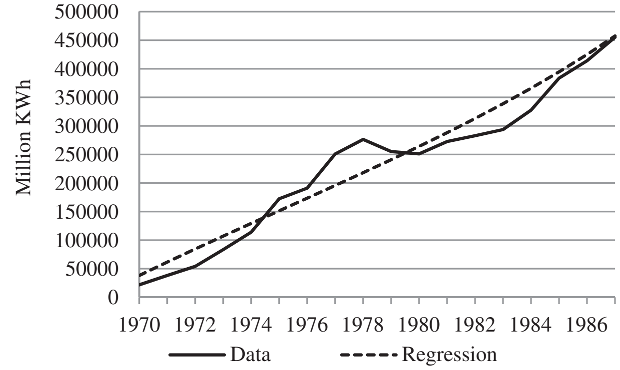


**Fig. 2.** Predicted and actual output of nuclear generation in the U.S.

[1] We originally estimated this relationship as quadratic, but found the quadratic term to be extremely small and statistically insignificant, so have dropped that term.

our equations. We focus on the period from 1969 to 1987, with the estimation series starting in 1970 (because the independent variable is lagged one period) because that is the period of most rapid expansion. Nuclear generation began to really take off in 1970 (when it was 1.4% of the electricity mix) and grew rapidly until about 1987 when generation began to level off due to safety concerns and siting issues. The estimated parameter with standard errors in parentheses is: $\beta_1 = 1.064$ (0.042) with a $p$-value of 2.61E−14 and an $R^2$ of 0.975.

A challenge of this work relates to the market share of the technology analogues. The solar and wind technologies, while considered success stories and world market leaders in their commercialization, have generally not achieved market penetration beyond a few percentage points. The limited penetration, along with short time periods, means that even while parameter estimates are statistically significant, we may be extrapolating outside the data range.

The nuclear power examples give us the longest data series, but nuclear power is not without its issues as an analogue. In France, it expanded to a very large share of the market (over 75%), and so toward the end of the period expansion was governed more by demand growth. In the U.S., concerns about safety added to the cost of construction, so even though it had only achieved about 20% of the market, the demand for nuclear expansion largely evaporated. The period over which nuclear expanded rapidly provides a useful analogue, but it is not clear to us how to precisely identify just that period where supply considerations were limiting. As noted above, we have focused on the initial period of rapid growth, starting from when the technology was 1–1.5% of the total market and ending when growth began to slow down. The end point for the regression is therefore somewhat arbitrary, and so we have tested the sensitivity of parameter estimates to truncating the data at different points.

Shale gas in the U.S. also provides an example of penetration to a fairly high level (nearing 40% of the gas market). In fact, the rapid expansion began to drive down the gas price in the U.S., which appeared to undermine the demand for more expansion in later years of the shale gas boom. It could also be argued that this was not a fundamentally new technology subject to bottlenecks—the process used known drilling technology that could be redeployed from conventional oil and gas fields. Nevertheless, there were issues of expanding rapidly into new geographic areas where the supporting infrastructure was not fully in place.

While in principle estimating the potential adjustment costs and limits to expansion should not depend on whether the source of sudden demand for the technology was due to market forces or to public policies, different forces were at work among these technology examples. Incentives for PVs in Germany were very strong for several years. Shale gas in the U.S. was mainly a market driven phenomenon. Wind expansion in the U.S. and China has depended on various government incentives that have not always been consistent. Federal tax incentives for wind in the U.S. have had sunset clauses, leading to an off-again, on-again investment pattern. Nuclear expansion in France was a direct decision of the government. In the U.S., nuclear was a market-driven phenomenon partly shaped by regulatory policies, and ultimately derailed by regulation and siting issues. Ideally, we would see a consistent demand for continued expansion in our examples, but both public policy and market forces can be fickle.

#### 4.2.3. Final steps of parameterizing technology-specific factor

For implementation in EPPA, we impose a value for $\theta_{TSF} = .01$ and choose *inishTSF* in each region, r, to be consistent with the data used to estimate Eq. (6):

$$inishTSF_{S,R} = \theta_{TSF}\left[TOUT_{r,t0} \cdot ISh\right] \tag{9}$$

where *TOUT* is total regional electricity output in the base year of the model and *ISh* is the share of the example technology at that start of the regression period (e.g. 1–1.5%). Using nuclear in the U.S. for Eq. (6), *ISh* = 1.4% as the nuclear share of total U.S. electricity generation in 1970 was 1.4%. The value of $\theta$ is set arbitrarily small, but, once set, consistency with the estimation of our other equations demands that *inishTSF* be determined by Eq. (10). Eq. (10) further implies that the initial capacity to produce the technology scales with the size of the electricity sector in the regional economy.

Given the other parameter values, the elasticity between TSF and other inputs, $\sigma_{TFF}$, must be set so that, when forced with a carbon price high enough to create demand for the new technology, the new technology expands at a rate similar to the historical expansion of the technology analogue used to estimate the TSF parameters. We tested different values for $\sigma_{TFF}$ (we show results of a sensitivity analysis in Section 5.7) under the different TSF parameterizations based on the different technology examples. We find that for each of our TSF parameterizations, an elasticity of 0.3 results in an initial rate of expansion of the advanced technology similar to the historical 5- and 10-year expansion rates of our technology examples. For example, based on the data, nuclear generation in the U.S. increased 11.5 times between 1970 and 1980. Using an elasticity of 0.3, under a $200 carbon price, advanced nuclear increases 13.4 times in the ten years from 2020 to 2030. An elasticity of 0.2 results in a 7.6 times increase in those ten years.

#### 4.2.4. Capital vintaging

Vintaging of capital has been a standard feature in EPPA (see e.g. Paltsev et al., 2005). Briefly reviewing this structure, we distinguish between malleable and non-malleable (rigid) capital. The malleable portion of the capital stock in each sector is described by the nested CES production functions as shown in Fig. 1, and the non-malleable portion by Leontief production functions. Input share parameters for the Leontief production functions for each vintage of capital are the actual input shares for the period when the capital was put in place, reflecting the substitution possibilities as described by the CES production functions and the relative prices in that period. This formulation means that EPPA exhibits a short-run and a long-run response to changes in relative input prices, as no substitution exists with rigid capital, and only over time does the rigid capital depreciate to be replaced with technology that reflects new relative input prices.

