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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 relevant policies are in place. To improve the representation of the penetration of advanced technologies, we present a formulation that is parameterized based on observations, while capturing elements of rent and real cost increases if high demand suddenly appears due to large policy shock. The formulation is applied to a global economy-wide model to study the roles of low-carbon alternatives in the 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—the rate at which advanced technologies will expand is endogenous to economic incentives. The policy simulations are designed to illustrate the response under sudden increased demand for the advanced technologies, and are not intended to represent necessarily realistic price paths for greenhouse gas emissions.

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1. INTRODUCTION

The study of energy futures as they relate to greenhouse gas emissions requires consideration of advanced technologies as possible substitutes 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. Nordhaus (1979) introduced the concept of a backstop technology—a perfect substitute for fossil energy—available at a fixed marginal cost. 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), fuels, and electricity with various

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alternatives (solar, biofuels, nuclear, wind, etc.) that differentially competed to supply these energy services; and 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 role of advanced technology within a traditional general equilibrium modeling system. This marries together standard economic modeling (based on expenditure data that allows disparate goods to be added together) with an economic representation of the technology options that do not yet exist at significant levels in the economy (based on engineering cost and efficiency data) (e.g. McFarland, *et al.*, 2004; Paltsev *et al.*, 2005).

Modeling of technology for climate change has also drawn on basic observations from the more general literature on technology adoption. For example, technologies tend to be adopted over some period of time, often characterized by an S-shaped relationship between market share and time: 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 over the traditional non-hybridized seed. Another key observation from earlier studies 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 result of the "learning-by-doing" process.

A variety of possible explanations for gradual adoption and falling costs have been offered, leading to different adoption model formulations (e.g. Gerowski, 2000). The S-shaped penetration of hybrid corn seemed best explained by the following process: a few early adopters were willing to try new things; as word of their success spread, many others adopted; and finally, penetration slowed again as adoption reached mainstream levels, with few farmers remaining 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 as well. With other goods, especially consumer goods, the applicability of a new technology may vary by consumer or application. Electric vehicles may be useful for short trips, but less suitable for consumers who drive long distances; therefore, to expand the market, the cost advantage for the long-distance drivers would need to be larger than for others, or further advance in the technology may be needed. This has led to estimation of technology diffusion using a probit model, where the likelihood of adoption depends on characteristics of the potential adopters. In this model, the exact nature of the penetration of the new technology depends on the distribution of differences among consumers, and how changing conditions may make the technology appeal to more consumers.

Another strong theme in economic studies is the adjustment costs associated with a sudden increase in demand (e.g. Lucas, 1967; Gould, 1968). These costs would certainly play an important role in a new technology sector (and even in conventional sectors) if conditions suddenly change to create demand for a technology where before there was little or none. Due to sunk capital costs in the old technology, even 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: 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 monopoly pricing offers a very specific reason for why the price is initially high and then falls.

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 drivers of change, even for historical technologies that have been successful. The simplest idea—that of a learning curve—relies on cost and cumulative output, but cost itself can be hard to measure. The selling price is far easier to observe, but may include monopoly rents, inducements aimed at expanding the market to gain economies of scale, and, especially with advanced energy technologies, various government subsidies that may reduce the private cost. Learning curves alone do not necessarily explain gradual market penetration; one would need to combine a learning curve with diverse potential consumers, some of whom are willing to pay a high price initially. Alternatively, 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.

2. AN APPROACH FOR REPRESENTING ADOPTION IN A CGE FRAMEWORK

We seek a relatively simple formulation that can be parameterized based on observations, while capturing elements of rent and real cost increases if high demand suddenly appears due to a big policy shock. We aim to make the process consistent with a general equilibrium framework, applying our formulation to the Economic Projection and Policy Analysis (EPPA) model (which will be briefly discussed in Section 3). First and foremost, we represent alternative technologies in the electricity sector. Here, the output for base load technologies is indistinguishable—electricity is electricity, so adoption theories based on differences among consumers are less compelling. Adjustment costs—costs associated with scaling up the capability to meet demand for new plants—are a more relevant issue for these technologies (and are well established as an economic principle). Accordingly, we focus on a method that incorporates adjustment costs.

2.1 Overview of the Approach

We focus on three components of the processes described above: (1) vintaging of capital stock, (2) initially limited technology-specific resources required for production of the new technology, with the expansion of such resources dependent on the amount of previous investment, and (3) adjustment costs driven by rents on limited technology-specific resources.

Vintaged capital is technology and sector specific, available in a fixed supply in a given period, and determined by investment in previous periods. As a result of its fixed supply in any given period, the rental price/return on capital in each 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 (or lower-carbon vintages) at the expense of high-carbon technology or vintages. Reflecting 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 partially or entirely unused. This follows observations that often the oldest, dirtiest power plants have low capacity factors. Meeting environmental requirements is easier and less expensive with newer, more efficient fossil power plant vintages or completely new technologies (wind, solar, advanced nuclear); however, 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 vintages become 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 alone tends 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, having multiple vintages with different efficiencies subject to gradual depreciation, it would take an extreme policy to create a sudden switch. The "premature" retirement increases economic cost through greater investment required in the new technology combined with decreased output from the sector.

Our modeling of adjustment costs presumes there is a pre-existing technology-specific factor available in limited supply that is an input in the production function and required to produce the new technology. This resource is latent until there is demand for output from the new technology. The technology-specific factor, as with all factors of production, is owned by the representative household, and there is a unique factor for each technology. Intuitively, the factor is an investor/inventor with an idea and the potential to produce the technology, waiting until there is market demand. Since it is difficult to predict when and how much demand will appear, actual investment in physical plant and 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 technology-specific fixed factor—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 technology-specific factor and other inputs. The amount of the technology-specific factor would prescribe exactly the level of output in any period, according to the amount and share of the factor required to produce the good. In this case, greater demand simply results in a higher rent on the technology-specific factor. The cost to the economy of the constraint is less consumption of the good than would be desired if the price were equal to the marginal cost of production, less the scarcity rent. Here, there are no adjustment costs.

Now consider a production function where we allow substitution of capital, labor and other inputs for the technology-specific factor. This substitution allows expansion of production beyond what would otherwise be prescribed by the available technology-specific factor, 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. Faster production leads to increased cost; hence, in this formulation, sudden demand for the advanced technology causes its price to rise, partly due to rents on the technology-specific production factor and partly due to higher real cost. In general, rents to the technology-specific factor can include specific monopoly rents associated with a license or patent, but can also include bidding up wages of technical specialists needed to develop and produce the technology, or 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 technology-specific resource input—so both the real cost of production and the rent will tend to fall. The expectation is that expansion of the technology-specific factor 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, which falls with cumulative experience, and there is no process that creates monopoly rents. In our formulation, the dependence on growth of the technology-specific factor on previous investment levels creates a similar dependence of the cost (and price) on previous capacity. 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.

A final element of our approach is that we depreciate the technology-specific factor each period. With growth in demand for the good there will be additions to the amount of technology-specific factor in excess of depreciation. By depreciating the sector-specific factor we allow for a situation where demand for the technology potentially disappears for some decades and then reappears. Nuclear power is an example of a technology that expanded rapidly before demand collapsed and much of the capacity to build plants depreciated away. Without depreciation of the technology-specific factor, production from the technology could restart immediately at a very high level in later periods. With depreciation, production capability must be gradually built back up. To allow restart of the technology in later periods, we set the amount of the technology-specific factor in any period equal to the greater of the depreciated level plus new additions in that period or the initial endowment.

