Learning or Lock-in: Optimal Technology Policies to Support Mitigation☆

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Abstract

We investigate conditions that amplify market failures in energy innovations, and suggest optimal policy instruments to address them. Using an intertemporal general equilibrium model we show that "small" market imperfections may trigger a several decades lasting dominance of an incumbent energy technology over a dynamically more efficient competitor, given that the technologies are very good substitutes. Such a "lock-in" into an inferior technology causes significantly higher welfare losses than market failure alone, notably under ambitious mitigation targets. More than other innovative industries, energy markets are prone to these lock-ins because electricity from different technologies is an almost perfect substitute. To guide government intervention, we compare welfare-maximizing technology policies including subsidies, quotas, and taxes with regard to their efficiency, effectivity, and robustness. Technology quotas and feed-in-tariffs turn out to be only insignificantly less efficient than first-best subsidies and seem to be more robust against small perturbations.

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1. Introduction

Whether technology policy is needed in addition to carbon pricing to combat global warming efficiently is still debated controversially. The straight-forward approach suggests that addional externalities – for example innovation spillovers – require additional instruments (Fischer and Preonas, 2010). In contrast, some economists have argued that existing, technology unspecific instruments like patents and research subsidies are sufficient to foster innovations in the energy sector (Nordhaus, 2009). In particular, there is concern that the social costs of technology-specific policies (due to rent-seeking, transaction costs and information problems) outweigh the benefits.

Our paper takes this debate as starting point by focussing on three questions: (i) Are innovation-related market failures in the energy sector different from other sectors in the economy, in particular with respect to possible technology lock-ins? (ii) Is it likely for the social costs of innovation externalities to exceed the social costs of technology-specific instruments? (iii) In how far do policies with stronger technology discrimination outperform more general policies?

The first of our questions is addressed in Gerlagh et al. (2008), within a model of patents for innovations. The dynamic inefficiency of limited patent lifetime leads to a bias towards innovations with pay-back time during the patent lifetime. As climate change is a stock-pollutant problem, the benefits of innovation in energy technologies materialize in the distant future when atmospheric carbon concentration is high. Hence, investments into energy innovation may be less than into other innovations. Several modeling studies incorporating carbon externalities and innovation address the second and the third question. With regard to the technological structure, Kverndokk and Rosendahl (2007) and Rivers and Jaccard (2006) are close to our model but do not consider intertemporal resource extraction and endogenous savings dynamics. Fischer and Newell (2008) use a partial two-period equilibrium model calibrated to the US economy for very moderate mitigation targets. Gerlagh et al. (2004) and Gerlagh and Lise (2005) analyze the impact of constant ad-hoc carbon taxes under (perfectly internalized) technological change within an intertemporal general equilibrium model. Finally, Popp (2004, 2006) studies the impact of R&D expenditures on carbon prices and mitigation costs within a social planner model. Grimaud et al. (2010) use a similar technological structure to analyze carbon pricing and R&D policies in a decentralized economy.

Another strand of research has focused on the high inertia of energy markets due to long investment cycles, increasing returns to scale and networt externalities (Unruh, 2000, 2002; Foxon and Pearson, 2007; Schmidt and Marschinski, 2009). This strand is partly based on the concept of 'lock-in' – a market dominance of an inferior incumbent technology at the expense of a superior contender technology (Arthur, 1989, 1994). Well-known examples include keyboard layout and video recorders (David, 1985; Cusumano et al., 1992) but also energy technologies (Cowan and Hulten, 1996; Islas, 1997). Due to the inertia of the energy sector, carbon pricing may have only little impact on investments and innovation, making additional instruments necessary.

We differ from these models in analyzing the possibility and intensity of technology lock-ins within an intertemporal general equilibrium model. Furthermore, we provide an extensive policy analysis considering first-best and several welfare maximzing second-best instruments. In the model we describe in Sec. 2, lock-ins rise due to imperfections in the innovation process and the competition between technologies that are almost perfect substitutes: Technological progress in the learning carbon-free sector is driven by learning-by-doing with intra-sectoral knowledge spillovers. We furthermore explore the possibility of high effective discount rates in the learning technology sector. The discount rate mark-ups might evolve from risk premiums due to uncertainty and imperfect commitment about future climate policy which effects the profitability of early learning-by-doing. We consider three energy technologies: (i) fossil energy, (ii) a learning carbon-free energy where significant learning-by-doing occurs as expected for many renewable energy technologies, and (iii) a mature (non-learning) carbon-free energy where technology has already experienced past learning and considerable up-scaling. Candidates for the mature carbon-free energy technology are nuclear power or hydropower.

We find that a possible lock-in into the inferior (non-learning) technology can be very costly compared to the costs of the innovation market failure alone, i.e. when the inferior technology would not be available at all (Sec. 3). Incomplete appropriation of the gains of innovation generally leads to higher prices. This is the case for all technology development that exhibits spillovers, but given sufficient product differentiation, consumers will buy new products even at higher prices. Impacts of spillovers will be small because the demand of variety-loving consumers triggers further technological progress and cost reductions. Electricity, however, is a very homogeneous good, and thus price competition dominates the market. The currently cheapest technology crowds out other technologies that may be dynamically more efficient. Hence, due to the very good substitutability between energy from technologies with different innovation potential markets suffer more from spillovers than many other innovative industries.

Due to the good substitutability, seemingly small market failures have a considerable impact on the energy mix, welfare and carbon prices. We therefore analyze the performance of different policies in preventing lock-ins by calculating optimal first-best and second-best policy instruments (Sec. 4). We distinguish the following policy instruments: (i) subsidies for the learning carbon-free technology; (ii) quotas (i.e. portfolio standards) with different degree of technology discrimination, (iii) feed-in-tariffs, (iv) taxes on the mature carbon-free technology, and (v) second-best carbon pricing. We find that only the subsidy achieves the social optimum, but feed-in-tariffs and quotas specifically targeting the learning technology only incur very small welfare losses. The other instruments exhibit larger welfare losses up to the point of showing no improvement compared to the laissez-faire market equilibrium with a carbon price only. Limited commitment and political-economy aspects motivate our analysis of policy stimuli, i.e. subsidies that are only available for a certain time (Sec. 5). It turns out, that an optimal subsidy stimulus of only a few decades reduces consumption losses substantially. Finally, by considering small perturbations of the optimal policies we find that the optimal feed-in-tariff and quota turn out to be fairly robust, while a deviation from the optimal subsidy of as little as one percent may render the subsidy ineffective in preventing a lock-in (Sec. 6).

2. The model

We use an intertemporal general equilibrium model that distinguishes household, production, fossil resource extraction and several energy sectors.[1] In addition to energy generated by combustion of fossil resources, there are two carbon-free energy sources: a mature energy sector, and a more expensive yet learning competitor technology. A further sector extracts fossil resources from a finite resource stock. For simplicity, we use labor only as input in the production sector and not in the energy sector as only a minor share of the labor force is allocated to the energy sector (in EU-27 approx. 3% (Eurostat, 2009)). Furthermore, capital and fuel costs clearly dominate operation and maintenance costs (which include labor costs) for all major energy generation technologies (IEA, 2010, Tab. 6.2). We assume standard constant elasticity of substitution (CES) production functions stated in detail in the appendix. The economic sectors are in a competitive market equilibrium within a closed economy. Global warming policy is addressed by a carbon bank – an independent institution that manages a given carbon (permit) budget intertemporally. The government, which anticipates the equilibrium response of the economy, imposes policy instruments on the economy to maximize welfare. Fig. 1 gives an overview of the equilibrium and the role of the government.

[1]The model is built to deal with a large set of climate policy issues like delayed carbon pricing, supply-side dynamics and double-dividend aspects which go beyond the research question of this paper.

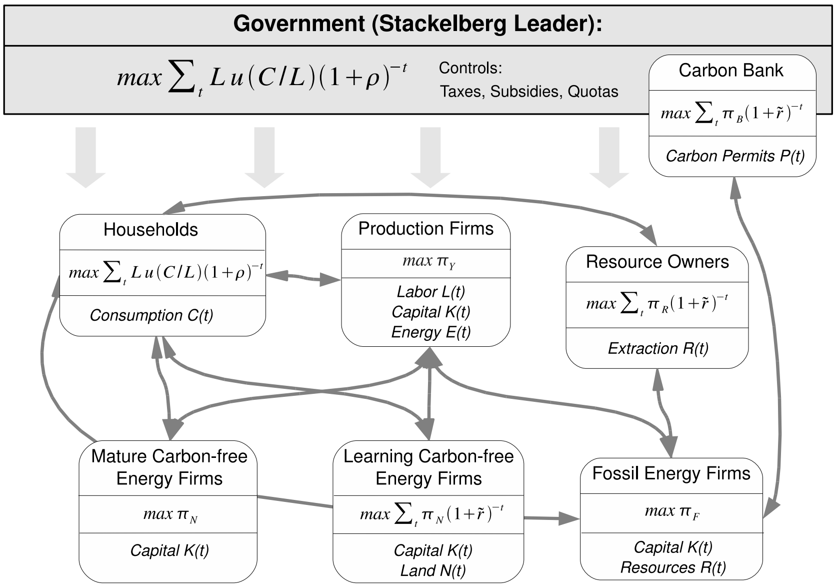


Figure 1: Overview of the modeling framework.

2.1. The decentralized economy

Here, we concentrate on the description of the agents' optimization problem and the interplay with government's policies; the mathematical description of production technology as well as the derivation of the first-order conditions can be found in Appendix A and Appendix B, respectively.