Letting $K^m$ represent the malleable portion of capital and $K^r$ the rigid portion, the procedure can be described as follows. New capital installed at the beginning of each period is malleable. At the end of the period a fraction, $\varphi$, becomes rigid. The fraction $(1-\varphi)$ that remains malleable can essentially be retrofitted to adjust to new input prices, can take advantage of intervening improvements in energy efficiency or can be reallocated to other sectors. Malleable capital in period $t+1$ is:

$$K^m_{t+1} = I_t + (1-\varphi)(1-\delta)K^m_t \tag{10}$$

The model preserves v vintages of rigid capital, $v=1,\dots,4$ for each sector/technology. In period $t+1$, the first vintage of non-malleable capital is the portion $\varphi$ of the malleable stock at time $t$ in sector $i$ that survives depreciation, but remains in the sector in which it was installed with its factor proportions frozen in place:

$$K^r_{i,t+1,v} = \varphi(1-\delta)K^m_{i,t} \text{ for } v = 1 \tag{11}$$

For each sector/technology, the quantity of capital in each of the remaining vintages (2–4) is simply the amount of each vintage that remains after depreciation:

$$K^r_{i,t+1,v+1} = (1-\delta)K^r_{i,t,v} \text{ for } v = 2,3,4 \tag{12}$$

Our starting point is to have a 25-year lifetime of capital for all sectors and technologies. The model's time step is five years, so when capital is first built, it is new malleable capital for 5 years, then vintaged capital for 20 years, going through 4 vintages, for a life of 25 years.

### 4.3. Implementation within the Economic Projection and Policy Analysis (EPPA) model

We incorporate the technology structure above within the EPPA model. The EPPA model is a multi-region, multi-sector general equilibrium model of the world economy and its relationship to the environment, with a focus on energy, agriculture, land use, and pollution policies. Toward that end, it provides detail on sectors that contribute to environmental change and that are affected by it including households, energy, agriculture, transportation, and energy-intensive industry. As a full multi-sector model, it includes explicit treatment of inter-industry interactions. The core Social Accounting Matrices (SAMs) that include the basic Input-Output (I-O) data for each region are from the Global Trade Analysis Project (GTAP) with a benchmark year of 2004 (Narayanan and Walmsley, 2008). These data also provide base year trade flows. The current application of EPPA in this study is based on a version of EPPA documented in Chen et al. (2017). The regions, sectors, and primary factors represented in the model are provided in Appendix A in the supplementary material.

## 5. Example results

The main advanced technologies of interest are low-carbon electricity generation alternatives. In general, these do not enter the market without further policy incentives. The behavior of our technology penetration formulation is best illustrated by a sudden increase in demand for the technology. The lack of demand for the technology in a reference case with no policy incentives conveniently allows us to create demand for the technology by introducing a carbon price sufficient to overcome the higher cost of the backstop. While climate policy is often conceived of as gradually ramping up with a slowly rising $CO_2$ price, the real test of our formulation is a sudden significant demand. We are also interested in the behavior when the demand for the new technology is relatively constant. Thus, our experimental design is to impose a $CO_2$ price in the U.S. beginning in 2020, and hold the price steady at that level through 2100. We include $CO_2$ prices per ton of $0, $100, $125, $150, $200, and $300. Our base TSF setting uses the TSF parameterization based on nuclear expansion in the U.S.

### 5.1. Advanced nuclear results

To focus clearly on the technology penetration phenomenon by itself, we examine one technology at a time, beginning with results when only the advanced nuclear backstop technology available. We show results of these simulations in six panels in Fig. 3: (a) generation from advanced nuclear through 2035; (b) generation through 2100; (c) the total stock of TSF; (d) the rental price of the TSF; (e) the electricity price and (f) the stock of vintage capital in conventional electricity that is unused.

As expected, the higher the $CO_2$ price, the faster the penetration of the advanced technology. We focus on the results through 2035 (Panel a) to emphasize the important differences in the early years. For the $CO_2$ prices of $200 and above, expansion begins to slow by 2030. For the carbon price of $100, generation peaks in 2030 and declines slightly by 2035. The long-term behavior of the technology is exhibited in Panel b. For carbon taxes of $125 and greater, the generation level from advanced nuclear all converge by 2045 to an essentially steady state growth path dictated by the underlying growth in demand for electricity. With higher $CO_2$ prices there is slightly less nuclear generation due to the fact that the higher carbon price has a bigger negative effect on overall economic output and income in the economy. Thus, electricity demand is reduced slightly due to lower income in households and lower output of the economy.

The $100 tax offers more interesting behavior in the model. Here advanced nuclear begins to penetrate and then goes away only to come back in later years. We traced the main cause of this result to improving conversion efficiency over time in the conventional power sector, which lowers the cost of this generation (sensitivity results demonstrating this are included in Appendix B in the supplementary material). The penalty needed to bring in a backstop like nuclear depends directly on the cost of backstop relative to the conventional technology. The $100 carbon price is initially enough to bring in advanced nuclear, but as conventional fossil becomes more efficient, the $100 carbon price is no longer sufficient to give the edge to advanced nuclear. Continuing increases in fossil fuel prices, driven by demand and depletion, eventually lead to advanced nuclear becoming economic again. The implication here is that with the $100 $CO_2$ price, advanced nuclear has just a slight advantage over the conventional fossil sector and so small changes can erase the advantage.

Panels c and d show the behavior of the stock of TSF and its rental price. In the short run, TSF is scarce relative to demand for it, and so the price rises. Once the level of generation reaches the turnpike growth rate, TSF grows at the same rate, and its rental price falls to near zero. With the rental price near zero, there is no incentive to substitute other inputs for TSF, and also little or no impact on electricity prices. The implication is that the cost of electricity generation has reached its long run marginal cost. We see this behavior reflected in the electricity price (Panel e). Except for the $100 $CO_2$ price scenario, electricity prices overshoot the long-run cost of the policy—the higher the carbon price, the bigger the overshoot. Given the equilibrium conditions of the solution, this price must equal the cost of producing electricity from all technologies that are producing non-zero levels of output in the period. If under low carbon prices, there is still some expansion of fossil generation, then this price is equal to the full cost of that generation plus the carbon price charge, less any downward impact on input markets to conventional generation. The main price impacts are on coal generation. It also must equal the cost of producing electricity from advanced nuclear, if it is produced. Without the adjustment cost formulation, nuclear would be less expensive than conventional generation, but, in our formulation, the TSF rent and substitution of other inputs raise the marginal cost to be necessarily equal to the marginal cost of other generation options that remain active.

The long run price of electricity is identical across the carbon price scenarios because advanced nuclear has no direct emissions of $CO_2$. Given the I-O structure of the model, other inputs used to build nuclear will have GHG emissions, to the extent there remain emissions, and hence there is some pass through of different costs. However, that effect is negligible. The $100 price scenario diverges slightly from the others over the middle of the century because advanced nuclear is not in the mix.

Finally, in Panel f we see that in the short term, there is significant idle conventional generation capacity when the carbon price is above $150. Because the TSF price is above zero, even with the $100 carbon price, the tax policy is imposing some windfall losses on conventional generation—the rental price on this capital has fallen, but remains above zero which means the plants are still operating, but not recovering the full cost of building them again, at least with the technology that existed when they were originally built. The $100 price is very close to leading to a switch in generation from conventional fossil to nuclear, and so relatively small changes in other variables lead to nuclear entering, exiting, and re-entering.