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 previously, separating even costs from rents, and then further identifying cost reductions due to learning vs. overcoming adjustment costs is difficult in practice.

2.2 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:

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

where X_{KL} is an output of a *K-L* service, θ is the share of capital (and $1-\theta$ is the share of labor), and γ determines σ, the elasticity of substitution among inputs, where $\sigma = 1/(1-\gamma)$. An equivalent formulation is to replace γ 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, that structure requires an identical σ across all input pairs. This restriction can be relaxed by creating input bundles, presaged by the definitions in Equation 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:

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

While the same structure, here we are free to choose values for γ_E different from γ in equation 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, often referred to as a Leontief production function:

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

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 Υ=0 we get the Cobb-Douglas production function where the elasticity of substitution between inputs is 1:

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

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, specify the share $\theta_{TSF,S}$ for technology S required to produce a unit of output, and endow the economy with an initial amount of the 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 Equation 3, then the first year production level will be determined. With, for example, the $\theta_{TSF} = 0.01$, here suppressing the technology subscript, and we endow the economy with \$1, and denote this endowment by $inishTSF$, then, if there is demand, 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 $inishTSF$. **Figure 1** illustrates the technology-specific resource as it enters the production nest structure of an advanced electricity generation technology in EPPA.

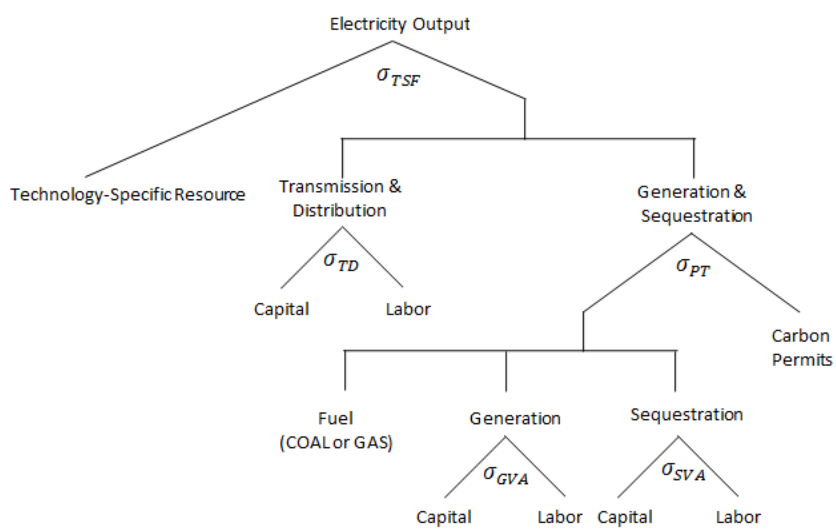

Figure 1. Example of the technology-specific resource in production structure nest for advanced generation technologies.

TSF also depreciates and accumulates with lower limit of the initial endowment:

$$TSF_{t+1} > TSF_t \cdot (1 - \delta_{TSF}) + INVTSF_{t+1} \text{ or } TSF_{t+1} = inishTSF \tag{5}$$

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 noted earlier, we argue that $INVTSF$ is a function of the TSF that existed in the previous period. As long as there is TSF in the economy, it provides a source of expertise for creating more capacity. That is, there is some level of $INVTSF$ that can be achieved without driving up the cost further. We estimate this relationship as quadratic:

$$INVTSF_{t+1} = \beta_1 TSF_t + \beta_2 TSF_t^2 \tag{6}$$

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. If so, we can estimate Equation 6 as

$$OUT_{t+1} = \beta_1 OUT_t + \beta_2 OUT_t^2 \tag{7}$$

where OUT is technology output, recognizing that OUT can be considered an approximate scalar for inputs in which we are directly interested such as production capital and knowledge. If the production function is Leontief, then it is an exact scalar. With this assumption, we recognize that the added production capacity in $t+1$ is

$$INVOUT_{t+1} = OUT_{t+1} - OUT_t\,(1 - \delta_0) \tag{8}$$

where $INVOUT$ is investment in the capability to produce OUT, and is needed to meet the difference between output in $t+1$ and that in t, less replacement of depreciated capacity to produce OUT in t, where δ_0 is the depreciation rate of production capital. Then by defining a value for θ_{TSF} in our production process, $INVTSF_{t+1} = \theta_{TSF}\, INVOUT_{t+1}$. By substituting Equation 7 into Equation 8, our equation for $INVTSF$ is:

$$NVTSF_{t+1} = \theta_{TSF}\{\beta_1[OUT_t - OUT_{t-1}(1-\delta_0)] + \beta_2[OUT_t^2 - (1-\delta_0)OUT_{t-1}^2]\} \tag{9}$$

The challenge of estimating Equation 7 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 intend to apply this to technologies in the electric sector that are fairly capital intensive and so, for example, the diffusion of hybrid corn would seem inappropriate. A good analogue is the expansion of nuclear power in the US from its inception in the late 1960's to the mid-80's when expansion was derailed by safety concerns and siting issues. While expanding, it 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 from 1969 to 1987 in the U.S. (EIA, 2014) to estimate Equation 7, with the estimation series starting in 1970 because the independent variable is lagged one period. The estimated parameters with standard errors in parentheses are: $\beta_1 = 0.9625\ (0.1577)$, $\beta_2 = 1.3129 \cdot 10^{-7}\ (3.8782 \cdot 10^{-7})$ with an R^2 of 0.97. Predicted and actual values for output are given in **Figure 2**.

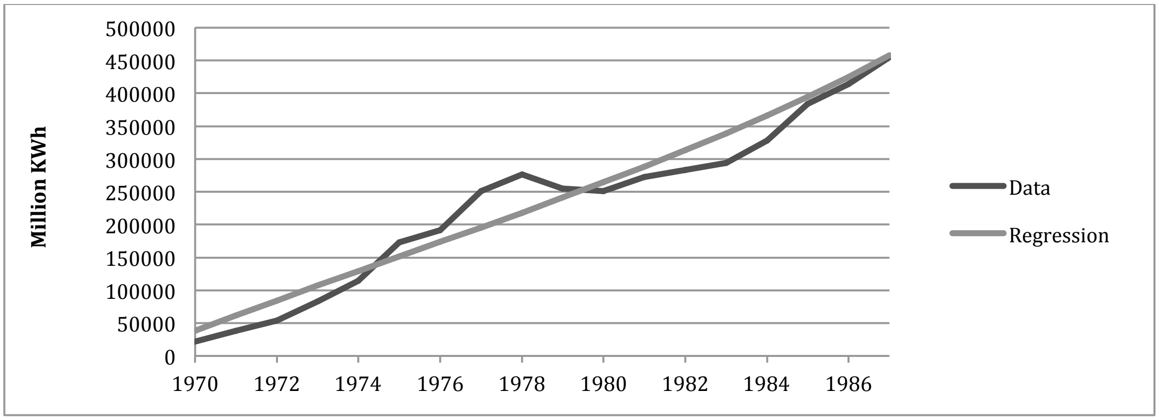

Figure 2. Predicted vs. actual output of nuclear generation in the US, 1970-1987.