The representative household

We assume a representative household with the objective to maximize the sum of discounted utility U, which is a function of per-capita consumption C/L:[2]

$$\max_{C_t} \quad \sum_{t=0}^{T} (1+\rho)^{-t} L_t \mathbf{U}\left(C_t/L_t\right)$$

where ρ is the pure rate of time preference.

The household owns labor L, capital stocks K_j, and the firms, and therefore receives the factor incomes wL and rK_j, as well as the profits of all firms π_j, where $j \in \{Y, F, R, N, L\}$ enumerates the sectors (consumption good sector Y, fossil energy sector F, resource extraction sector R, mature (non-learning) carbon-free energy sector N, learning carbon-free energy sector L). Wage rate w, interest rate r, profits π_j and lump-sum transfers from the government Γ are taken as given from the household's perspective. The household is assumed to take the depreciation of capital at rate δ into account in its investment decision.[3]

[2] In the following, we often omit the time-index variables t in the main text to improve readability.

[3] Imposing the depreciation dynamics on the saving-side (households) instead of the investment-side (firms) is done for technical reasons. It does not change investment behavior but simplifies the capital dynamics within the economic model.

The household therefore faces the following constraints:

$$C_t = w_t L_t + r_t K_t - I_t + \pi_t + \Gamma_t \tag{1}$$

$$K_t = \sum_j K_{j,t}, \qquad I_t = \sum_j I_{j,t}, \qquad \pi_t = \sum_j \pi_{j,t} \tag{2}$$

$$K_{j,t+1} = K_{j,t} + I_{j,t} - \delta K_{j,t}, \qquad K_0 \text{ given} \tag{3}$$

The production sector

The representative firm in the consumption good sector maximizes its profit π_Y by choosing how much capital K_Y and labor L to rent, and how much energy to purchase from the various sources: fossil fuels sector, mature and learning carbon-free energy sectors (E_F, E_N, and E_L, respectively).[4] It has to consider the production technology $\mathbf{Y}(\cdot)$ and the given factor prices for capital (r), labor (w), fossil (p_F), mature carbon-free (p_N) and learning carbon-free (p_L) energy (the price of consumption goods is set to one). Furthermore, the production sector may need to consider government intervention in form of a feed-in tariff ς_F. The feed-in-tariff takes the form of a subsidy but is cross-financed by a tax τ_F on energy from the fossil and the mature carbon-free technology energy sectors.

$$\begin{aligned}\pi_{Y,t} = \mathbf{Y}(K_{Y,t}, L_t, E_{F,t}, E_{L,t}, E_{N,t}) - r_t K_{Y,t} - w_t L_t - (p_{F,t} + \tau_{F,t})E_{F,t} - (p_{L,t} - \varsigma_{F,t})E_{L,t} \\ - (p_{N,t} + \tau_{F,t})E_{N,t}\end{aligned} \tag{4}$$

The nested CES production function $\mathbf{Y}(\mathbf{Z}(K_Y, A_Y L), \mathbf{E}(E_F, \mathbf{E_B}(E_L, E_N)))$ combines a capital-labor intermediate with energy, assuming an elasticity of substitution of σ_1. Capital and labor are combined to an intermediate input Z using the elasticity of substitution σ_2; similarly, fossil energy and carbon-free energy are combined to final energy with the elasticity of substitution σ_3. Finally learning and mature carbon-free energy are combined to aggregate carbon-free energy E_B using the elasticity of substitution σ_4.[5] Population L and productivity level A_Y grow at an exogenously given rate.

Additionally, the government may impose quotas to influence the energy portfolio. Three quotas are included, differing with respect to how specifically they can foster energy from the learning carbon-free technology: Quotas of the first kind, ψ_L^T, set a minimum share of energy from the learning carbon-free (E_L) relative to total energy use. The second type ψ_L^B requires a minimum share of E_L relative to all carbon-free energy. Finally, the quota ψ_B^T determines the minimum share of energy from either carbon-free technology relative to total energy use.

$$E_{L,t} \geq \psi_{L,t}^T (E_{F,t} + E_{N,t} + E_{L,t}) \tag{5}$$

$$E_{L,t} \geq \psi_{L,t}^B (E_{N,t} + E_{L,t}) \tag{6}$$

$$E_{L,t} + E_{N,t} \geq \psi_{B,t}^T (E_{F,t} + E_{N,t} + E_{L,t}) \tag{7}$$

The fossil energy sector

The fossil energy sector maximizes profits π_F with respect to capital K_F and fossil resource use R, subject to the CES production technology E_F and given factor prices for fossil energy, capital and resources

[4] The intertemporal profit maximization problem of the production, fossil energy and mature carbon-free energy sector boils down to a static problem.

[5] We do not integrate fossil, learning and non-leaning energy on the same CES-level because we assume that substitutability between the two carbon-free energies E_L and E_N should be higher than between a carbon-free and a fossil energy E_F and E_L. This is due to the fact that carbon-free energy is usually considered in the electricity sector while fossil energy covers electric as well as non-electric energy consumption.

(p_R). Additionally, it may consider a carbon tax τ_R or carbon permit price p_C:

$$\pi_{F,t} = p_{F,t}\mathbf{E_F}(K_{F,t}, R_t) - r_t K_{F,t} - (p_{R,t} + \tau_{R,t} + p_{C,t})R_t \tag{8}$$

The fossil resource sector

The fossil resource sector extracts resources from an exhaustible stock S using capital K_R. Its objective is to maximize the sum of profits over time, discounted at the rate $r_t - \delta$[6]:

$$\max_{R_t} \sum_{t=0}^{T} \pi_{R,t} \Pi_{s=0}^{t} \left[1 + (r_s - \delta)\right]^{-1}$$

Resource owners rent the capital used in the extraction process at the market interest rate. The productivity of capital $\partial\mathbf{R}/\partial K_R$ decreases with ongoing depletion of the exhaustible resource stock (Rogner, 1997; Nordhaus and Boyer, 2000). The resource sector, therefore, has to consider the following constraints:

$$\pi_{R,t} = p_{R,t}\mathbf{R}(S_t, K_{R,t}) - r_t K_{R,t} \tag{9}$$

$$S_{t+1} = S_t - R_t, \qquad S_t \geq 0, \qquad S_0 \text{ given} \tag{10}$$

The learning carbon-free energy sector

The learning carbon-free sector maximizes profit π_L under capital input and with a fixed amount of land N. It considers interest rate, the price of the learning carbon-free energy as well as an output subsidy τ_L as given and may additionally consider a risk premium $v \geq 0$ which effectively increases the discount rate above the market interest rate. The risk premium reflects uncertainty and imperfect commitment regarding the stringency of future mitigation policies (and, thus, carbon prices). Another rationale for imperfect foresight is provided by Rivers and Jaccard (2006) who argue that the variance of learning investments is larger than for other investments. Risk premiums evolve if capital or insurance markets are not perfect (i.e. due to asymmetric information) or investors are risk-averse. As the learning-by-doing dynamics implies an additional inertia through the knowledge stock, the learning sector is more vulnerable to uncertainty than non-learning sectors.[7] The optimization problem of the sector reads:

$$\max_{K_{L,t}} \sum_{t=0}^{T} \pi_{L,t} \Pi_{s=0}^{t} \left[1 + (r_s + v - \delta)\right]^{-1}$$

$$\pi_{L,t} = (p_{L,t} + \tau_{L,t})\mathbf{E_L}(\mathbf{A_L}(H_t)K_{L,t}, N) - rK_L \tag{11}$$

$$H_{t+1} = H_t + (E_{L,t} - E_{L,t-1}), \qquad H_0 \text{ given} \tag{12}$$

The productivity $\mathbf{A_L}$ depends on cumulative output H according to $A_L = \frac{A_{L,max}}{1+\left(\frac{\Omega}{H}\right)^{\gamma}}$ and converges to $A_{L,max}$ when $H \to \infty$. This formulation is based on Arrows's learning-by-doing approach (Arrow, 1962) and widely used in energy economic models (e.g. Kverndokk and Rosendahl, 2007; Fischer and Newell, 2008).

[6] As the interest rate already reflects depreciation of capital due to our formulation of the representative household (see Eqs. 1–3), consumption has to be discounted by the interest rate net of depreciation.

[7] By the same token, imperfect commitment also concerns the fossil resource owners. Under a mitigation policy, however, high carbon prices dilute the intertemporal rent dynamics of the fossil resource sector. Fossil resource rents become almost zero under ambitious mitigation targets. Introducing high risk premiums does therefore not affect the resource extraction which is dominated by the carbon price (see Kalkuhl and Edenhofer, 2010, for an analytical analysis).

Ω is a scaling parameter, and γ is the learning exponent. It is related to the learning rate lr by $\gamma = -\ln(1-lr)/\ln 2$, which measures by how much productivity increases when cumulative capacity is doubled.

As shown in Appendix B, the firms' internal value of learning μ_t is given by $\mu_{t-1} = \frac{1-\phi}{1+r_t+v+\delta}(p_{L,t} + \tau_{L,t} + \mu_t)\frac{\partial \mathbf{E_L}}{\partial H_t}$. The spillover rate $\phi \in [0, 1]$ is introduced to indicate how much of the learning-by-doing effect is anticipated by the individual firm. This approach is in more detail explained in Fischer and Newell (2007) and relies on the learning-by-doing dynamics elaborated in Spence (1984) and Ghemawat and Spence (1985). It is consistent with econometric studies on external learning-by-doing spillovers which suggest that learning does not only depend on the individual firm's cumulative production but also – to some extent – on the other firms' cumulative output (Irwin and Klenow, 1994; Barrios and Strobl, 2004). From a social planner's perspective, all externalities are internalized and spillovers are irrelevant as cumulative output determines learning. In contrast, in a decentralized economy, only a share $(1 - \phi)$ of learning is appropriated by the firm. Hence, ϕ describes an incentive problem.[8]

The learning carbon-free sector covers mainly renewable energy technologies requiring large amounts of land. As best sites (regarding solar radiation, wind speed etc.) are used first, marginal costs increase with ongoing deployment (if productivity is held constant) (cf. Edenhofer et al., 2011, Ch. 10). The learning-by-doing effect may offset these diminishing returns in particular for the early deployment phase.