### 5.2. Other technology analogues

To isolate the effect of TSF parameterization, we again focus on scenarios with a single backstop (advanced nuclear) available and a carbon price of $200 or $125/ton $CO_2$. We use each of the TSF parameterizations found in bold in Table 1. Fig. 4 shows the resulting backstop output, with the left panels (Panels a and c) showing the short-term results to 2035 and the right panels (Panels b and d) showing the long-term results to 2100. The different TSF parameterizations have almost no impact on the long-run penetration of the backstop. However, they do cause

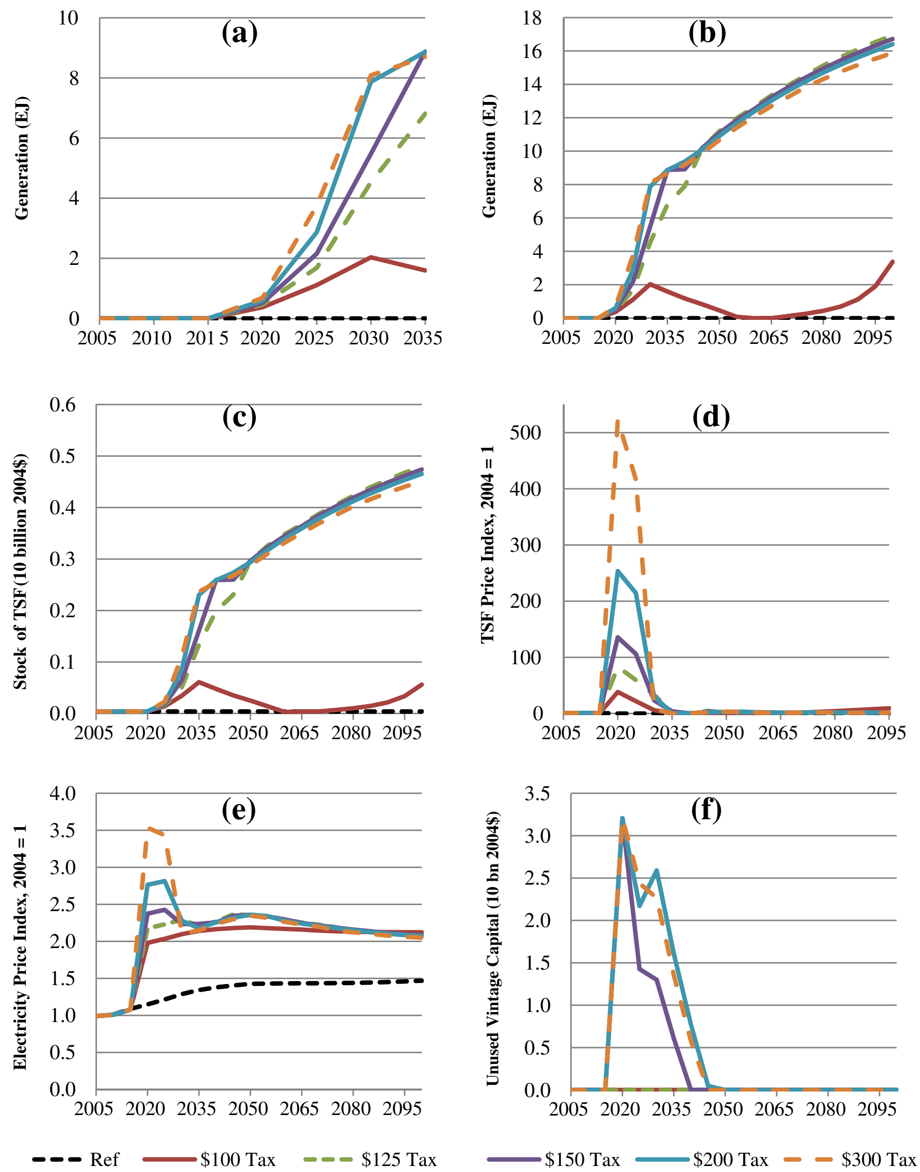


**Fig. 3.** Impact of carbon price on advanced nuclear: (a) advanced nuclear generation to 2035, (b) generation to 2100, (c) total stock of TSF, (d) TSF rental price, (e) electricity price, and (f) unused vintage fossil capital.

some differences in the initial penetration. The differences are minor under the $200 carbon price. They are more noticeable, though still relatively small, under the $125 carbon price. This suggests that, given the range of TSF parameter values we estimated, the TSF parameter value is most important under circumstances when the advanced technology is only slightly more competitive than other technologies. When the advanced technology has a clear economic advantage, the TSF parameter value is less important (provided it is in the range of the examples we found).

As described in previous sections, there are challenges to estimating the TSF parameter value, and so there is some uncertainty in the estimates. However, given consistent demand for a technology, it appears that the exact parameter value, within a given range, only makes a small difference in the initial expansion (depending on the economic circumstances), and virtually no difference on the long-run expansion. The difference could be important under tight near-term targets.

Also of note is that three of the technology analogues—nuclear in the U.S., wind in the U.S. and solar in Germany—yield very similar TSF parameter values and nearly identical results. For the remainder of this paper we use the TSF parameterization based on nuclear in the U.S.

### 5.3. Wind results

We turn next to a case where the only backstop technology is wind, as shown in Fig. 5 with the following three panels included: (a) wind generation, (b) the TSF price, and (c) the electricity price. The EPPA model addresses the intermittency of wind by requiring natural gas backup generation, that operates at low capacity levels (7%), to capture the fact that it is not possible to shift loads fully to meet the daily and monthly pattern of wind power production (Morris et al., 2010). Wind with gas backup as defined in the model is a more expensive technology than advanced nuclear because retaining the capital cost of gas backup that is rarely actually used adds substantially to the cost. Other options such as storage (pumped hydro, compressed air, batteries) are possible, but in general are more expensive still. As a result, it takes a higher carbon price ($200) to achieve significant penetration of this technology. An interesting feature that shows up under a $200 tax is that after the initial expansion of wind with gas backup, there is a decline in generation from 2045 to 2060, followed by further expansion (Panel a), similar to the entry, exit, and re-entry of advanced nuclear under a $100 tax.