We impose a value for $\theta_{TSF} = .01$ and choose $inishTSF$ in each region *r* to be consistent with the data used to estimate Equation 7:

$$inishTSF_{S,R} = \theta_{TSF}[OUT_{r,t0} \cdot NSh] \tag{10}$$

where OUT is total regional electricity output in the base year of the model and NSh is the nuclear share of U.S. generation in 1970. *NSh* was 1.4%. We set σ_{TFF} to 0.3 for all technologies, and later examine the sensitivity of results to this value. The value of θ is set arbitrarily small, but once set, consistency with the estimation of Equation 9 demands that $inishTSF$ be determined by Equation 10. Equation 10 further implies that the initial capacity to produce the technology scales with the size of the electricity sector in the regional economy.

Vintaging has been a standard feature in EPPA. Briefly reviewing this structure, we distinguish between malleable and non-malleable (rigid) capital. In each sector, the malleable portion is described by nested CES production functions (see Figure 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 short-run and long-run responses to changes in relative input prices: no substitution exists with rigid capital, but over time the rigid capital depreciates and is replaced by 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, φ, 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:

$$K_{t+1}^m = I_t + (1 - \varphi)(1 - \delta)K_t^m \tag{11}$$

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 φ 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:

$$K^r_{i,t+1,v} = \varphi(1-\delta)K^m_{i,t} \ \text{ for } \ v = 1 \qquad (12)$$

For each sector/technology, the quantity of capital in each of the remaining vintages (v = 2, 3, 4) is simply the amount of each vintage that remains after depreciation:

$$K^r_{i,t+1,v+1} = (1-\delta)K^r_{i,t,v} \text{ for } v = 2,3,4 \qquad (13)$$

Because there are four vintages and the model's time step is five years, the vintaged capital has a maximum life of 25 years.

3. APPLICATION: 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. EPPA 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. It is an update of a previous version of EPPA described in Paltsev *et al.* (2005). The current version is described in detail in supplemental information provided in Reilly *et al.* (2012). The basic regions, sectors, and primary factors represented in the model are shown in **Table 1**.

Table 1. Regions, sectors and primary factors in the EPPA model.

Regions	Sector		Primary Factors
United States (USA)	*Non Energy*	*Energy*	Capital
Canada (CAN)	Crop (CROP)	Coal (COAL)	Labor
European Union+ (EUR)*	Livestock (LIVE)	Crude oil (OIL)	Cropland
Japan (JPN)	Forestry (FORS)	Refined oil (ROIL)	Pasture
East Europe (ROE)	Food (FOOD)	Natural gas (GAS)	Harvested forest**
Australia & New Zealand (ANZ)	Services (SERV)	Liquid fuel from biomass (BOIL)	Natural grass
Brazil (BRA)	Energy intensive (EINT)	Oil from shale (SOIL)	Natural forest
Russia (RUS)	Other industry (OTHR)	Electric	Oil
India (IND)	Industrial transport. (TRAN)	- Fossil (ELEC)	Shale oil
Africa (AFR)	Household transport. (HTRN)	- Hydro (H-ELE)	Coal
China (CHN)		- Nuclear (ADV-NUCL)	Natural gas
Middle East (MES)		- Wind (WIND)	Hydro
Rest of Asia (REA)		- Solar (SOLAR)	Nuclear
Mexico (MEX)		- Biomass(BIOELEC)	Solar and wind
Latin America (LAM)		- NGCC	
Fast growing Asia (ASI)		- Gas with CCS	
		- Coal with CCS	
		- Wind w/ gas backup (WINDGAS)	
		- Wind w/ biomass backup (WINDBIO)	

* The European Union plus Norway, Switzerland, Iceland, and Liechtenstein.
** Harvested forest includes managed forest areas for forestry production as well as secondary forests from previous wood extraction and agricultural abandonment.

4. EXAMPLE RESULTS

The main advanced technologies of interest are low-carbon electricity generation alternatives, which generally do not enter the market without policy incentives. The behavior of our technology penetration formulation is best illustrated by a sudden increase in demand for the technology. Starting with a reference case with no policy incentives and therefore no demand for a new technology, we create demand for the technology by introducing a carbon price sufficient to overcome the higher cost of the backstop.

To focus clearly on the technology penetration phenomenon by itself, we examine results one technology at a time, beginning with those with only the advanced nuclear backstop technology available. 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 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, and show results of these simulations in **Figure 3**.

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 levels from advanced nuclear all converge by 2045 to an essentially steady growth path dictated by the underlying demand for electricity. With higher CO_2 prices there is slightly less nuclear generation due to the price's negative effect on overall economic output and income in the economy. Thus, electricity demand is reduced slightly, due to lower household income and lower economic output. 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. With improving conversion efficiency over time in the conventional power sector and gradual replacement of conventional capacity with higher efficiency capital, conventional generation becomes competitive again in later years. However, fossil fuel prices continue to rise over time, and eventually advanced nuclear becomes 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 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, 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 little or no impact on electricity prices, and also no incentive to substitute other inputs for TSF. 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