The mature carbon-free energy sector

The mature carbon-free sector sector maximizes profit π_N subject to capital input K_N:

$$\pi_{N,t} = (p_{N,t} - \tau_{N,t})\mathbf{E_N}(K_{N,t}) - r_t K_{N,t} \tag{13}$$

It takes interest rate and energy price as given and has to consider an output tax τ_N on energy generation if it is imposed by the government. Being a rather generic sector, we employ an AK-technology function where a change of the productivity level A_N changes the marginal productivity of capital.

The carbon bank

We assume that society's mitigation goal is formulated as an upper constraint on cumulative carbon extraction – a so-called carbon budget –, and that the government has appointed an institution, the carbon bank, to manage the corresponding carbon permits efficiently. Equivalently, the government could issue all available carbon permits to the market and allow for free intertemporal permit trade. The carbon bank has the objective to maximize the revenues π_C from a given carbon budget $B_0 \geq 0$. It decides how much carbon permits P to issue in each time period. As each unit of carbon R extracted by the fossil resource sector requires the purchase of one carbon permit, it follows that $P = R$.

$$\max_{R_t} \sum_{t=0}^{T} \pi_{B,t} \Pi_{s=0}^{t} \left[1 + (r_s - \delta)\right]^{-1}$$

$$\pi_{B,t} = p_{C,t} R_t \tag{14}$$

$$B_{t+1} = B_t - R_t, \qquad B_t \geq 0, \qquad B_0 \text{ given} \tag{15}$$

Similar to an exhaustible resource, the carbon budget is a stock of permits which can be used throughout the planning horizon. The resulting carbon price set by the bank therefore follows the Hotelling rule.

[8] A spillover rate of 100 percent implies that firms perceive the productivity increase as fully exogenous. In contrast, a 0 percent spillover rates implies a perfect internalization of learning by firms. Learning then is a pure private good.

While there are some economists arguing for such an independent institution to increase commitment and reduce regulatory uncertainty (Barnes et al., 2008; Brunner et al., 2011) , we use this approach mainly for didactical reasons. If there are no further externalities, such a Hotelling price path leads always to an efficient abatement profile (Goulder and Mathai, 2000; Kalkuhl and Edenhofer, 2010). When market failures in other sectors, however, cannot be corrected, it can be beneficial to deviate from the Hotelling price path. As we want to study the potential of such second-best carbon pricing seperately (Sec. 4.5), we use the Hotelling carbon price as default implementation of the government's mitigation policy.

2.2. *Equilibria of the economy*

In this study, we distinguish three types of equilibria for the economy outlined above. The social optimum given by the choice of a benevolent social planner serves as the benchmark equilibrium. In the Stackelberg equilibria, a welfare-maximizing government selects the optimal trajectory of policy instruments from a pre-defined subset of available policy instruments given the implicit reaction functions of the economic sectors (see for example Dockner et al. (2000, p. 111)). Thirdly, we consider a laissez-faire market equilibrium with no government intervention.

Social optimum

The intention of considering the social optimum of our model economy, is to measure the extend to what second-best policies fall short of the first-best. The socially optimal allocation is determined by solving the welfare maximizing problem subject to investment, fossil extraction, carbon budget, technology and macroeconomic budget constraints according to:

$$\max_{\{K_{j,t}\}} \quad \sum_{t=0}^{T} (1+\rho)^{-t} L_t \mathbf{U}(C_t/L_t) \tag{16}$$

subject to Eqs. 2, 3, 10, 12, 15, A.1–A.13

and $C_t = Y_t - I_t$

Stackelberg equilibrium

The first-order conditions of the sectors described above (and spelled out in Appendix B) define an intertemporal market equilibrium for given policy instruments. The government considers all technology constraints, budget constraints, equations of motion and first-order and transversality conditions and chooses policy instruments to maximize welfare (see Fig. 1).

Furthermore, the government balances incomes and expenditures in any time with households' lump-sum tax Γ. In case of the feed-in-tariff, the subsidy ς_F for the learning energy is financed by the tax for fossil and mature energy τ_F.

$$\Gamma_t = \tau_{N,t} E_{N,t} - \tau_{L,t} E_{L,t} + \tau_{R,t} R_t + \pi_{B,t} \tag{17}$$

$$\varsigma_{F,t} E_{L,t} = \tau_{F,t}(E_{F,t} + E_{N,t}) \tag{18}$$

Hence, the government's optimization problem is described by:

$$\max_{\Theta} \quad \sum_{t=0}^{T} (1+\rho)^{-t} L_t \mathbf{U}(C_t/L_t) \tag{19}$$

subject to Eqs. 1–15, 17–18 , A.1–A.13, B.1–B.20

$\Theta = \{\tau_{L,t}, \tau_{N,t}, \tau_{R,t}, \varsigma_{F,t}, \psi^T_{L,t}, \psi^B_{L,t}, \psi^T_{B,t}\}$ is the set of government policies. For the purpose of our paper it will be convenient to restrict policies to a single instrument while all other instruments are set to zero.

Laissez-faire equilibrium

The laissez-faire market equilibrium is a special case of the Stackelberg equilibrium. Here we set all policy instruments to zero – thus, $\Theta \equiv \mathbf{0}$. Note that this does not include climate policy, as we always assume that climate policy in form of a carbon budget is implemented by the carbon bank setting p_C.

2.3. Calibration and implementation of the model

Model parameters are chosen to reproduce a global-economy baseline from a model comparison project in the social optimum without any carbon budget (Edenhofer et al., 2010). We use a carbon budget of 450 GtC for the mitigation scenario. This limits global warming to 2°C above the preindustrial level with a probability higher than 50 percent (Meinshausen et al., 2009). The endogenous fossil energy price starts at 4 ct/kWh in 2010 and increases up to 8 ct/kWh in 2100 (under business as usual) due to increasing extraction costs. The mature carbon-free technology refers to nuclear or hydropower as their learning rates are very low (1-9%) compared to renewable energy technologies like solar, wind and ethanol (8-35%) (IEA, 2000; McDonald and Schrattenholzer, 2001). The parameters describing the non-learning carbon-free technology are chosen to reproduce constant energy costs at 15 ct/kWh. This is at the upper bound of IEA's cost estimate for nuclear and gas (IEA, 2010).[9] The recent IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation cites 41 learning rate estimations for renewable energy ranging from 0% to 45% with a mean of 16.4% (Edenhofer et al., 2011, Ch. 10, Tab. 10-10). For the learning carbon-free energy we will mainly consider two parameterizations: a moderate learning parameterization with a 17% learning rate and 9 ct/kWh generation costs in 2100 (standard parameterization); and a high learning scenario with a 25% learning rate and 5 ct/kWh generation costs in 2100. Initially, the average costs are around 28 ct/kWh. The discounted consumption losses due to the consideration of the carbon budget (i.e. the mitigation costs) are 1.7% for the 25% learning rate and 4.0% for the 17% learning rate scenario.

The climate externality can be easily incorporated by a fixed carbon budget consistent with a certain temperature target. The magnitude of the innovation market failure, however, i.e. learning spillovers and risk premiums, seems to be difficult to quantify. Several econometric studies confirm the existence of learning-by-doing spillovers in the manufacturing and semiconductor industry; the estimated spillover rates are usually between 20% and 60% (Irwin and Klenow, 1994; Gruber, 1998; Barrios and Strobl, 2004).[10] The literature on R&D and innovation externalities indicates that social rates of return into innovations exceed the private rates of return by the fourfold (cf. Nordhaus, 2002). As only one fifth of the value of innovation can be appropriated by the innovator, the resulting spillover rate is 80%. In our model, however, we do not consider R&D externalities explicitly to avoid the interference of too many innovation externalities. In order to still account for the high magnitude of innovation externalities, we chose a learning-by-doing spillover rate of 60%, but we consider also lower and higher values. Due to the lack of empiric evidence, we assume that the risk premium is zero ($\nu = 0$). Nevertheless, we elaborate the impact of deviations from these values in Sec. 3. We set $\sigma_3 = 3$, implying a good substitutability between fossil and carbon-free energy. As the carbon-free energy sector covers mainly electric energy, we assume a high

[9] We use a small negative external learning rate in Eq. A.13 of $g_N = -0.4\%$ to obtain constant costs for the non-learning carbon-free energy because the interest rate falls over time. A negative learning rate can also be justified by increasing resource or site scarcities or increasing safety standards which raised capital costs for nuclear power plants in the past (Du and Parsons, 2009). However, we ran our model also for $g_N = 0$ and did not observe qualitative differences in the economic dynamics.

[10] These spillover rates refer to countries that already have a comprehensive patent legislation. The knowledge transfer into countries with imperfect patent legislation should therefore be higher.

substitutability and set $\sigma_4 = 21$.[11]

The optimization problems as defined by (16) and (19) form a non-linear program (NLP) which is solved numerically with GAMS (Brooke et al., 2005). All parameters of the model are listed in Appendix D. Additional figures with several model results can also be found in the supplementary material.