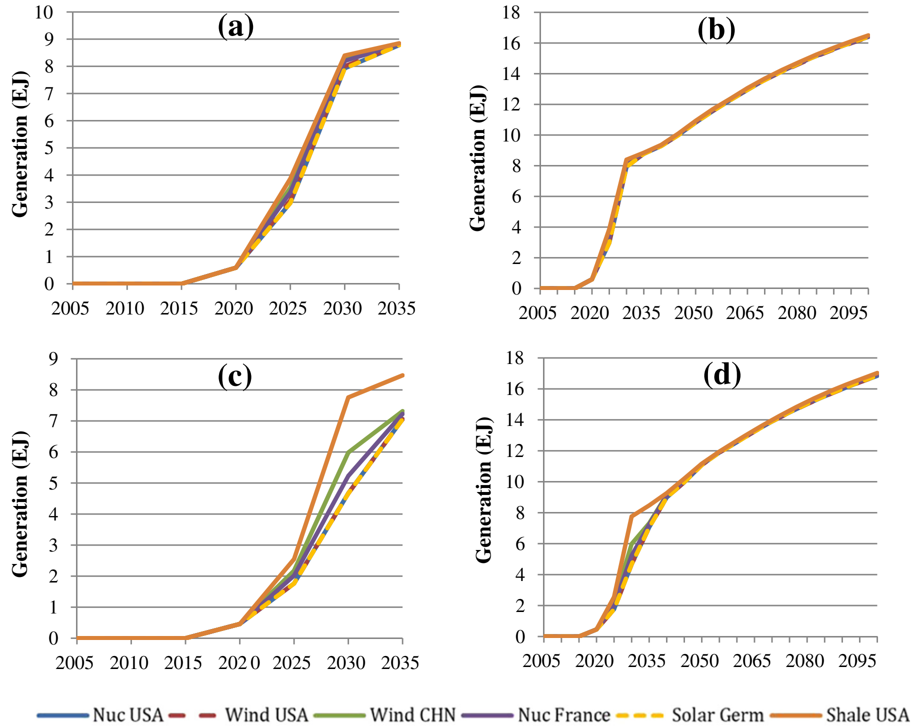


**Fig. 4.** Impact of TSF parameterization based on different technology analogues: (a) \$200 carbon price, advanced nuclear generation to 2035, (b) \$200 carbon price, advanced nuclear generation to 2100, (c) \$125 carbon price, advanced nuclear generation to 2035, and (d) \$125 carbon price, advanced nuclear generation to 2100.

We traced this behavior in both cases to an assumption of an underlying trend of exogenous efficiency improvements for fossil generation. By chance, under a flat \$200 carbon price, during the period of 2045–2060 the gain in fossil efficiency, combined with changes in fuel and factor prices, cause fossil generation costs to fall enough to again compete effectively with wind with gas backup. As a result, fossil generation recovers during that period while wind declines. After 2060 wind with gas backup once again becomes the more cost effective technology and expands rapidly, while fossil declines and phases out of the generation mix, due to rising costs of fossil fuels with depletion. We demonstrated this as the source of the behavior by eliminating the autonomous energy efficiency improvement (AEEI) in conventional fossil generation (blue dashed line in the figure). In this case the dip in wind generation disappears.

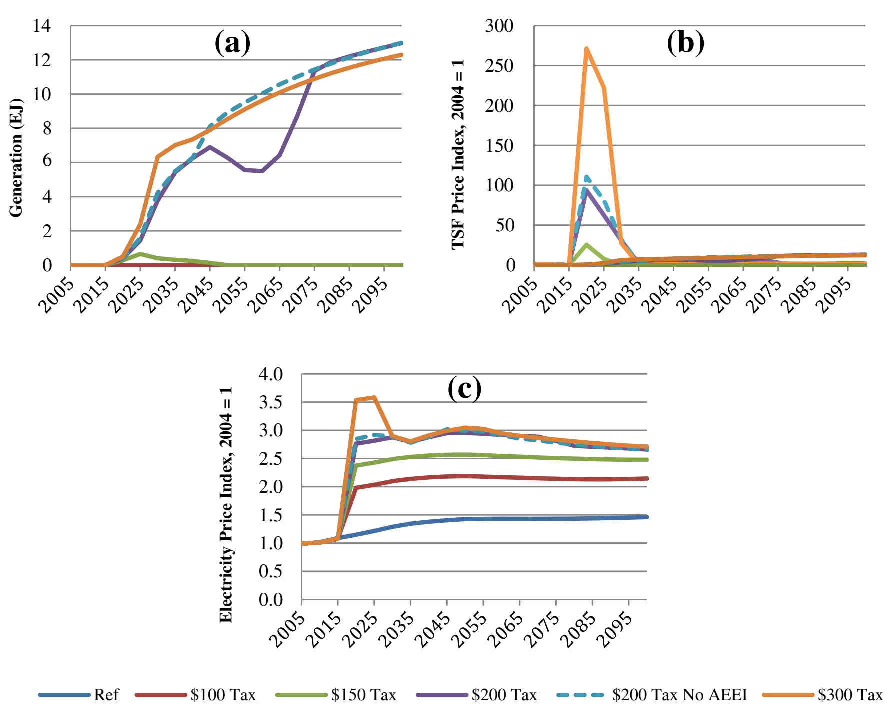


**Fig. 5.** Impact of carbon price on wind with gas backup: (a) generation to 2100, (b) TSF price, and (c) electricity price.

Panel b of Fig. 5 shows the TSF price for wind with gas backup. The pattern is the same as for advanced nuclear, but the price does not rise as high because wind with gas backup is more expansive than advanced nuclear, the demand for it is not as high and it does not expand as quickly. The electricity price is shown in Panel c. The taxes below $200 are not sufficient to bring in the technology, and so the higher electricity price reflects the higher cost of the carbon tax on generation. The $200 and $300 taxes show the same pattern as advanced nuclear: after the initial increase, the price converges to approximately the same level once the TSF is no longer a constraint. The higher carbon price will have some effect on the prices of all inputs in the wind generation production function to the extent fossil energy is used in their production. The gas backup will also contribute to small differences: the gas backup operates at very low capacity factor, and thus the price effect is minimal. Although not shown in the figure, wind also shows the same pattern of behavior as advanced nuclear for the stock of TSF and the amount of unused vintage fossil capital.

### 5.4. Results with all technologies competing

We also ran scenarios where all advanced technologies are available and compete among each other, again with a fixed carbon price. Fig. 6 shows the resulting electricity mix under two cases of the $200 carbon price, each with a different cost for advanced nuclear. A key assumption is the cost of backstop technologies compared with the conventional technology for which they are perfect substitutes. Cost assumptions for electricity sector technologies are provided in Appendix C in the supplementary material. The default cost assumptions for advanced nuclear and gas CCS lead to them being 1.47 and 1.42 times the cost of conventional coal generation at base year prices, respectively. Panel a shows the electricity mix that results using the base cost assumption. Once the carbon price is introduced, a mix of advanced technologies is seen. But ultimately, advanced nuclear takes over the market, becoming the dominant source of generation. With several alternatives that can expand independently, fossil generation leaves the market more quickly than when only a single backstop was available.

Panel b of Fig. 6 shows the electricity mix that results when the cost of advanced nuclear is increased to 1.55 that of conventional coal. The higher cost of nuclear leads to a larger market for gas CCS. Toward the end of the period, gas CCS declines. The rising natural gas price reaches a level toward the end of the century that favors nuclear.