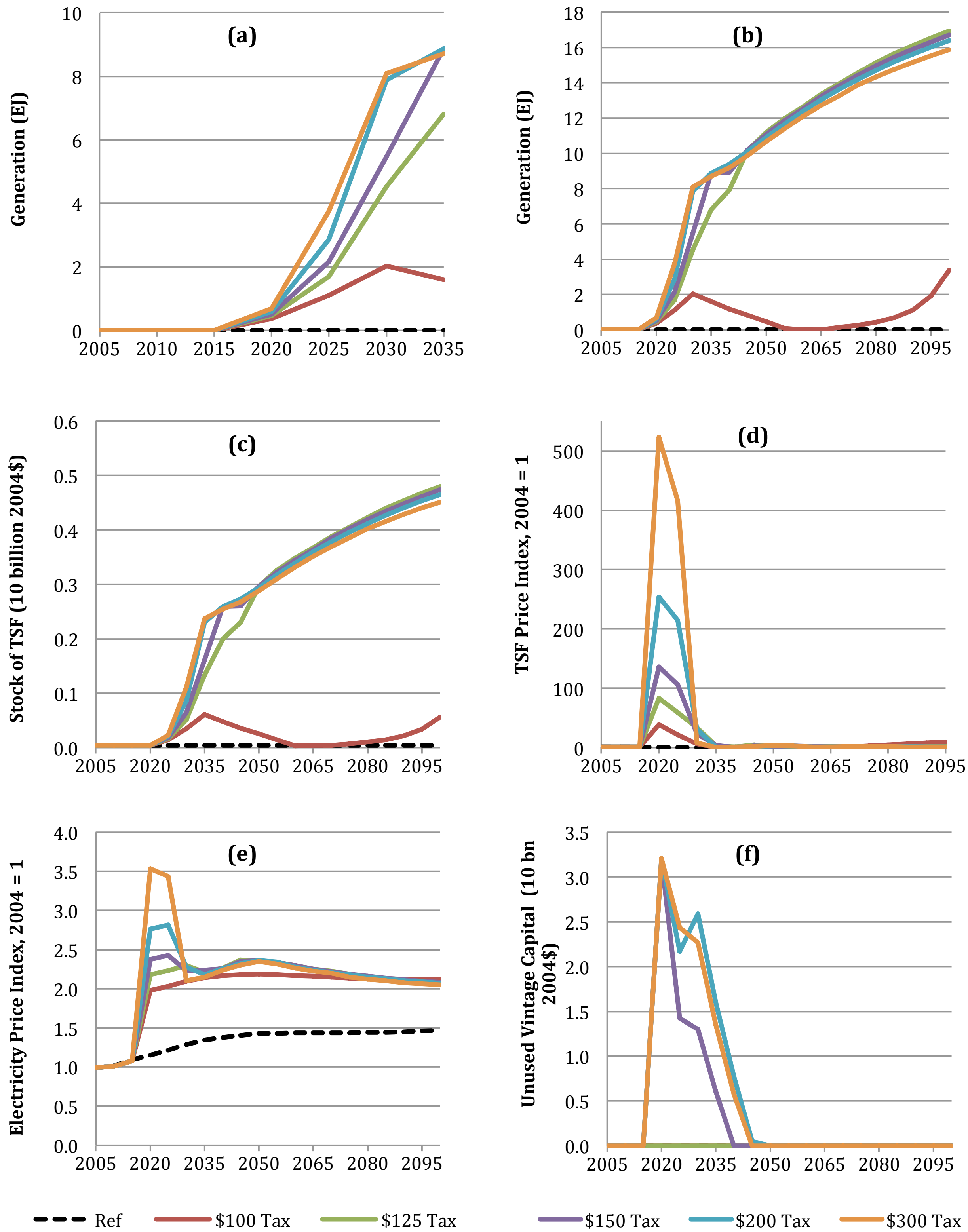

Figure 3. Impact of carbon price on advanced nuclear: (a) advanced nuclear generation to 2035, (b) generation to 2100, (c) total stock of TSF, (d) TSF rental price, (e) electricity price, and (f) unused vintage fossil capital.

policy: the higher the price, the bigger the overshoot. Given the equilibrium conditions of the solution, this price must equal the cost of electricity production from all technologies that are producing non-zero levels of output in the period. Under low carbon prices, if 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, which—if it is produced—also must equal the cost of advanced nuclear electricity production. 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 that of other active options.

At higher carbon prices, there is no incentive to add additional conventional capacity, and the endogenously-determined rent on older vintages falls so that the marginal cost equals the electricity price, and again, TSF rent and input substitution lead to a higher marginal cost for advanced nuclear generation. At even higher carbon prices, the endogenous rental price of older vintages of conventional generation capital falls to zero, and because the stock is in excess supply, some or all of it remains unused. Newer, more efficient vintages of conventional generation may continue to be used, but the rental price of their capital also falls. This decreasing rental price of vintaged capital reflects what is sometimes referred to as stranded assets—because of the unanticipated policy change, the assets are worth less than expected, and the owners suffer windfall losses. Here those losses accrue to the representative household, and are reflected in less generation, higher electricity prices, and the need to dedicate capital to a new technology when, in principle, the existing capital for conventional electricity could have still been used.

The long-run price of electricity is identical across the carbon price scenarios because advanced nuclear has no direct emissions of CO_2.[1] 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 CO_2 price is above $150. Because the TSF price is above zero even with the $100 CO_2 price, the tax policy imposes some windfall losses on conventional generation capital. 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 rebuilding, at least with the technology that existed when they were originally built. The $100 price nearly leads to a switch from conventional fossil generation to nuclear, and relatively small changes in other variables lead to nuclear entering, exiting, and re-entering the market.

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[1] Given the I-O structure of the model, other inputs used to build nuclear will have GHG emissions (to the extent there remain emissions), so there is some pass-through of costs. However, the effect is negligible.

We turn next to a case where the only backstop technology is wind. **Figure 4** includes the following three panels: wind generation (a), the TSF price (b), and the electricity price (c). The EPPA model addresses the intermittency of wind by requiring natural gas back-up generation that operates at low capacity levels to capture the fact that it is not possible to shift loads fully to meet the daily and monthly pattern of wind power production. Wind with gas backup (as defined in the model) is more expensive 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 are generally even more expensive. As a result, a higher carbon price ($200) is required to achieve significant penetration of wind with gas backup. An interesting feature occurs under a $200 tax: after the initial expansion, there is a decline in wind 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.

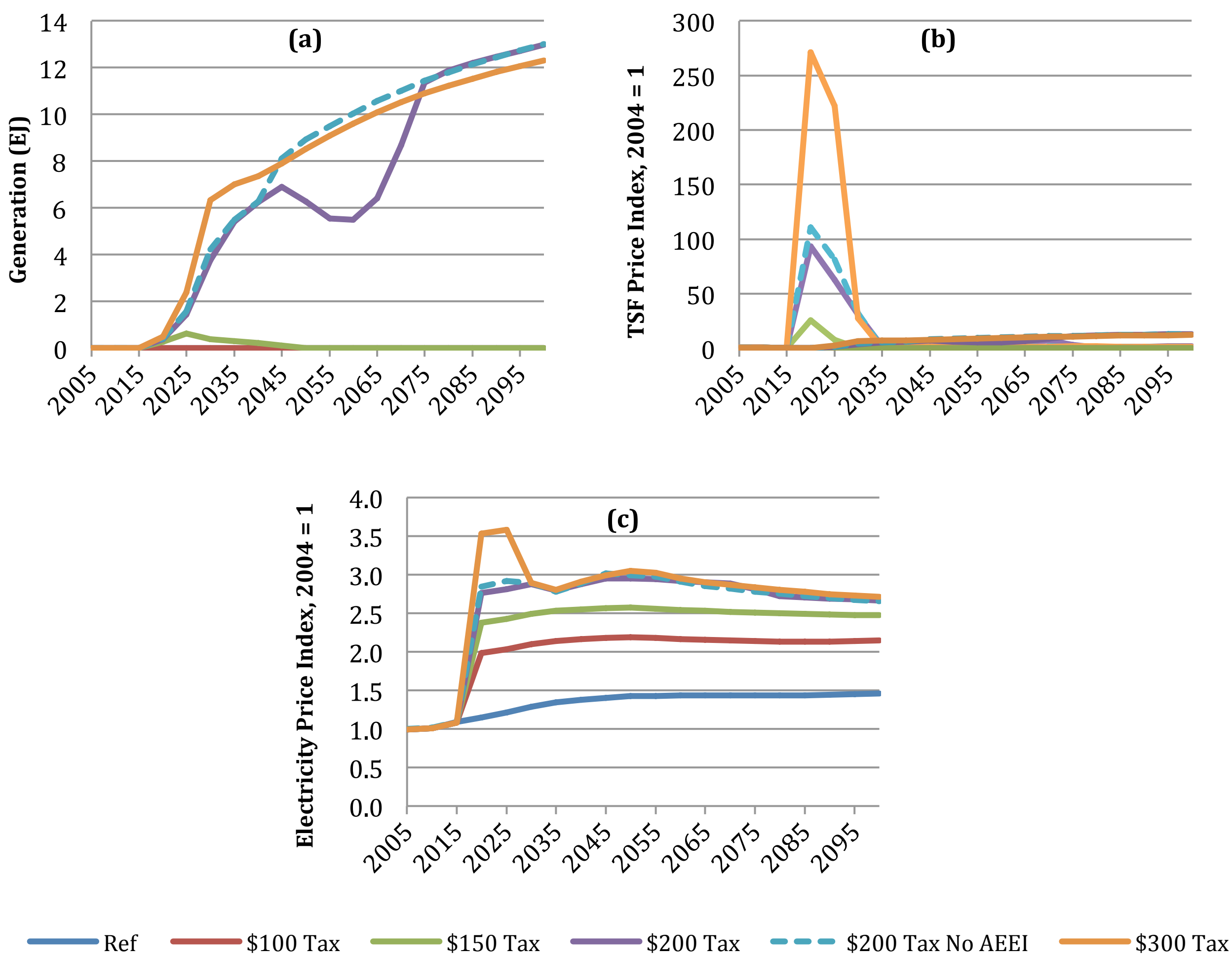

Figure 4. Impact of carbon price on wind with gas backup: (a) generation to 2100, (b) TSF price, and (c) electricity price.