3. The lock-in effect

In this section, we compare the laissez-faire market equilibrium (with Hotelling carbon price) with the optimal solution. In order to compare the dynamic outcome of several equilibria we introduce two metrics: (i) *consumption losses* refer to the relative deviation of discounted consumption from the social optimum under the same technological parameters (we use a 3% discount rate); (ii) the *delay* of learning carbon-free generation (compared to the social optimum) is measured by the difference in years until the learning carbon-free energy achieves a share of 10% in the total energy.

3.1. Why the energy sector is highly vulnerable to lock-ins

Fig. 2a shows carbon-free energy generation and costs in the social optimum (which is equivalent to the laissez-faire equilibrium for $\phi = 0$ and $\nu = 0$, i.e. without market failures) for two different elasticities of substitution σ_4 between E_L and E_N. Energy from learning carbon-free technology is used significantly, although its average unit costs are initially higher compared to those of the mature technology. But when the learning curve and spillovers are internalized, future cost reductions for the learning technology are fully anticipated. Hence, the learning technology dominates the mature carbon-free technology.

Fig. 2b shows the generation in the laissez-faire equilibrium with intrasectoral learning spill-overs. The spillovers lead to an imperfect anticipation of the future benefits of learning-by-doing. For a low elasticity of substitution ($\sigma_4 = 3$), the laissez-faire outcome does not differ significantly from the optimal solution. For a higher elasticity of substitution, however, this changes fundamentally: The learning carbon-free technology is delayed significantly and energy demand is met by energy from the mature carbon-free technology. This has a clear and intuitive explanation: a low elasticity creates a niche demand for the learning carbon-free energy even when it is more expensive than the mature carbon-free. Driven by such a niche demand the learning sector may gain experience and reduce production costs until it becomes competitive. But at high elasticities of substitution niche demand vanishes. In this case, the technology with the lowest market price wins.

Fig. 2 shows that a dynamically inferior technology dominates the dynamically efficient technology for many decades. The energy sector "locks-in" into the mature energy which competes with a learning technology that cannot internalize the value of future learning appropriately into its price. The energy sector is highly vulnerable to lock-in because electricity is an almost perfect substitute for consumers. In contrast, many innovations in the manufacturing or entertainment electronic sector provide a new product different from existing ones (e.g. flat screens vs. CRT monitor). The low substitutability implies a high niche demand and, thus, provokes ongoing learning-by-doing although considerable spillovers exist and market prices are distorted.

[11] IAMs use different elasticities of substitutions between energy technologies. Some models assume perfect substitutability (Messner, 1997; Kverndokk et al., 2004; Edenhofer et al., 2005; Kverndokk and Rosendahl, 2007), others use values of 0.9 (Goulder and Schneider, 1999), 2 (van der Zwaan et al., 2002; Böhringer and Rutherford, 2008) or 8.7 (Popp, 2006). Gerlagh and Lise (2005) use a variable elasticity of substitution ranging from 1 to 4. IAMs with differentiation between electric and non-electric energy usually assume high (Cian et al., 2009) or perfect (Manne et al., 1995; Leimbach et al., 2010) substitutability between electric energy technologies while using lower elasticities of substitution between electric and non-electric energy.

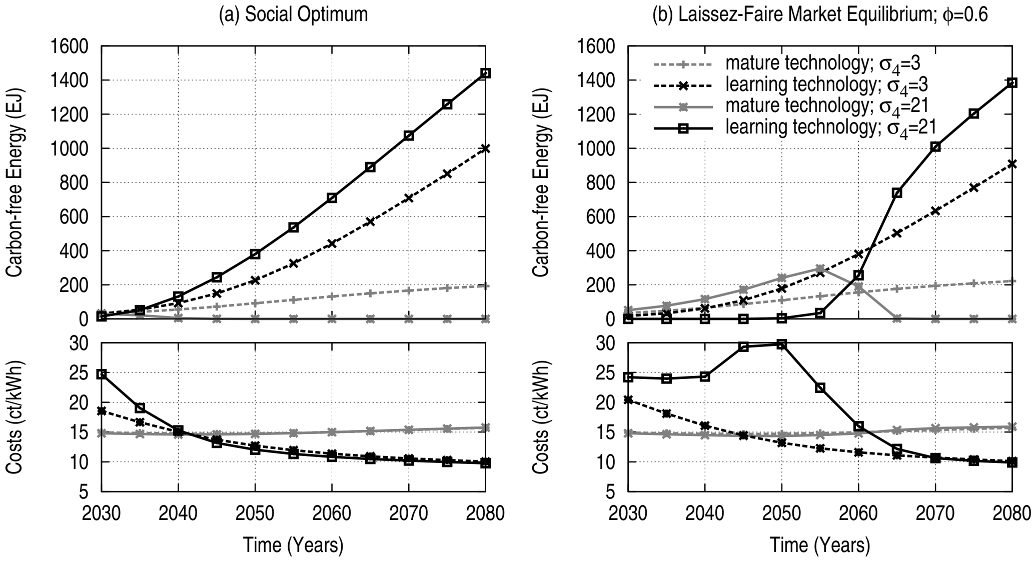


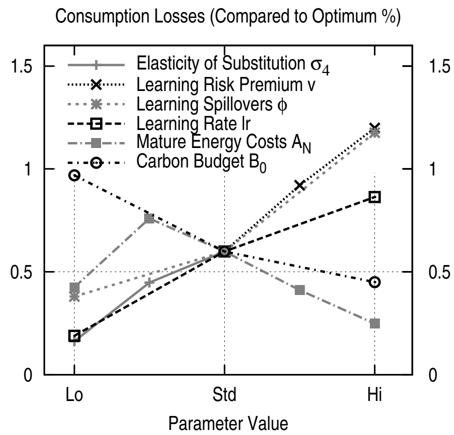
Figure 2: Carbon-free energy generation and costs (2030-2080) for two different elasticities of substitution ($\sigma_4 \in \{3, 21\}$) between learning and mature carbon-free energy: (a) optimal outcome and (b) laissez-faire equilibrium with 60 percent spillovers and no additional technology policy instruments.

3.2. Economic impacts of lock-ins

In our standard parametrization the consumption losses due to the lock-in are 0.6%. Fig. 3 shows how this value changes if several parameters are modified. As we already argued, a high elasticity of substitution is an important condition for a lock-in to occur. A second important condition is that the generation cost of mature carbon-free energy is at a critical level: In the case of $0.2 \leq A_N \leq 0.25$, which corresponds to production costs between 12 and 15 ct/kWh, the mature carbon-free energy is an attractive option before learning has started and an expensive one after considerable learning took place. Thirdly, there must exist a market failure in the learning carbon-free sector, which is introduced by the spillover rate or the discount rate mark-up (risk premium). Beside these three necessary conditions, Fig. 3 indicates that learning rates and mitigation targets influence the magnitude of consumption losses. Hence, ambitious climate targets (like 200 GtC) become more expensive if energy markets do not perform well although an efficient carbon pricing instrument is applied.

Generally we can distinguish two sources of welfare losses. First, the intertemporally suboptimal deployment of the learning carbon-free energy causes consumption losses even if no competitive mature carbon-free technology is available (and no lock-in occurs). A doubling of the mature carbon-free production costs (i.e. $A_N = 0.1$) for example, makes the learning technology competitive even if high spillovers exist. In this case the mature carbon-free energy generation is virtually zero. The resulting consumption losses due to spillovers are smaller than 0.3% and there is almost no delay in learning carbon-free generation (< 5 years). In contrast, the simply existence of a competitive non-learning technology delays the learning technology deployment due to lock-in substantially and reduces consumption even more. This second kind of welfare loss is more severe than the impact of suboptimal deployment in a world where no non-learning carbon-free energy is available.

In Fig. 3 only one parameter is varied at a time. This ignores that changes in multiple parameters may cancel each other out or may mutually reinforce their effect on the technology lock-in. Indeed, Tab. 1 shows



Parameter		Lo	Std	Hi
Elasticity of Substitution	σ_4	3	21	
Learning Risk Premium	v		0.0	0.15
Learning Spillovers	ϕ	0.5	0.6	0.75
Learning Rate	lr	0.1	0.17	0.25
	Ω	20000	200	60
	$A_{L,\mathrm{max}}$	0.6	0.6	0.8
Mature Energy Cost	A_N	0.3	0.2	0.1
Carbon Budget	B_0	200	450	700

Figure 3: Consumption losses due to lock-in for several parameter variations around the standard parameterization.

	lr	ϕ	v	B_0	σ_4	Consumption losses	Delay (years)	Initial carbon price (1=optimal)
1	17%	25%	15%	450	21	0.4%	16	1.16
2	17%	25%	15%	200	21	0.7%	20	1.14
3	17%	50%	15%	450	21	0.9%	27	1.23
4	17%	50%	15%	200	21	1.4%	35	1.17
5	17%	75%	10%	450	16	1.5%	40	1.27
6	17%	75%	10%	200	16	2.2%	50	1.18
7	25%	25%	15%	450	21	0.6%	16	1.51
8	25%	25%	15%	200	21	0.7%	13	1.49
9	25%	50%	15%	450	21	1.1%	24	1.83
10	25%	50%	15%	200	21	1.3%	22	1.77
11	25%	75%	15%	450	13	2.0%	34	2.27
12	25%	75%	15%	200	13	3.4%	41	2.09
13	25%	100%	0%	200	13	8.0%	87	2.15

Table 1: Parameter values that provoke lock-ins: Impact on consumption losses, delay of achieving 10% learning carbon-free energy share and initial carbon price.

further parameter sets that cause particularly severe lock-ins with consumption losses greater than one percent. Even if spillovers are only 25 percent, the existence of an additional high risk premium postpones learning carbon-free energy generation and provokes consumption losses of 0.7% under a carbon budget of 200 GtC. A (rather theoretically) upper bound for the consumption losses is given for the case where spillovers are 100% and the carbon budget is very ambitious. In this case, consumption losses increase to 8.0%.