Comparing Panel a and b illustrates that the model can be quite sensitive to small changes in a technology cost. This reflects the fact that these generation technologies are modeled as perfect substitutes. If the cost change flips the relative cost among competing technologies, the new lower-cost technology will tend to dominate. On other hand large changes in costs that do not flip the relative cost may little or no effect. With adjustment costs, multiple technologies can compete initially because expansion of the least expensive is slowed, but as capacity to expand it increases, it will dominate others. In the example here, the small increase in the cost of nuclear makes gas with CCS the least expensive option, at least until the gas prices rise.

### 5.5. The impact of technology costs

We further investigate the impact of technology costs by looking at the case of a $200 tax when advanced nuclear is the only backstop technology available. We test scenarios in which the initial cost of advanced nuclear is 1.47 (the base setting), 1.1 and 2.0 times the cost of conventional coal generation. As Panel a of Fig. 7 shows, the initial cost affects both the timing of penetration and the ultimate level of penetration. A relative cost of 2.0 compared to conventional coal is too expensive for significant penetration, and we see the technology initially expands, then contracts, and then expands again at the end of the period (i.e. the higher cost results in behavior for a $200 tax much like the behavior with the base cost and $100 tax in Fig. 3). This pattern is largely a function of the flat tax, coupled with the assumption of efficiency improvement for conventional generation and the endogenous, and generally rising, price of coal. As one would expect, the cheaper the technology, the greater the demand for it, resulting in a higher TSF price (Panel b). The technology cost also determines the ultimate level of the electricity price, with lower costs resulting in lower electricity prices (Panel c).

### 5.6. Impact of TSF depreciation

As discussed in Section 4, another important feature in our representation of technology penetration is depreciation of the TSF. This means that if investment is not continually made in the TSF for a technology, the ability to build that technology will gradually depreciate away. A major motivation for this approach was to recognize that if demand for the technology disappeared for a lengthy period of time, then the capacity to expand would erode away and would need to be rebuilt. To explore the impact of this TSF depreciation on the results, we developed a scenario in which a $200 carbon tax begins in 2020 and lasts until 2040, after which there is no tax until 2080 when the $200 tax resumes for the rest of the period to 2100. We run this scenario both with and without depreciation of TSF, using a TSF depreciation rate of 5% per year. In both cases, we assume that advanced nuclear is the only technology available. Fig. 8 shows the results of both cases, compared to the case of a constant $200 tax with TSF depreciation (the default case).

Panel a shows that for the middle years when the tax stops after 2040, the cases with and without TSF depreciation behave the same—advanced nuclear generation drops, falling to zero by 2060. The blue line is (nearly) completely covered by the green line through 2060, and from 2060 to 2080 there is no production in either case. When

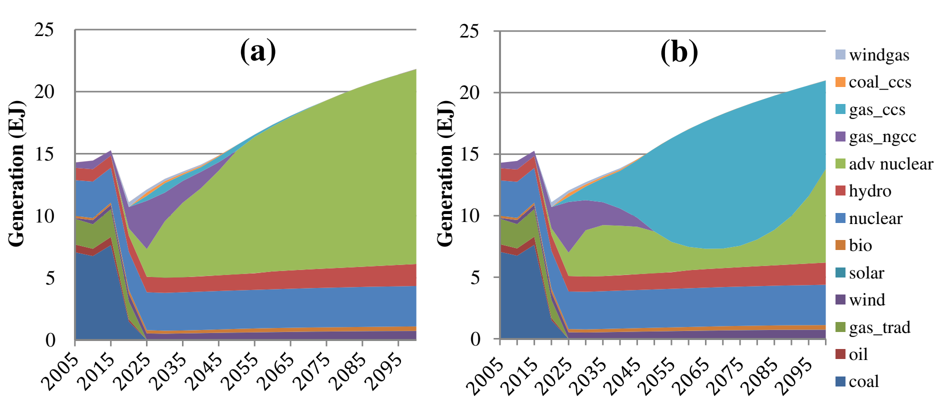


**Fig. 6.** Electricity mix under $200 tax when all advanced technologies are available: (a) advanced nuclear costs 1.47 times the cost of conventional coal, and (b) advanced nuclear costs 1.55 times the cost of conventional coal.

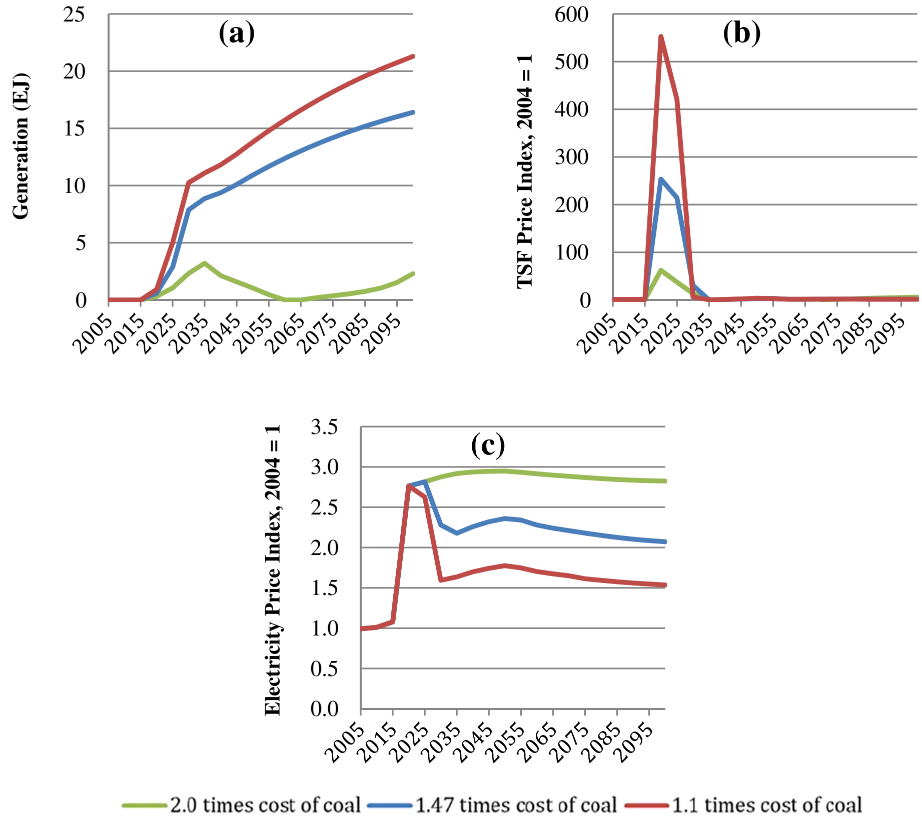


**Fig. 7.** Impact of technology cost under $200 tax when only advanced nuclear is available: (a) generation, (b) TSF price, and (c) electricity price.