In both of these cases, we traced this behavior 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, causes fossil generation costs to fall to a competitive level. 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 fossil fuel costs rising from depletion. We demonstrate 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). After this adjustment, the dip in wind generation disappears.

Panel b of Figure 4 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 expensive than advanced nuclear, and therefore the demand for it is not as high and it does not expand as quickly. The electricity price is shown in Panel c. 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, where prices converge once the TSF is no longer a constraint. 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.

We also ran scenarios where all advanced technologies are available and compete amongst each other, again with a fixed carbon price. **Figure 5** shows the resulting electricity mix under two cases of the $200 carbon price, each with a different cost for advanced nuclear. In the EPPA model, the costs of backstop technologies are initially defined by a "markup" determined by the cost of the technology relative to the cost of the conventional generation against which it competes in the base year of the model. Default markups are determined using a levelized cost of electricity calculation. The default markup for advanced nuclear is 1.47, meaning in the base year it is 47% more expensive than conventional coal generation. Panel a of Figure 5 shows the resulting electricity mix using the default markup cost for advanced nuclear. Initially, after the introduction of the carbon price, a mix of advanced technologies is seen—NGCC, some natural gas with carbon capture and storage (NGCAP), and very small amounts of coal with carbon capture and storage (IGCAP) and wind with natural gas backup—but ultimately, advanced nuclear takes over the market, becoming the dominant source of generation. With several alternatives expanding independently, fossil generation leaves the market more quickly after the implementation of the carbon price, and vintage conventional generation sits idle, despite the potential for production. By 2100, advanced nuclear and traditional nuclear together make up 87% of generation, with hydro, wind, biomass and solar making up the rest of the mix.

Panel b of Figure 5 shows the resulting electricity mix when the markup for advanced nuclear is increased by about 5% to 1.55. Once again, fossil generation leaves the market quickly and there is an initial mix of advanced technologies—advanced nuclear, NGCC, NGCAP, and small amounts of IGCAP and wind with gas backup. Advanced nuclear expands more at first, followed by a large expansion of NGCAP. Toward the end of the period, advanced nuclear expands again, while NGCAP declines. By 2100, the shares of advanced nuclear and NGCAP are about the same, and together comprise over 70% of the electricity mix. The rest is traditional nuclear, hydro and renewables. The changing dynamic between advanced nuclear and NGCAP is driven by the price of natural gas. NGCAP has an initial markup of 1.42, lower than that of advanced nuclear; however, its cost changes significantly with the price of natural gas as well as the carbon price (which must be paid for emissions that are not captured). When NGCAP overtakes advanced nuclear, the natural gas price is relatively low, but as the gas price increases, advanced nuclear regains the competitive edge.

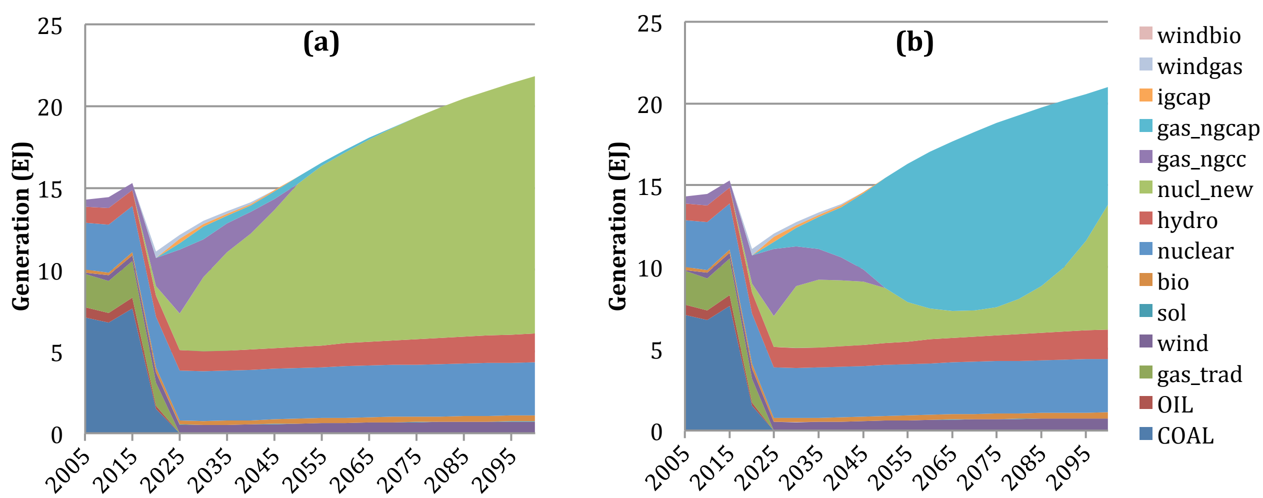

Figure 5. Electricity mix under \$200 tax when all advanced technologies are available: (a) advanced nuclear markup of 1.47, and (b) advanced nuclear markup of 1.55.

We further investigate the impact of markup costs by looking at the case of a \$200 tax when advanced nuclear is the only backstop technology available. In addition to the default markup of 1.47, we test markups of 1.1 and 2, representing a 25% decrease in cost and a 36% increase in cost, respectively. As Panel a of **Figure 6** shows, the initial markup cost affects both the timing of penetration and the ultimate level of penetration. A markup of 2 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. This pattern is largely a function of the flat tax, coupled with the assumption of efficiency improvement and the endogenous (and generally rising) price of coal. Essentially, the higher markup results in behavior for a \$200 tax much like the behavior with the \$100 tax in Figure 3. As the technology cost decreases, demand increases, resulting in a higher TSF price (Panel b). The markup cost also determines the ultimate level of the electricity price, with lower markups resulting in lower electricity prices (Panel c).