The lock-in does not only provoke consumption losses and delayed learning carbon-free generation, it furthermore modifies the Hotelling carbon price by changing the interest rate and the initial carbon price. While the impact on the interest rate is small, the initial carbon price level increases by 22 percent to meet the carbon budget in our standard parameterization. The medium-learning parameterizations in Tab. 1 show similar figures. In contrast, if the learning rate is high the initial carbon price increases by 49–127 percent compared to the case where no market failures exist.

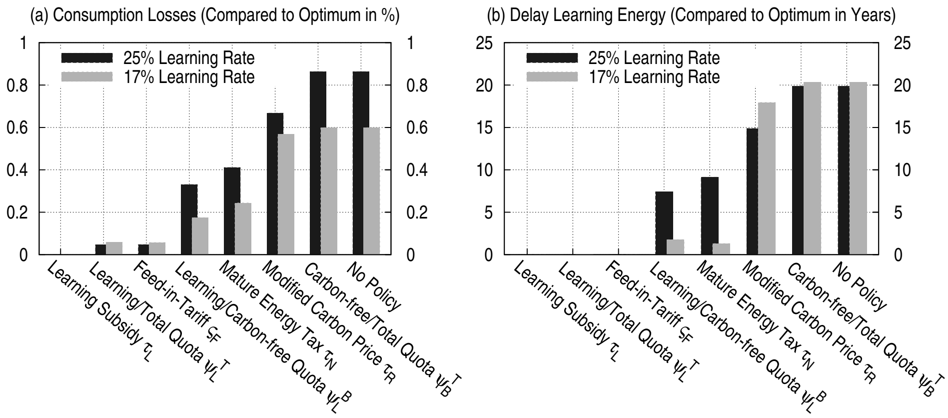


Figure 4: Performance of several policy instruments under the Stackelberg equilibrium: (a) Consumption losses relative to the optimal solution; (b) delay to achieve a share of 10% learning carbon-free energy.

4. Optimal policy instruments

The previous section showed that in absence of policy intervention there are significant consumption losses higher than one percent possible due to severe temporary lock-ins. This motivates the analysis of several policy instruments to prevent lock-ins and reduce welfare losses. We focus on two illustrative parameter settings: a high learning scenario (25% learning rate) and a medium learning case (17% learning rate). For a low learning rate (8%), innovation market failures cause only very small consumption losses (Fig. 3). As in this case technology policies hardly increase welfare, we omit the policy analysis for the 8% learning rate case. We calculate optimal policies for a 60% spillover rate and zero risk premiums; considering cases with lower spillover rates and additional risk premium leads to similar results.[12]

In the Stackelberg equilibrium, we calculate the welfare maximizing time paths of (i) subsidies for the learning technology, (ii) feed-in-tariffs, (iii) carbon-free energy quotas, (iv) mature carbon-free taxes, and (v) a modified carbon price. The instruments differ in two aspects: First, they comprise a different degree regarding the technology discrimination: While the subsidy or feed-in-tariffs target the learning technology only, carbon prices and carbon-free quotas do not discriminate between carbon-free technologies. Secondly, they rely on different financing mechanisms: The financial flows of subsidies and taxes are balanced by lump-sum transfers; in contrast, feed-in-tariffs and quotas are income-neutral.

The performance of each of these instruments with respect to consumption losses and delay of learning carbon-free deployment is shown in Fig. 4. In the following we discuss these instruments in detail.

4.1. *Subsidy for learning carbon-free energy*

Due to the learning-by-doing spillovers, the social value of the learning technology is higher than its private value. By equating the learning technology sector's first-order conditions of the optimal economy (without spillovers) with the imperfect economy, we can calculate the optimal subsidy that internalizes the value of learning and achieves an efficient allocation (see Appendix C). The optimal subsidy $\tau_{L,t} = \mu_t^*\left(1 - \frac{(1-\phi)(1+r_{t+1}+\delta)}{1+r_{t+1}+\nu+\delta}\right)$ basically adjusts the output price p_L by adding some fraction of the socially optimal value of learning μ_t^* (which can be obtained from the efficient intertemporal market equilibrium or the

[12]See the supplementary material for optimal learning subsidies for paramter choices according to Tab. 1.

social planner optimum). Obviously, the subsidy increases in ϕ and in ν. It converges to the maximum μ_t^* if $\phi \to 1$ or $\nu \to \infty$ and converges to zero if $\phi \to 0$ and $\nu \to 0$. In case of zero discount rate mark-ups ($\nu = 0$), the subsidy simplifies to $\tau_{L,t} = \phi\mu_t^*$; in case of zero spillovers and positive risk premiums, however, the optimal subsidy becomes $\tau_{L,t} = \mu_t^* \left(\frac{\nu}{1+r_{t+1}+\nu+\delta}\right)$. As the output subsidy is lump-sum financed, it does not cause further distortions in the economy.

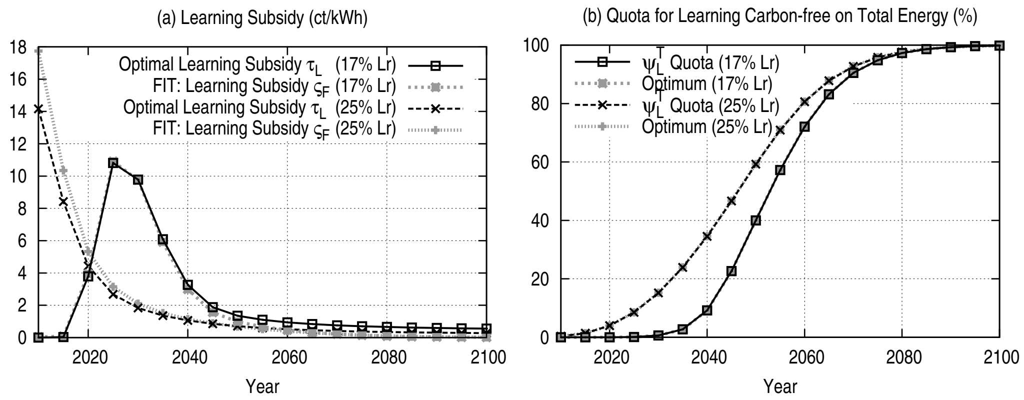


Figure 5: (a) Optimal subsidy and feed-in-tariff and (b) optimal quota for learning carbon-free energy on total energy.

The numerical calculation confirms that this subsidy is a first-best instrument. If learning rates are high, the subsidy is initially high as an early deployment of learning carbon-free energy is socially optimal (see Fig. 5a). For lower learning rates, fossil energy is more attractive in the first decades. Learning energy generation and the subsidy are delayed because postponed learning costs are lower due to discounting. Note that after an initial "activation" phase which shifts the energy generation from the niche to large-scale generation, the subsidy is declining because of diminishing learning with cumulative output.

4.2. *Feed-in-tariff*

Although a lump-sum financed subsidy is an efficient instrument, it is rarely employed in reality. Governments which prefer a price instrument to a quota widely choose feed-in-tariffs to encourage renewable energy generation. In contrast to the lump-sum-financed subsidy τ_L, the feed-in-tariff (ς_F) is a subsidy on learning carbon-free energy that is cross-financed by a tax on fossil and mature carbon-free energy τ_F. This captures the idea that the costs of feed-in-tariffs are borne by the entire energy sector.

The optimal path of the feed-in-tariff closely follows the lump-sum financed subsidy (Fig. 5a). As the cross-financing mechanism causes small distortions for fossil and mature carbon-free energy prices,[13] the feed-in-tariff converges faster to zero. Consumption losses, however, are small ($< 0.1\%$) and there is no delay in learning carbon-free energy deployment (Fig. 4).

4.3. *Quota on the energy mix*

Some governments use tradable quotas instead of subsidies to encourage renewable energy generation. In the following, we calculate the performance of several quota regimes which differ with respect to their degree of technological discrimination. In Eqs. (5–6), we introduced three different quota designs: (i) a

[13]The difference between lump-sum subsidy τ_L and feed-in-tariff ς_F becomes apparent in the first-order conditions (B.5–B.7) in Appendix B.

minimum quota for the carbon-free energy on the total energy generation (ψ_B^T), (ii) a minimum quota for the learning energy on the total energy generation (ψ_L^T), and (iii) a minimum quota for the learning energy on the total carbon-free energy generation (ψ_L^B).

Quota for (total) carbon-free energy

A quota on E_B does not increase welfare compared to the laissez-faire equilibrium in our model. Hence, it is therefore optimal to keep it at zero. A positive quota encourages both the learning and the mature carbon-free technology relative to the fossil energy technology. Hence, this quota instrument has a similar effect as the carbon tax but induces a further distortion due to the implicit income-neutrality while the carbon tax generates lump-sum income for the household. As the instrument is too unspecific to prevent the lock-in into the mature carbon-free, consumption losses remain substantial.