the tax resumes in 2080, the two cases are very different. Without TSF depreciation, generation is immediately able to resume at high levels. However, with TSF depreciation, when the tax returns, advanced nuclear generation must start at low levels until the TSF stock can be built back up once again. That is because the capability to build advanced nuclear (stock of TSF) depreciated and fell to near zero because the technology was not being built for a significant period of time (see Panel b). Without TSF depreciation, the stock of TSF (i.e. the capability to build the technology) does not disappear but remains where it last left off, despite not building the technology for many years. These patterns also impact the electricity price (Panel c). When the tax resumes in 2080, if there is no TSF depreciation the electricity price jumps back up to the level it would have been had the tax remained constant. However, with TSF depreciation, the electricity price jumps to a much higher

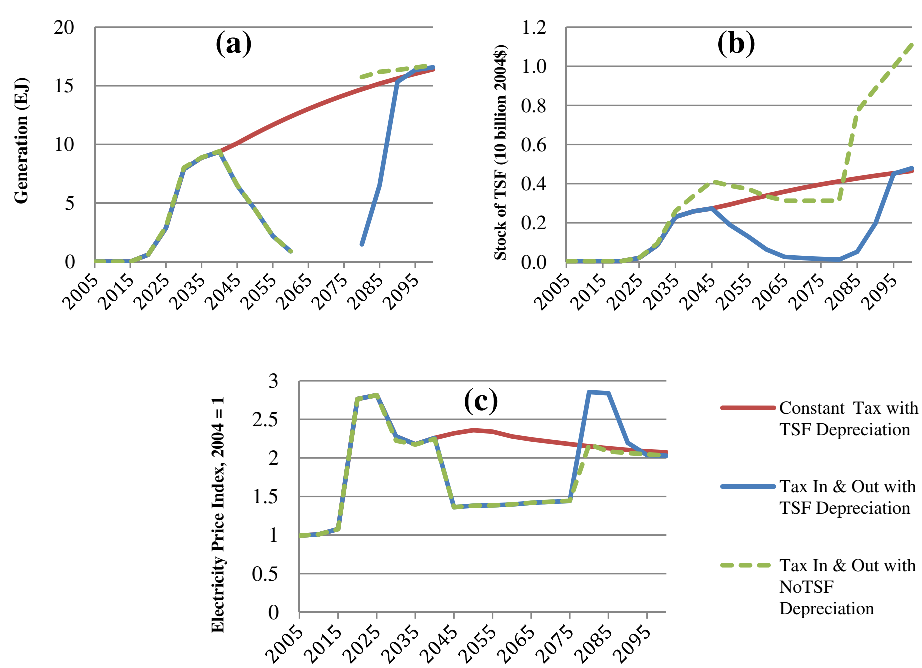


**Fig. 8.** Impact of TSF depreciation, case of $200 tax coming in, out and back in when only advanced nuclear is available: (a) generation, (b) stock of TSF, and (c) electricity price.

level when the tax returns, because the capacity to build advanced nuclear needs to be built back up.

As pointed out by Grubler and Nemet (2012), knowledge depreciation rates estimated in the literature vary widely. They find rates of 10 to 40% per year for energy and related industries. One might expect this wide range to have significant effects on the initial deployment and the ability of the technology to rebound after a gap in deployment. To appropriately consider the sensitivity of results to the range of depreciation rates, note that our estimated Eq. (6) includes knowledge depreciation. Thus, we re-estimated Eq. (6) for the range Grubler and Nemet find. As expected, the higher the depreciation rate, the higher the estimated $\beta_1$ parameter. We simulated results for deprecation rates of 10% and 40% per year where there is a break in support for advanced technologies: a \$200 carbon tax in place for 20 years (2020–2040), removed for 5, 10 or 20 years, and then reinstated. We run these tests with advanced nuclear as the only advanced technology available. As shown in Fig. 9 for the case with a 20-year break, there is virtually no effect on output for the period of initial growth of the new technology or the period of output decline once the carbon price is removed. There is a small effect on output growth once the carbon price is reinstated. Because the lower depreciation rate does not allow the stock of TSF to depreciate to as low of a level, it allows for a quicker rebound. For different lengths in break of support, including no break, and for other depreciation rates, the results are consistent with what we have shown in Fig. 9. Notably, the expansion path is virtually identical for depreciation rates when there is no break in policy as well as in the period prior to the rebound in all cases. The difference in the rebound is small in the 20-year policy break, but is even less evident for shorter breaks. Overall, the higher $\beta_1$ parameter and the higher depreciation rate largely offset each other.

### 5.7. Impact of TSF elasticity

An important sensitivity is the TSF elasticity ($\sigma_{TSF}$) – the elasticity of substitution between TSF and other factors of production (e.g. capital and labor). This determines how binding the constraint on the amount of TSF is in any period, and the adjustment costs of expanding faster. We explore this sensitivity using the scenario of a \$200 tax when advanced nuclear is the only backstop available. Panel a of Fig. 10 shows how this elasticity strongly affects the speed of expansion. The higher the elasticity, the greater the ability to overcome the limits of the TSF stock by using capital and labor instead to expand more rapidly. All elasticities ultimately achieve the same amount of output (Panel a), following a general S-shaped curve. In all results presented previously, a $\sigma_{TSF}$ of 0.3 was used as the default elasticity value.

The TSF elasticity also impacts the TSF price (Panel b). Initially counter-intuitive, the higher the elasticity, the greater the TSF price in the short run. Here we recognize that for $\sigma_{TSF} < 1$, the inputs are complementary in production, while if $\sigma_{TSF} > 1$ they are substitutes. As complements, when the quantity of one input increases then the quantity of the other input also increases. So the scarcity of TSF leads to substitution toward other inputs and an expansion of production. The expansion of production creates greater demand for both TSF and other inputs, and hence a tendency to increase price in a partial equilibrium setting. Since the elasticities of substitution tested here are all considerably less than one, the complementary nature of the production relationship means that expansion of output of the advanced technology allowed by the substitution elasticity is so large that it actually increases demand for TSF, and with TSF fixed in the short run, the price rises. With output larger in the first period, we then see that the investment in TSF follows closely, as modeled in the next period, and eventually the investment settles to levels consistent with the stationary growth. But, as shown in Panel c, the speed with which investment approaches the stationary growth level is slower the lower the elasticity.

Finally, it takes longer for the electricity price to fall to its long run level, the lower the elasticity of substitution (Panel d). In EPPA, prices are at the marginal cost. The electricity price is hence the marginal cost of production. As long as there is a significant scarcity of TSF, its price is endogenously determined so that the marginal cost is equal to the highest cost electricity technology, and that is the cost of electricity production from fossil fuel, inclusive of the carbon price related to coal use. That price is identical, regardless of the substitution elasticity. However, once the scarcity of TSF is no longer binding, the marginal cost of electricity is the long run cost of production from the advanced technology. With different elasticities, the electricity price follows the same long-run path, but drops down to the long-run cost of the advanced technology at a later date, the lower the elasticity.