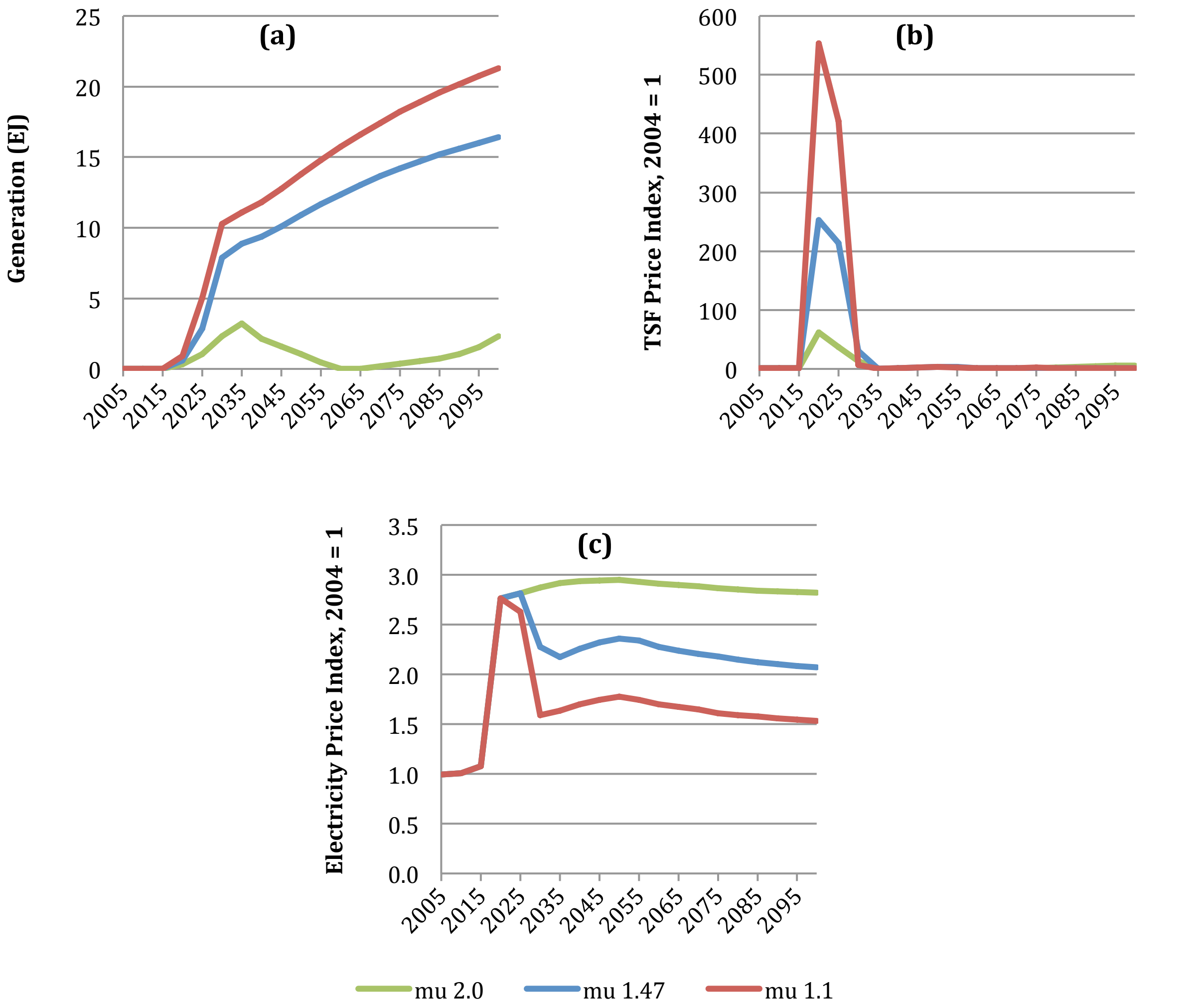

Figure 6. Impact of cost markup under $200 tax when only advanced nuclear is available: (a) generation, (b) TSF price, and (c) electricity price.

4.1 Impact of TSF Elasticity

An important sensitivity is the TSF elasticity (σ_{TSF})—the elasticity of substitution between TSF and other factors of production (e.g. capital and labor). This determines how binding the constraint on TSF is in any period, as well as the adjustment cost of faster expansion. We explore this sensitivity using the scenario of a $200 tax when advanced nuclear is the only backstop available. Panel a of **Figure 7** 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, following a general S-shaped curve. In all results presented previously, a σ_{TSF} of 0.3 was used as the default elasticity value. This is because an elasticity of 0.3 results in a rate of initial expansion similar to that of actual nuclear expansion in the 1970s in the US. Based on the data, nuclear generation in the US increased 11.5 times between 1970 and 1980. Using an

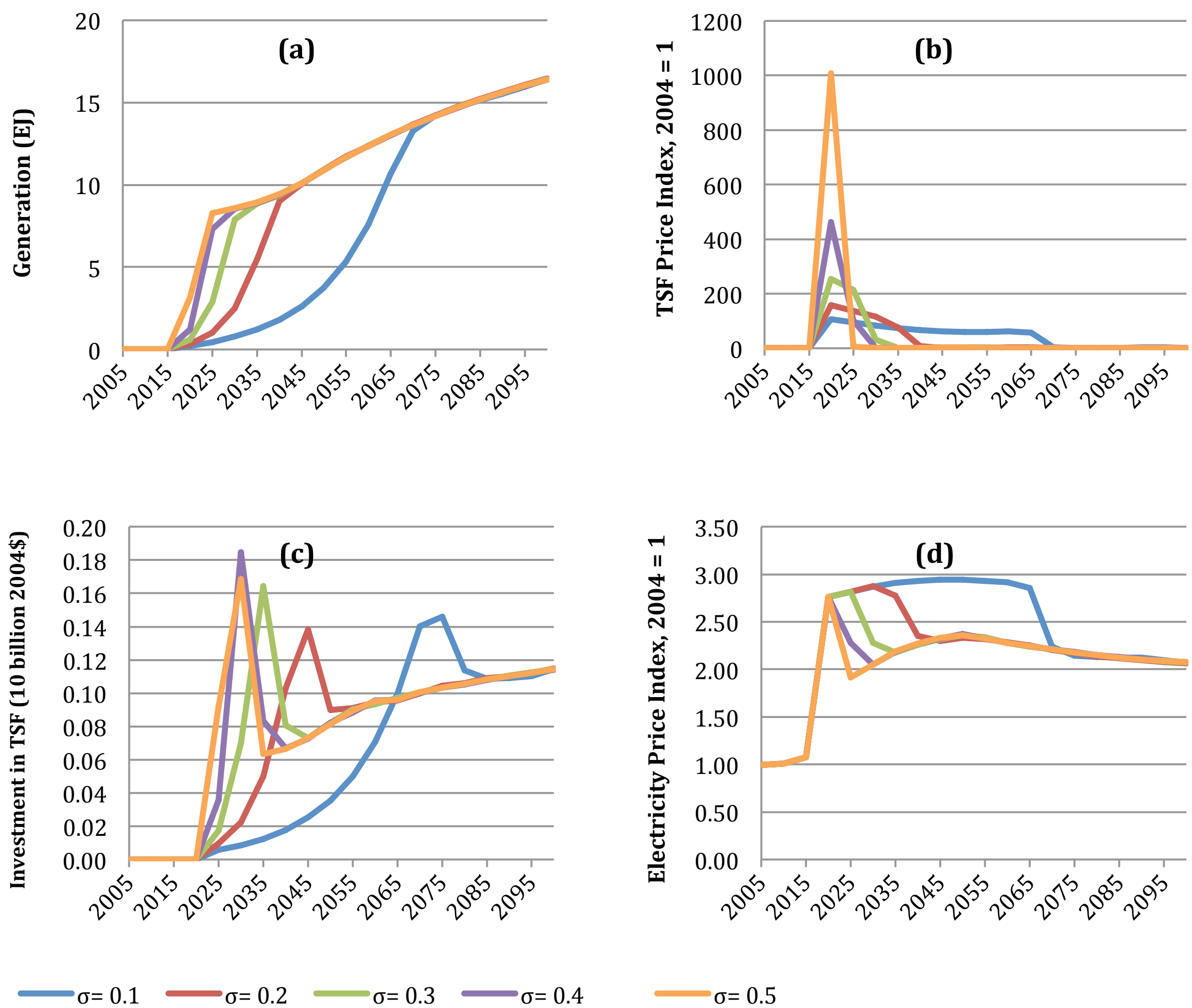

Figure 7. Impact of TSF elasticity, case of $200 tax when only advanced nuclear is available: (a) generation, (b) TSF Price, (c) investment in TSF, and (d) electricity price.

elasticity of 0.3, under a $200 carbon price, advanced nuclear increases 13.25 times from 2020–2030. An elasticity of 0.2 results in a 7.6 times increase in those ten years.