Quotas for learning carbon-free energy

This instrument is more specific. It can indeed increase the generation of learning carbon-free energy. However, we find that the reference point of the quota matters: if the quota is chosen relative to the shares of the two carbon-free energies (ψ_L^B), it can discriminate the mature against the learning technology and therefore prevent a (temporary) lock-in. Nevertheless, it cannot push the learning technology relative to the fossil energy which would be necessary to achieve an efficient timing of learning energy generation.

In contrast, the quota for learning energy relative to total energy (ψ_L^T) does not only prevent a lock-in, but also induces a more efficient learning energy generation at the expense of fossil energy generation. The optimal quota almost achieves the socially optimal energy generation (Fig. 5b). From the first-order conditions (B.5–B.7) follows that a binding quota ψ_L^T is equivalent to a feed-in-tariff if and only if the quota price $\phi_L^T = \tau_F/\psi_L^T = \varsigma_F/(1-\psi_L^T)$. Equally to the feed-in-tariff the quota operates like an implicit subsidy on E_L and an implicit tax on E_F and E_N while maintaining income neutrality. Overall consumption losses are small and of the same magnitude as for the feed-in-tariff.

4.4. Tax on the mature carbon-free energy

Instead of promoting the learning technology, the lock-in can alternatively be addressed by taxing the mature carbon-free technology which causes the lock-in. As shown in Fig. 4, this policy is relatively expensive compared to the optimal subsidy, the feed-in-tariff, or the optimal quota. However, consumption losses are mainly due to the delay of the learning carbon-free energy similar to the case where no (or only a prohibitively expensive) mature energy technology is available (as discussed in Sec. 3).

4.5. Modified carbon pricing

The management of the carbon budget by the carbon bank leads to a Hotelling carbon price. In a first-best setting (no technology failures) this is equivalent to an optimal carbon tax τ_R. However, when additional market failures such as learning spillovers are present, the second-best carbon price differs from the Hotelling carbon price. In our model the second-best carbon price deviates from the carbon bank's carbon price in the laissez-faire equilibrium only during the short transition phase when massive investments into the learning carbon-free technology are made. Nevertheless, the modified carbon tax cannot prepone this transition phase. A higher carbon price would primarily encourage the mature carbon-free technology. Hence, consumption losses remain almost unchanged compared to the laissez-faire outcome. Nevertheless, a second-best carbon price performs better than the technology-unspecific quota for carbon-free energy. Although both instruments encourage carbon-free energy at the expense of fossil energy, the quota instrument causes an additional distortion due to the implicit income-neutrality property.

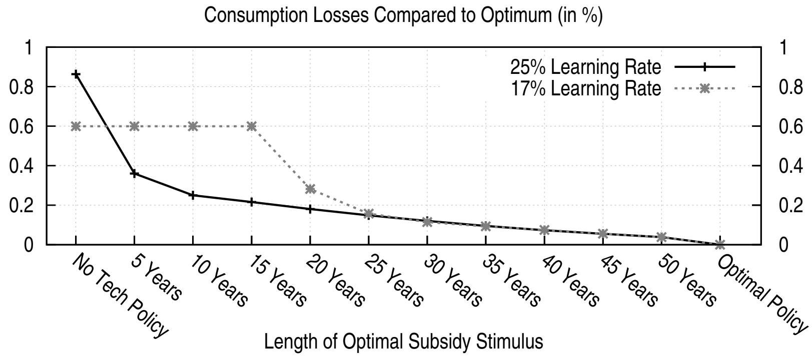


Figure 6: Consumption losses with respect to the length of optimal temporary subsidies (starting in 2010).

5. Policy stimulus

The policy instrument analysis in Section 4 calculated optimal first-best and second-best instruments for the entire time horizon (21st century). In reality such a long-lasting commitment by governments might be difficult to implement. Furthermore, long-term subsidies may have adverse side-effects if they cause rent-seeking behavior and transaction costs. A charming solution might be to limit the duration of policy intervention. We therefore calculated the optimal subsidy starting in 2010 for different time spans. The consumption losses of these policy stimuli are shown in Fig. 6. A policy stimulus of 25 years is sufficient to prevent lock-ins and decrease consumption losses below 0.2%. If learning is moderate the subsidy is relatively unimportant during the first 15 years as the large-scale learning energy deployment begins in 2030. Hence, it is important that the subsidy is implemented when the transition phase starts (under the high learning parametrization, this is immediately in 2010).

6. Robustness of optimal policy instruments

The previous analysis revealed that within our deterministic model setting there are only small differences between subsidies, feed-in-tariffs and technology-specific quotas. In particular, the latter two instruments are completely equivalent. This section provides some elementary considerations about the performance of these instruments when relaxing the assumption of perfect information. First, we study the behavior of the market equilibrium around the optimal instrument (sensitivity analysis). Second, we exemplarily consider the consequences of the government being wrong in its believe about the magnitude of the learning rate.

To assess the sensitivity of the 'optimal policies' with respect to small errors in their implementation, we calculate the consumption losses of varying the instrument by one percent relative to its optimal use. As shown in Fig. 7, changes in discounted consumption are small with one exception: when the subsidy is set too low, significant consumption losses in the range of the laissez-faire outcome can result. Lowering the subsidy by one percent results in a strong lock-in into the mature carbon-free technology because the subsidy then fails to make the learning technology competitive. The high sensitivity is mainly due to the high substitutability. It leads to strong quantity responses if the learning technology is slightly more expensive than the mature technology. This flipping behaviour occurs only if the subsidy is slightly too low as in this case the lock-in dynamics prevails. If the subsidy is higher than optimal, firms simply use slightly more learning carbon-free energy. This sensitive behavior does not occur for the other instruments. As

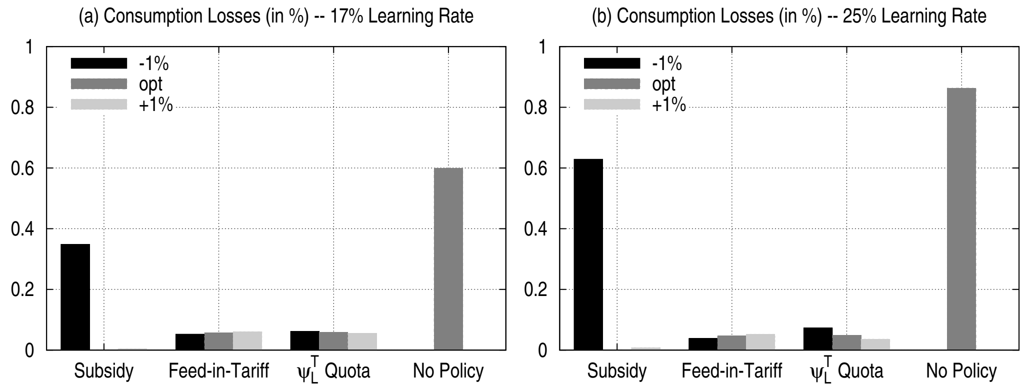


Figure 7: Consumption losses relative to the 1st-best optimum of optimal and 'close-to-be-optimal' (±1%) instruments.

Actual learning rate (%)	Assumed learning rate (%) for subsidy			No policy
	8	17	25	
8	0.00 (0)	0.15 (23)	0.18 (26)	0.19 (30)
17	0.07 (9)	0.00 (0)	0.48 (17)	0.60 (20)
25	0.62 (18)	0.24 (-6)	0.00 (0)	0.86 (20)
Mean	0.23	0.13	0.22	0.55

Table 2: Consumption losses in % and delay in years (in parentheses) relative to optimal policy if the government implements a learning subsidy assuming a different learning rate than actually prevails.

the 1%-lower-than-optimal feed-in-subsidy implies an additional taxation of fossil and mature carbon-free energy, it provides a greater buffer for the comparative advantage of the learning technology. For the quota, small perturbations translate directly into small deviations in production if the quota is binding; a lock-in cannot occur. Hence, the high sensitivity of the subsidy policy indicates that there may be a high risk of failure.

In our second analysis, we explore the consequences of imperfect information about the learning rate. To this end, we assume that the government derives its optimal policy based on the wrong learning rate and sticks to this assessment for the entire planning horizon. This is implemented by running the optimal policy from the presumed learning rate as an exogenously given policy for the 'true' learning rate. Tab. 2 shows the consumption losses if the government implements the optimal subsidy from the 8%, 17% and 25% learning scenario in all possible real-world learning scenarios. In all cases, consumption losses remain below the no-policy case. Expected consumption losses are lowest for the subsidy assuming a 17% learning rate (given that all three learning rates are equally likely). They are also lower than the expected losses in the no-policy scenario, hence imperfect information is no argument for non-action.

The reasons for the consumptions losses lie, of course, in the stringency of the policy, but also in its timing (see Fig. 5a). Consider, for example, implementing the subsidy from the 25% learning scenario: this subsidy path is initially high but declines rapidly, therefore influencing the learning technology use only in the first decade directly. If the actual learning rate is 25%, this subsidy induces a quick up-scaling of learning carbon-free energy which then displaces other energy technologies due to its high learning rate. At lower actual learning rates (e.g. 17%), however, the initial price advantage caused by the subsidy is too short to reduce costs below those of the incumbent technologies. Consequently, the non-learning carbon-free energy remains competitive for a long time and the deployment of learning carbon-free energy is delayed substantially. This causes consumption losses which are close to the no-policy case.

These considerations provide a first step regarding the robustness of policies. They also indicate the complexity of the intertemporal dynamics of learning spillovers. A profound stochastic analysis requires maximizing the expected intertemporal welfare for specific probability distributions of key parameters. Considering the long time horizon in this application, however, introducing learning for the government becomes crucial: realistically, part of the uncertainty about learning rates and spillovers will be resolved after a few decades giving the government ample reason to revise its formerly announced policy. In a consistent approach, the possibility to learning should itself be anticipated. A satisfying answer to the question whether quantity or price-based technology instruments perform better in an uncertain world is thus beyond the scope of this study, but an important topic for future work.