We noted earlier that monopoly pricing can explain slow penetration of new technologies. A long-standing derivation of the optimal monopoly price is to set production where the elasticity of demand is equal to 1. Expanding production beyond that level will begin reducing monopoly rents. Since the quantity of TSF is fixed in a period, the price is a direct indicator of the scarcity rent. If the expansion of output is actually being set to maximize the rent, then Panel b of Fig. 10 indicates that an owner of the patent on this new technology would increase monopoly rent by allowing faster expansion, at least through the range of elasticities we explored.

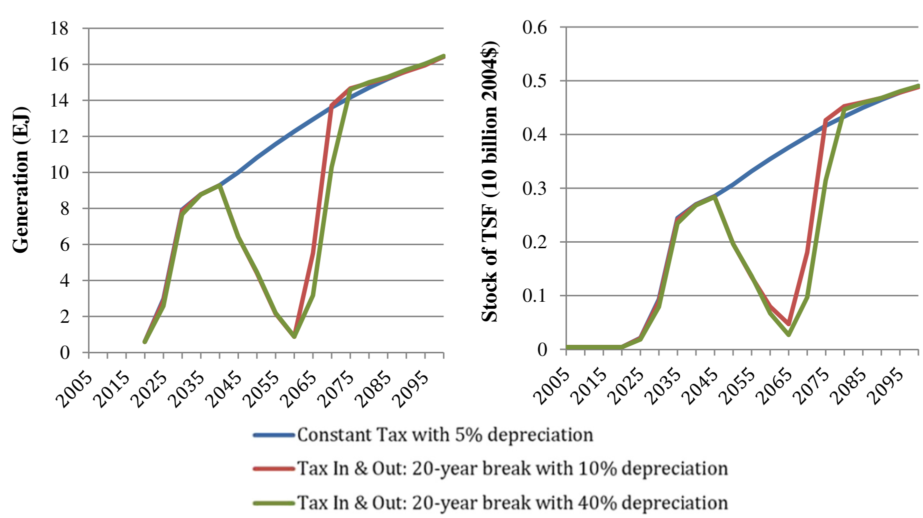


**Fig. 9.** Impact of TSF depreciation rate, case of \$200 tax coming in, out for 20 years and back in when only advanced nuclear is available: (a) generation and (b) stock of TSF.

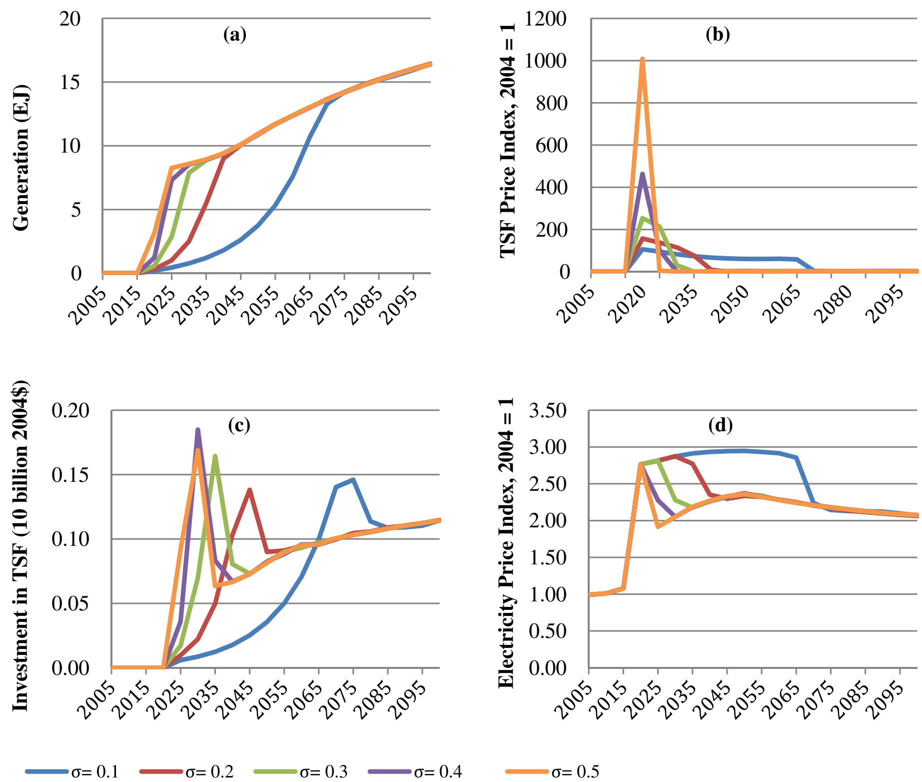


**Fig. 10.** Impact of TSF elasticity, case of $200 tax when only advanced nuclear is available: (a) generation, (b) TSF Price, (c) investment in TSF, and (d) electricity price.

Here is it is useful to understand that the cross-price elasticity, $\sigma$, is closely related to the own-price elasticity demand, $\epsilon_x$, for TSF. The formula for the relationship is given by:

$$\epsilon_x = -\sigma - \alpha(1-\sigma)\frac{p^{1-\sigma}}{x} \tag{13}$$

where $\alpha$ is the CES production function share of $x$ (the TSF input) into production and $p$ is the price of TSF, relative to the price of other inputs. As a point approximation, the price and quantity can be normalized to 1, eliminating the ratio. And if $\alpha$ is small as it is in our formulation, then $\epsilon_x$, is approximately equal to $-\sigma$. However, in our case even though $\alpha$ is very small (0.01), we are getting to prices of TSF that are very high (1000), and hence the ratio of $p^{1-\sigma}/x$ means that using $-\sigma$ to approximate $\epsilon_x$ will become less and less accurate. That ratio will become larger, and we will be subtracting a bigger quantity from a negative number. Hence, as the $p$ gets higher with higher elasticities of substitution, $\epsilon_x$, will be ever greater than $\sigma$. Thus we expect $\epsilon_x$ to equal 1, the optimal monopoly expansion rate in the first period, when $\sigma$ is something <1.

To further investigate, we extended our simulations to include elasticities of substitution well beyond 1.0, and to narrow in on the value of $\sigma$ that maximizes the rent in the first period, as presented in Fig. 11. We see, as expected, that the rent on TSF reaches a maximum and then declines. This occurs between an elasticity of substitution of 0.60 and 0.61 in 2020, somewhat below 1.0, as we expected. We also plot the price for future years, and the peak occurs at ever-lower levels of elasticity as time goes by. Again, given the structure of the model, this behavior is expected. Future rents are eroded because the amount of TSF increases the more expansion there was in earlier periods. Our assumption is that the limiting factor is not necessarily the monopoly pricing considerations, but rather barriers that slow expansion and availability of the technical resources required to expand capacity. Those barriers and limits will create scarcity rents that may accrue to various resources that are limited, i.e. knowledgeable technical people as well as owners of licenses, patents, or suppliers of components that are in limited supply.