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, the quantity of the other input also increases. The scarcity of TSF leads to substitution toward other inputs and an expansion of production. This expansion creates greater demand for both TSF and other inputs, and therefore tends to increase the TSF 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 allows expansion of output by the advanced technology so large that it actually increases demand for TSF, and with TSF fixed in the short run, the price rises. With larger output in the first period, we 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. However, as shown in Panel c, with lower elasticities, investment approaches the stationary growth level at slower rates.

Finally, the lower the elasticity of substitution, the longer it takes for the electricity price to fall to its long-run level (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: 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 general 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 Figure 7 indicates) 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.

Here is it is useful to understand that the cross-price elasticity σ is closely related to the own-price elasticity demand ϵ_x for TSF. The formula for the relationship is given by:

$$\epsilon_x = -\sigma - \alpha(1-\sigma)\frac{p^{1-\sigma}}{x} \tag{14}$$

where α 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. If α is small (as it is in our formulation), then ϵ_x is approximately equal to $-\sigma$. However, in our case even though α is very small (.01), we are getting to prices of TSF that are very high (1000); hence the ratio of $p^{1-\sigma}/x$ means that using $-\sigma$ to approximate ϵ_x will become less and less accurate. As p increases with higher elasticities of substitution, ϵ_x will be ever greater than σ, and we will be subtracting a bigger quantity from a negative number. Thus, when σ is less than 1, we expect ϵ_x to equal 1, the optimal monopoly expansion rate in the first period.

To further investigate, we extended our simulations to include elasticities of substitution well beyond 1.0, and to narrow in on the value of σ that maximizes the rent in the first period, as presented in **Figure 8**. The actual monopoly-maximizing problem would be to maximize rent over the life of a patent, and so that choice would take future periods into account. However, a patent life is 7 years, not so different than the 5-year period we simulate. As expected, 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 our expectation of 1.0. 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. While there is a monopoly rent motivation for slowing expansion, our choice of a seemingly lower-than-optimal (from a monopoly pricing perspective) value of σ stems from our assumption that the limiting factor is not the monopoly pricing considerations, but rather barriers that slow expansion and availability of the technical resources available 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 contain unique intellectual property.

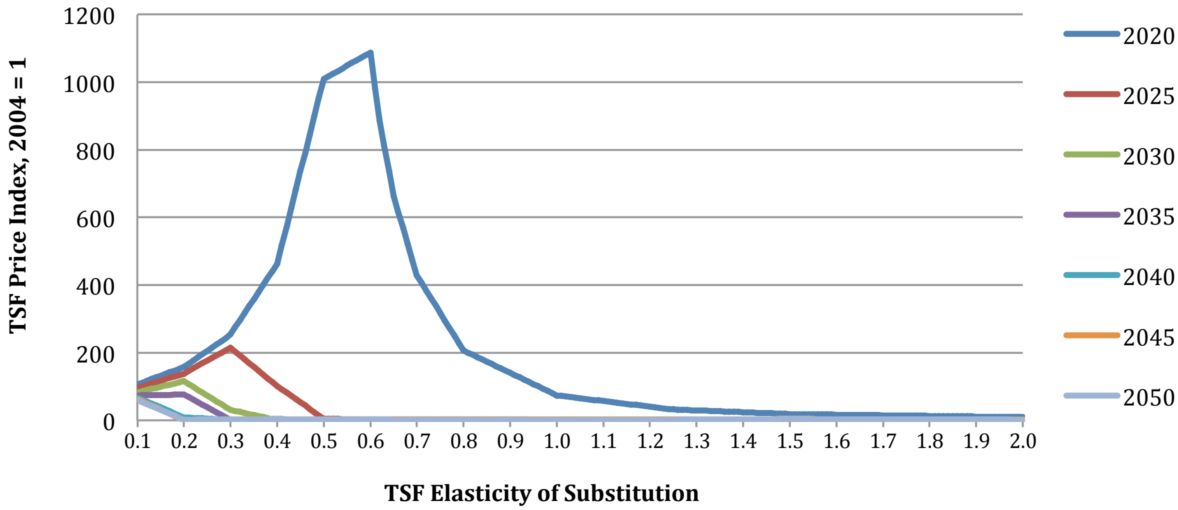

Figure 8. Impact of the TSF elasticity on the TSF rental price, 2020–2050.

4.2 Impact of TSF Depreciation

Another important feature in our representation of technology penetration is depreciation. As Equation 5 shows, we depreciate the stock of TSF over time at a rate of $\delta_{TSF} = 5\%$ per year. 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 disappears for a lengthy period of time, then the capacity to expand would erode away, and would need to be rebuilt should demand for that technology return. 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. In both cases we assume that advanced nuclear is the only technology available. **Figure 9** shows the results of these cases, compared to the case of a constant \$200 tax with TSF depreciation (the default case).

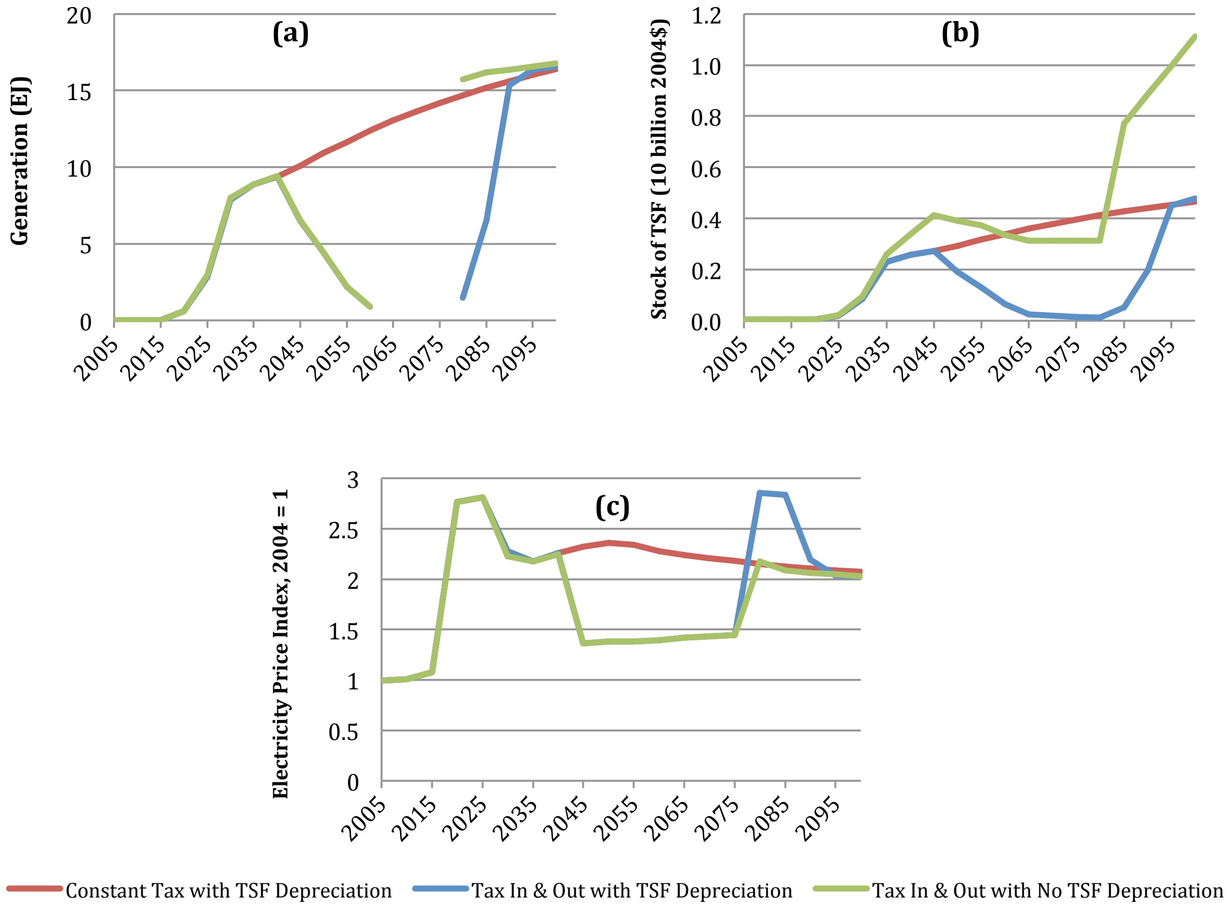

Figure 9. Impact of TSF depreciation, case of $200 tax coming in, out and back in when only advanced nuclear is available: (a) generation, (b) stock of TSF, and (c) electricity price.