7. Conclusions

Our model provides important insights into the causes and implications of market failures for energy innovations (Sec. 3). We identified a *trio infernale* of necessary conditions that provoke a lock-in into a mature (non-learning) technology although a superior (learning) contender technology is available: (i) learning spillovers and/or risk premiums, (ii) a high substitutability between these two technologies, and (iii) a critical range of present and future generation costs of the competing technologies. The cost level must be such that the contender technology is more expensive than the mature technology in the short term, yet cheaper in the long run due to its learning potential. If only (i) and (ii) or (i) and (iii) hold, the market failure is small and the associated welfare losses may be exceeded by the transaction costs of addressing it. For example, if the high-cost carbon-free energy is prohibitively expensive, no lock-in occurs, and thus, consumption losses of only 0.3% are caused by suboptimal timing of innovation alone. Similarly, if substitutability is imperfect, the innovative technology gains experience in niche markets. In this case, consumption losses are also low (0.2%). If all three conditions hold, however, the innovation process may be delayed by several decades. For plausible parameters, this causes consumption losses ranging from 0.4% to 3.4% and carbon price increases by 14–127 percent. Hence, lock-ins between low-carbon technologies interfer with climate policy: Higher carbon prices and mitigation costs make it difficult for governments to seek for ambitious temperature targets.

Market failure due to spillovers may not only affect the energy sector but all innovative sectors in the economy. But in contrast to electronic, information and entertainment industries, energy – and in particular electricity – is a homogeneous good where almost no product differentiation is possible.[14] Thus, while in many economic sectors condition (i) and (iii) hold, condition (ii) is violated. Spillovers and discount rate mark-ups have only small impact on welfare and may not justify (technology-specific) policy intervention.

An optimal policy has to internalize spillovers. This can be done by a subsidy on learning carbon-free energy which is lump-sum financed (Sec. 4). Feed-in-tariffs and minimum quotas on learning carbon-free energy also provide a way to promote a technology. However, these are cross-financed by an implicit tax on mature carbon-free and fossil energy. The distortionary financing mechanism leads to the occurrence of small inefficiencies (around 0.1%). All these instruments require the regulator to pick the “winner”, i.e. to support the dynamically more efficient technology while discriminating the other technologies. In reality,

[14] An exception might be niche markets due to imperfect grid access or benevolent consumers that are aware of the social costs of lock-ins and therefore purchase the more expensive learning technology at their own costs. However, consumers must be aware of choosing not only the carbon-free technology (which includes A_N), but the *learning* (carbon-free) technology at higher costs.

the regulator might not have this option due to information, incentive and political-economy problems. Instead of picking-the-winner, the regulator could "drop-the-losers", i.e. discriminate the non-learning technologies by a tax. In particular, this could be useful if it was easier to identify technologies which need to be avoided, than to determine which (maybe yet not existing) technology will be essential for future energy generation. This also enhances competition under several learning technologies. Technology-unspecific carbon-free energy quotas and modified carbon pricing are poor instruments resulting in negligible or zero welfare gains.

We performed our analysis within a global-scale economic model to analyse the dynamics and implications of technological market failures for climate change mitigation. The conditions for the occurence of lock-ins and their implications should be transferable to a regional or national economy with similar cost parameters, learning rates and technological substitutability. One crucial issue, however, concerns the nature of spillovers: On the one hand, the knowledge transfer could be higher on a regional level (e.g. due to higher mobility of skilled employees between firms); on the other hand, imperfect patent legislation may lead to higher knowledge transfers in respective countries. If spillovers are global (and experience is thus a global public good), a globally coordinated technology policy would become necessary. Such a policy would suffer from the common free-rider and enforcing problems as studied for other global public good problems. In contrast, if spillovers are national, it is in the interest of every government to internalize knowledge externalities by specific policies.

Regarding the robustness of instruments, the implementation of the subsidy carries the risk of being ineffective if it deviates only slightly from the optimal value. In contrast, the consumption losses for feed-in-tariffs and quotas are always small if realized implementation differs from the optimal values (Sec. 6) although they are never first-best in a deterministic setting. If the regulator does not know the actual learning rate, assuming a medium learning reate seems to be a good strategy. Nevertheless, implementing a subsidy based on a wrong belief in the learning rate leads to higher consumption than implementing no subsidy at all. A concluding evaluation of these risks requires a comprehensive stochastic analysis which considers uncertainties in several economic parameters and learning about uncertainty. While this is beyond the scope of this paper, it indicates an important question for future research.

Appendix A. Technology

The following functional forms for utility and production are used:

$$\mathbf{U}(C/L) = \frac{\left(\frac{C}{L}\right)^{1-\eta}}{1-\eta} \tag{A.1}$$

$$\mathbf{Y}(Z,E) = \left(a_1 Z^{\frac{\sigma_1-1}{\sigma_1}} + b_1 E^{\frac{\sigma_1-1}{\sigma_1}}\right)^{\frac{\sigma_1}{\sigma_1-1}} \tag{A.2}$$

$$\mathbf{Z}(K_Y,L) = \left(a_2 K_Y^{\frac{\sigma_2-1}{\sigma_2}} + b_2 (A_Y L)^{\frac{\sigma_2-1}{\sigma_2}}\right)^{\frac{\sigma_2}{\sigma_2-1}} \tag{A.3}$$

$$\mathbf{E}(E_F,E_B) = \left(a_3 E_F^{\frac{\sigma_3-1}{\sigma_3}} + b_3 E_B^{\frac{\sigma_3-1}{\sigma_3}}\right)^{\frac{\sigma_3}{\sigma_3-1}} \tag{A.4}$$

$$\mathbf{E_B}(E_L,E_N) = \left(a_4 E_L^{\frac{\sigma_4-1}{\sigma_4}} + b_4 E_N^{\frac{\sigma_4-1}{\sigma_4}}\right)^{\frac{\sigma_4}{\sigma_4-1}} \tag{A.5}$$

$$A_{Y,t+1} = A_{Y,t}\left(1 + \frac{1}{1-g_0 e^{-\zeta t}}\right) \tag{A.6}$$

$$L_t = L_0(1-q_t) + q_t L^{max}, \qquad q_t = \frac{e^{ft}-1}{e^{ft}} \tag{A.7}$$

$$\mathbf{E_F}(K_F, R) = \left(aK_F^{\frac{\sigma-1}{\sigma}} + bR^{\frac{\sigma-1}{\sigma}}\right)^{\left(\frac{\sigma}{\sigma-1}\right)} \tag{A.8}$$

$$\mathbf{R}(S, K_R) = \kappa(S)K_R \tag{A.9}$$

$$\kappa(S) = \frac{\chi_1}{\chi_1 + \chi_2\left(\frac{S_0-S}{\chi_3}\right)^{\chi_4}} \tag{A.10}$$

$$\mathbf{E_L}(A_L, K_L, N) = A_L K_L^{\gamma} N^{\nu-1} \tag{A.11}$$

$$\mathbf{A_L}(H) = \frac{A_{L,max}}{1+\left(\frac{\Omega}{H}\right)^{\gamma}} \tag{A.12}$$

$$\mathbf{E_N}(K_N) = A_N e^{1g_N t} K_N \tag{A.13}$$

Appendix B. First-order conditions of decentralized agents

Household sector. Maximizing the Lagrangian
$\mathcal{L}_H = \sum_{t=0}^{T}(L_t U(C_t/L_t)\,[1+\rho]^{-t} + \lambda_{H,t}(K_{t+1} - K_t - (I_t - \delta K_t)))$ with respect to C_t and K_t and by using the substitution (1) yields the following first-order conditions:

$$L_t \frac{\partial \mathbf{U}}{\partial C_t} = \lambda_{H,t} \tag{B.1}$$

$$\lambda_{H,t} - \lambda_{H,t-1}(1+\rho) = -\lambda_{H,t}(r_t - \delta) \tag{B.2}$$

$$0 = \lambda_{H,T} K_{T+1} \tag{B.3}$$

Production sector. Maximizing the Lagrangian $\mathcal{L}_{Y,t} = \pi_{Y,t} + \phi^T_{B,t}(E_{L,t} + E_{N,t} - \psi^T_{B,t}(E_{F,t} + E_{N,t} + E_{L,t})) + \phi^B_{L,t}(E_{L,t} - \psi^B_{L,t}(E_{N,t} + E_{L,t})) + \phi^T_{L,t}(E_{L,t} - \psi^T_{L,t}(E_{F,t} + E_{N,t} + E_{L,t}))$ with respect to $K_{Y,t}, L_t, E_{F,t}, E_{L,t}$ and $E_{N,t}$ and using the substitutions (4) and (A.2–A.5) leads to the first-order conditions:

$$r_t = \frac{\partial \mathbf{Y}(\mathbf{Z}, \mathbf{E})}{\partial K_{Y,t}}, \qquad w_t = \frac{\partial \mathbf{Y}(\mathbf{Z}, \mathbf{E})}{\partial L_t} \tag{B.4}$$

$$p_{F,t} = \frac{\partial \mathbf{Y}(\mathbf{Z}, \mathbf{E}(\mathbf{E_F}, \mathbf{E_B}))}{\partial E_{F,t}} - \tau_{F,t} - \phi^T_{B,t}\psi^T_{B,t} - \phi^T_{L,t}\psi^T_{L,t}, \tag{B.5}$$

$$p_{L,t} = \frac{\partial \mathbf{Y}(\mathbf{Z}, \mathbf{E}(\mathbf{E_F}, \mathbf{E_B}(\mathbf{E_L}, \mathbf{E_N})))}{\partial E_{L,t}} + \varsigma_{F,t} + \phi^T_{B,t}(1-\psi^T_{B,t}) + \phi^B_{L,t}(1-\psi^B_{L,t}) + \phi^T_{L,t}(1-\psi^T_{L,t}), \tag{B.6}$$

$$p_{N,t} = \frac{\partial \mathbf{Y}(\mathbf{Z}, \mathbf{E}(\mathbf{E_F}, \mathbf{E_B}(\mathbf{E_L}, \mathbf{E_N})))}{\partial E_{N,t}} - \tau_{F,t} - \phi^B_{L,t}\psi^B_{L,t} - \phi^T_{L,t}\psi^T_{L,t} + \phi^T_{B,t}(1-\psi^T_{B,t}) \tag{B.7}$$