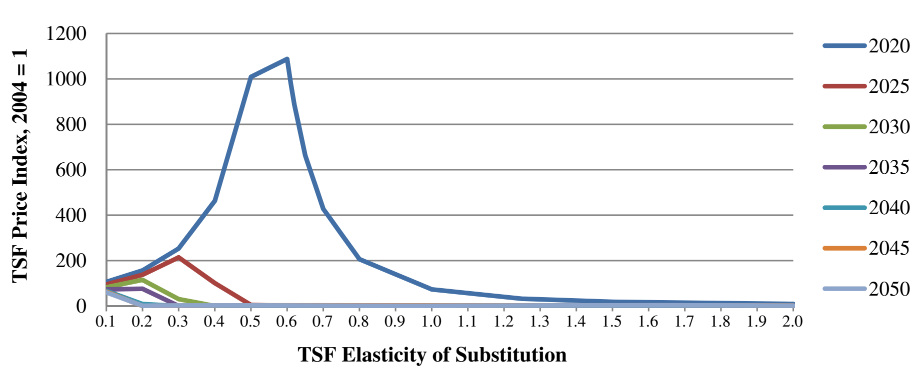


**Fig. 11.** Impact of the TSF elasticity on the TSF rental price, 2020–2050.

## 6. Conclusions

It has been widely recognized that significant mitigation of greenhouse gas emissions will require advanced technologies. Technology penetration is a phenomenon that has been widely studied. General observations are that often the price of a new technology will drop over time, and that technology penetration takes time. In general, we would expect this to raise the cost of mitigation as higher initial prices and slower penetration will mean added cost directly because of the higher initial cost of the technology and longer reliance on the old technology. There are a variety of underlying theoretical explanations that can explain at least some part of these observations: the old technology will hang around because of sunk costs, there may be monopoly pricing of the new technology, the technical resources to expand capacity may be limited causing scarcity rents and/or adjustment costs, there may be learning, and there may be obstacles and barriers to expansion.

Most likely, all of these factors can play some role, under some circumstances. However, it can be very difficult to empirically separate these different factors. We can usually directly observe price, but it can be hard to determine the extent of rents that may exist in that price. The eventual erosion of rents can lead to a drop in price over time. Short run adjustment costs that eventually are overcome can also lead to high prices with sudden demand for the technology. Barriers to expansion, such as siting or regulatory issues also can constrain expansion. In all of these, the result will be a combination of increased real cost in an attempt to overcome the barriers along with rents due to high demand that cannot be met in the short run.

Our modeling approach has vintage capital in it, and so the role of sunk costs in preserving a technology already existed. We also had a kind of fixed factor for technologies in earlier versions of the model. The goal of this paper was to further develop that approach, link it to theoretical underpinnings, provide a sounder empirical foundation for the parameterization of the components of the structure, and to fully explore the behavior of the revised structure to assure that it was operating as expected, and consistent with observations about how technology penetrates in practice. We use the structure of a technology-specific factor of production, available in initially limited supply that grows as a function of how much actual production of the technology there was in the previous period. We made a stronger link to the actual investment level in expanding the technology because the argument for capacity expansion is one of how much ability to expand capacity exists rather than how much actual production there was in the previous period. We carefully identified that several parameters needed to be jointly determined so that penetration behaved as it did for the technology analogue, which we used to estimate the relationship between capacity to expand in time t and previous expansion rates.

We explored several technology analogues, including nuclear in the U.S. and France, wind in the U.S. and China, solar in Germany and shale gas in the U.S. We found that within the range of TSF parameter values from these examples, model results are quite similar when the advanced technology has a clear competitive edge. When there is closer competition with other technologies, the TSF parameter value can lead to differences in the initial penetration of the advanced technology. The estimated TSF parameter values, and resulting model behavior, are very similar for nuclear in the U.S., wind in the U.S. and solar in Germany. We use nuclear in the U.S. for our base TSF parameterizations.

We also added depreciation of the technology-specific factor to create the behavior where if the technology were not used for some decades, it would face a new set of adjustment costs to scale up again. We explored a range of TSF depreciation rates and found that, because depreciation is included in our regression estimation, higher depreciation rates are mostly offset by higher TSF expansion parameter values (e.g. $\beta_1$), with different depreciation rates having only a small difference in how quickly a technology can rebound after being inactive. We often examine policy measures where a carbon price remains indefinitely or starts low and grows. Under those circumstances, a technology appearing, disappearing, and reappearing is unlikely. Nevertheless, having a structure that is robust to extreme and odd scenarios is useful.

We believe the new structure behaves well. Under our base TSF parameterization, when forced with a carbon price high enough to create demand for the new technology, we have expansion rates very similar to what we saw for our technology analogues. Thus, the modeled expansion is realistic, as we have seen these rates in the past. We find that many people have difficulty believing expansion can be rapid, but often we believe the reason is that the technology on which they are focusing is really not economic now, and so it is difficult to imagine a reality where it suddenly becomes economic. Under current conditions, it is hard to imagine the U.S. building over 75 nuclear power plants in 15 years, but that is what happened between 1970 and 1985. In a model, it is easy to create a condition where a technology like nuclear is suddenly economic, and then explore the expansion rate. In our formulation, $CO_2$ prices of $125 per ton or above, are enough to create a strong incentive to replace the existing fossil fuel fleet with nuclear power, assuming that is the only non-carbon option. We would likely agree with most analysts in that we do not think we will see that level of expansion in the next 15 years. The main reason is that we do not expect a carbon price anywhere near the level that would make advanced nuclear highly competitive.

There are also other low-carbon alternatives that might carve out some of the market. We tested some of these other technologies, by themselves, and when all those we represent are available. As with other studies we have done, which one of these technologies wins in the long run depends on which one has the lowest long-run cost. The particular reference formulation we have has a particular winner—advanced nuclear—but slight changes in its cost, or in the cost of its near competitors, can easily change that result.

The formulation for new technology penetration creates adjustments costs, quasi-rents, has prices falling over time, and gradual penetration of the new technology. Sunk capital costs in the old technology can slow penetration, but if the economic advantage of the new technology is great enough, then our approach endogenously retires the oldest and most inefficient vintages first, and if the advantage is great enough, all of the old capital. This makes capital depreciation in our model essentially endogenous. Of course, it is more costly to build new capacity and prematurely retire old capital, but if the incentive is great enough then the existence of old vintages is not an absolute constraint on how fast we can transform the energy system. We see in many European countries with strong renewable generation incentives that other capacity is idled or operating far below full capacity, and similarly in the U.S., the tightening of pollution standards and cheap natural gas has led to retirement of or low capacity factors for old coal plants. Other modeling approaches often dial in very specific constraints on expansion, or have existing capacity as a hard constraint on the rate of transformation of a sector. Our approach is based on the assumption, and observation, that these rates and constraints are not absolute but depend on economic incentives. We believe our approach is consistent with a large body of economic theory and reasoning, and leads to a set of results that is consistent with observation.

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## Appendix A. Supplementary data

Supplementary material to this article can be found online at https://doi.org/10.1016/j.eneco.2019.01.034.

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