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 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 restart at low levels until the TSF stock can be built back up once again. 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 level when the tax returns, because the capacity to build advanced nuclear needs to be rebuilt.

5. CONCLUSIONS

Significant mitigation of greenhouse gas emissions will require advanced technologies. Technology penetration is a phenomenon that has been widely studied and 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 due to both the higher initial costs of new technologies and their slow penetration which extends reliance on the old technology. A variety of underlying theoretical explanations can explain at least some part of these observations: the old technology may hang around because of sunk costs; there may be monopoly pricing of the new technology; the technical resources to expand capacity may be limited; there may be learning; and there may be obstacles and barriers to expansion.

All of these factors likely play some role, under certain circumstances. However, empirically separating these factors can be very difficult. We can usually directly observe price, but determining the extent of rents existing in that price can be difficult. The eventual erosion of rents can lead to prices dropping over time. Short-run adjustment costs that are eventually 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 attempt to overcome barriers increases costs, and rents increase due to high demand that cannot be met in the short run.

Our modeling approach accounts for vintage capital, and so we can observe the role of sunk costs in preserving existing technology. We also had a technology-specific fixed factor in earlier versions of the model. Our goals with this report were to further develop that approach, link it to theoretical underpinnings, provide a sounder empirical foundation for parameterization of the structural components, and fully explore the behavior of the revised structure to assure that it operates consistent with observations about technology penetration. We continued the structure of a technology-specific factor of production, available in initially limited supply that grows as a function of the amount of production from the technology 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 about the existing ability to expand, not the amount of production in the previous period. We identified that, for penetration to behave as it did for the analogous historical technology, several parameters needed to be jointly determined. We then used those parameters to estimate the relationship between capacity to expand in time *t* and previous expansion rates. We added depreciation of the technology-specific factor, so if a technology is not used for some time it will face a new set of adjustment costs to scale up again.[2]

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[2] We often examine policy measures with a constant or increasing carbon price. 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. When forced with a carbon price high enough to create demand for the new technology, we see expansion rates very similar to those of nuclear power in the US from 1970 to 1985. Thus, the expansion is not unrealistic, as we have seen this rate in the past. We find that many people have difficulty believing expansion can be rapid, but very 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 is 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. With that price, and our new formulation, we see expansion of nuclear in the U.S. similar to the 1970 to 1985 period. 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. Additionally, other low-carbon alternatives may carve out some of the market. We tested some of these other technologies, by themselves and with all other represented technologies available. As with other studies we have done[3], the long-run winner is the technology with the lowest long-run cost. The particular reference formulation of our focus had a clear winner—advanced nuclear—but slight changes in the cost of advanced nuclear or its near competitors can easily change that result.

The formulation for new technology penetration creates adjustments costs and quasi-rents, has prices falling over time, and allows for 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 old capital, removing the oldest and most inefficient vintages first. This makes depreciation in our model essentially endogenous. Of course, building new capacity and prematurely retiring old capital is more costly, but with a great enough incentive, the existence of old vintages is not an absolute constraint on how fast we can transform the energy system. Many European countries with strong renewable generation incentives have other capacity that is idled or operating far below full capacity. Similarly, in the US, 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 instead depend on economic incentives. We

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[3] For instance, see Chen *et al.* (2011), Karplus *et al.* (2009), and Paltsev *et al.* (2005).

believe this approach is consistent with a large body of economic theory and reasoning, and leads to results that are consistent with observation.

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3. REFERENCES

Arrow, K., 1962: The economic implications of learning by doing. *Review of Economic Studies*, 29(3): 155–179.

Chen, Y.-H.H., J.M. Reilly and S. Paltsev, 2011: The prospects for coal-to-liquid conversion: A general equilibrium analysis. *Energy Policy*, 39(9): 4713-4725.

Edmonds, J. and J. Reilly, 1985: *Global Energy: Assessing the Future*. Oxford University Press, Oxford, UK, 317 pp.

EIA [U.S. Energy Information Administration], 2014: *Monthly Energy Review*, February 2014.

Geroski, P.A., 2000: Models of technology diffusion. *Research Policy*, 29: 603–62.

Gould, J.P., 1968: Adjustment costs in the theory of the firm. *Review of Economic Studies*, 354(1): 47–55.

Griliches, Z., 1957: Hybrid corn: an exploration of the economics of technological change. *Econometrica*, 25(4): 501–522.

Karplus, V.J., S. Paltsev and J.M. Reilly, 2009: Prospects for Plug-in Hybrid Electric Vehicles in the United States and Japan: A General Equilibrium Analysis. MIT Joint Program for the Science and Policy of Global Change *Report 172*, April, 32 p. (http://globalchange.mit.edu/files/document/MITJPSPGC_Rpt172.pdf).

Lucas, R.E. Jr., 1967: Adjustment costs and the theory of supply. *Journal of Political Economy*, 75(4): 321–334.

McFarland, J.R., J.M. Reilly, H.J. Herzog, 2004: Representing energy technologies in top-down economic models using bottom-up information. *Energy Economics*, 26: 685–707.

Narayanan, B.G. and T.L. Walmsley, 2008: *Global Trade, Assistance, and Production: The GTAP 7 database*. Center for Global Trade Analysis, Purdue University, West Lafayette, IN

Nordhaus, W.D., 1979: *The Efficient Use of Energy Resources*. New Haven, CT, Yale University Press, 161 pp.

Paltsev, S., J. Reilly, H.D. Jacoby, R.S. Eckaus, J. McFarland, M. Sarofim, M. Asadoorian and M. Babiker, 2005: The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Version 4. MIT Joint Program for the Science and Policy of Global Change *Report 125*, August, 72 p. (http://globalchange.mit.edu/files/document/MITJPSPGC_Rpt125.pdf).

Reilly, J.M., J.M. Melillo, Y. Cai, D.W. Kicklighter, A.C. Gurgel, S. Paltsev, T.W. Cronin, A.P. Sokolov and C. A. Schlosser, 2012: Using land to mitigate climate change: Hitting the target, recognizing the tradeoffs. *Environmental Science and Technology*, 46(11): 5672–5679, with supplemental information at: http://pubs.acs.org/doi/suppl/10.1021/es2034729/suppl_file/es2034729_si_001.pdf

Wright, T.P., 1936: Factors affecting the cost of airplanes, *Journal of Aeronautical Science*, 3: 122–128.

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