With the KKT conditions for the inequaltiy constraints (5–7):

$$0 = \phi^T_{L,t}(E_{L,t} - \psi^T_{L,t}(E_{F,t} + E_{N,t} + E_{L,t})) \tag{B.8}$$

$$0 = \phi^B_{L,t}(E_{L,t} - \psi^B_{L,t}(E_{N,t} + E_{L,t})) \tag{B.9}$$

$$0 = \phi^T_{B,t}(E_{L,t} + E_{N,t} - \psi^T_{B,t}(E_{F,t} + E_{N,t} + E_{L,t})) \tag{B.10}$$

Fossil energy sector. By maximzing π_F given by (8), the common static conditions apply:

$$p_{R,t} + \tau_{R,t} + p_{C,t} = p_{F,t}\frac{\partial \mathbf{E_F}}{\partial R_t}, \qquad r_t = p_{F,t}\frac{\partial \mathbf{E_F}}{\partial K_{F,t}} \tag{B.11}$$

Fossil resource extraction sector. Maximizing the Lagrangian $\mathcal{L}_R = \sum_{t=0}^{T} \left(\pi_{R,t}\Pi_{s=0}^{t}[1 + r_s - \delta]^{-1} + \lambda_{R,t}(S_{t+1} - S_t + R_t)\right)$ with respect to R_t and S_t and the substitutions (9) and (A.9–A.10) leads to the first-order conditions:

$$\lambda_{R,t} = p_{R,t} - r_t/\kappa_t \tag{B.12}$$

$$\lambda_{R,t} - \lambda_{R,t-1}(1 + (r_t - \delta)) = -(p_{R,t} - \lambda_{R,t})\frac{\partial \mathbf{R}}{\partial S_t} \tag{B.13}$$

$$\lambda_{R,T} S_{T+1} = 0 \tag{B.14}$$

Learning carbon-free energy sector. Maximizing the Lagrangian $\mathcal{L}_L = \sum_{t=0}^{T}(\pi_{L,t}\Pi_{s=0}^{t}[1 + r_s + \nu - \delta]^{-1}\,\lambda_{L,t}(H_{t+1} - H_t - (E_{L,t} - E_{L,t-1})))$ with respect to $K_{L,t}$ and H_t and introducing the spillover rate ϕ leads to the first-order conditions:

$$0 = \left(p_{L,t}\frac{\partial \mathbf{E_L}}{\partial K_{L,t}} - r_t\right)\Pi_{s=0}^{t}[1 + r_s + \nu - \delta]^{-1} + (\lambda_{L,t+1} - \lambda_{L,t})\frac{\partial \mathbf{E_L}}{\partial K_{L,t}}$$

$$0 = (1 - \phi)\frac{\partial \mathbf{E_L}}{\partial H_t}\left(p_{L,t}\Pi_{s=0}^{t}[1 + r_s + \nu - \delta]^{-1} + \lambda_{L,t+1} - \lambda_{L,t}\right) - \lambda_{L,t} + \lambda_{L,t-1}$$

$$0 = \lambda_T = \lambda_{T-1}$$

With $\tilde{\mu}_t := \lambda_t\Pi_{s=0}^{t}[1 + (r_s + \nu - \delta)]$ we can transform this into $r_t = \left(p_{L,t} + \tau_{L,t} - \tilde{\mu}_t + \frac{\tilde{\mu}_{t+1}}{1+r_{t+1}+\nu-\delta}\right)\frac{\partial \mathbf{E_L}}{\partial K_{L,t}}$ and $\tilde{\mu}_t - \tilde{\mu}_{t-1}(1 + r_t + \nu - \delta) = (1-\phi)\frac{\partial \mathbf{E_L}}{\partial H_t}\left(p_{L,t} + \tau_{L,t} - \tilde{\mu}_t + \frac{\tilde{\mu}_{t+1}}{1+r_{t+1}+\nu-\delta}\right)$. Finally, with $\mu_t = \tilde{\mu}_{t+1}(1 + r_{t+1} + \nu + \delta) - \tilde{\mu}_t$, we obtain:

$$r_t = (p_{L,t} + \tau_{L,t} + \mu_t)\frac{\partial \mathbf{E_L}}{\partial K_{L,t}} \tag{B.15}$$

$$\mu_{t-1} = \frac{1 - \phi}{1 + r_t + \nu + \delta}(p_{L,t} + \tau_{L,t} + \mu_t)\frac{\partial \mathbf{E_L}}{\partial H_t} \tag{B.16}$$

$$\mu_T = 0 \tag{B.17}$$

Mature carbon-free energy sector. The common static condition applies:

$$A_N e^{g_N t}(p_{N,t} - \tau_{N,t}) = r_t \tag{B.18}$$

Carbon bank. Intertemporal optimization results in a Hotelling price:

$$p_{C,t} = (1 + r_t - \delta)p_{C,t-1} \tag{B.19}$$

$$p_{C,T} B_{T+1} = 0 \tag{B.20}$$

Appendix C. Optimal first-best subsidy

Let * denote the solution from the efficient intertemporal market equilibrium, i.e. where $\phi = 0$ and $\nu = 0$ and there is no subsidy $\tau_{L,t} = 0$. Hence, Eqs. (B.15–B.16) read

$$r_t^* = (p_{L,t}^* + \mu_t^*)\frac{\partial \mathbf{E}_\mathbf{L}^*}{\partial K_{L,t}} \tag{C.1}$$

$$\mu_{t-1}^* = \frac{1}{(1 + r_t^* - \delta)}\frac{\partial \mathbf{E}_\mathbf{L}^*}{\partial H_t}\left(p_{L,t}^* + \mu_t^*\right) \tag{C.2}$$

Equating (C.1) with the original first-order condition (B.15) where $\phi, v, \tau_{L,t} \geq 0$ and solving for $\tau_{L,t}$ in the optimum yields:

$$\tau_{L,t} = \mu_t^* - \mu_t \tag{C.3}$$

Substituting (C.3) into the RHS of (B.16), we obtain for the optimum:

$$\mu_{t-1} = \frac{(1-\phi)}{(1+r_t+v-\delta)} \frac{\partial \mathbf{E}_{\mathbf{L}}^*}{\partial H_t} \left(p_{L,t}^* + \mu_t^*\right) \tag{C.4}$$

Substituting (C.3) into the LHS of (C.4) as well as plugging (C.2) into the RHS of (C.4), we finally obtain for τ:

$$\tau_{L,t} = \mu_t^* \left(1 - \frac{(1-\phi)(1+r_{t+1}+\delta)}{1+r_{t+1}+v+\delta}\right) \tag{C.5}$$

Appendix D. Parameters and initial values for numerical solution

Symbol	Parameter	Value
ρ	pure time preference rate of household	0.03
η	elasticity of intertemporal substitution	1
δ	capital depreciation rate	0.03
L^{max}	population maximum (bill. people)	9.5
f	population growth parameter	0.04
a_1	scale parameter in final good production	0.95
b_1	scale parameter in final good production	0.05
σ_1	elasticity of substitution energy–intermediate	0.5
a_2	scale parameter in intermediate production	0.3
b_2	scale parameter in intermediate production	0.7
σ_2	elasticity of substitution labor–capital	0.7
a_3, b_3, a_4, b_4	scale parameter (energy usage)	1
σ_3	elasticity of substitution fossil–carbon-free energy	3
σ_4	elasticity of substitution learning–mature carbon-free	21
g_0	productivity growth parameter	0.026
ζ	productivity growth parameter	0.006
a	scale parameter in fossil energy generation	0.8
b	scale parameter in fossil energy generation	1.65E-4
σ	elasticity of substitution energy–intermediate	0.15
χ_1	scaling parameter	20
χ_2	scaling parameter	700
χ_3	resource base (GtC)	4000
χ_4	slope of Rogner's curve	2
v	share parameter learning carbon-free energy generation	0.95
$A_{L,max}$	maximum productivity learning carbon-free energy	0.6
Ω	scaling parameter	200

γ	learning exponent	0.27
N	land	1
ν	risk premium (learning technology)	0.0
ϕ	spillover rate (learning technology)	0.6
A_N	productivity mature energy technology	0.2
g_N	productivity change rate	-0.004
K_0	Initial total capital stock (trill. US$)	165
S_0	Initial stock of fossil resources (GtC)	4000
B_0	Carbon budget (GtC)	450
H_0	Initial experience stock	0.2
L_0	Initial population (bill. people)	6.5
$A_{Y,0}$	Initial productivity level	6
T	time horizon (in years)	150

Table D.3: Parameters used for the numerical model.

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