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

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Abstract

We investigate conditions that aggravate 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 in addition to carbon pricing 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.

JEL-Code: O380, Q400, Q540, Q550.

Keywords: renewable energy subsidy, renewable portfolio standard, feed-in-tariffs, carbon pricing.

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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. Some researchers have argued that existing, technology unspecific instruments like patents and research subsidies are sufficient to foster innovations in the energy sector (Nordhaus, 2009). But other researchers maintain that policy intervention is necessary: Some identify spillovers as the cause of suboptimal innovation in carbon-free technologies (Kverndokk and Rosendahl, 2007; Fischer and Newell, 2008; Popp, 2006) while others see an initially high innovation rate in the carbon-intensive sector as the reason for suboptimal green innovation (Acemoglu et al., 2009). These papers, however, do not provide a convincing rationale why regulators should focus on market failures in *energy* innovations rather than in innovations in general: What is special about innovations in the energy sector to make technology-specific policy intervention necessary? This paper addresses this question using an intertemporal general equilibrium model with two competing low-carbon energy technologies. Our analysis draws on two strands of literature: the first discusses policy instruments to address climate change and innovation processes, the second investigates technological lock-ins.

Several modeling studies addressing technology policy in the context of global warming have been published. 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. We differ from these models in analyzing the intensity of technology lock-ins depending on important technological parameters (like the substitutability between energy technologies), spillover rates and discount rate mark-ups. Furthermore, we provide an extensive policy analysis within an intertemporal general equilibrium framework considering first-best and several welfare maximzing second-best instruments. The other strand of literature explores how lock-ins arise due to increasing returns going back to the seminal work by Arthur (1994). Here, lock-in is understood as market dominance of an inferior incumbent technology at the expense of a superior contender technology. This view is supported by micro-modeling (Arthur, 1989) and various case studies; 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). In the context of global warming, research has focused on lock-in into fossil fuel technologies exacerbating the switch to carbon-free energy (Unruh, 2000, 2002; Foxon and Pearson, 2007; Schmidt and Marschinski, 2009). In contrast, this paper examines the case of two competing low-carbon energy technologies. As the lock-in literature stresses the role of additional market barriers such as private and public institutions, lock-ins are hard to overcome by common policy instruments like taxes or subsidies.

For our analysis, we develop an integrated policy assessment model which provides a consistent and flexible framework to calculate optimal policies and to conduct a precise welfare analysis (Sec. 2). In our intertemporal general equilibrium model, lock-ins rise due to imperfections in the innovation process: Technological progress in the learning backstop sector is driven by learning-by-doing with intra-sectoral knowledge spillovers. Additionally, we consider the case 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 backstop energy where significant learning-by-doing occurs as expected for many renewable energy technologies, and (iii) a mature (non-learning) backstop energy where technology has already experienced past learning and considerable up-scaling. Candidates for the mature low (or zero) carbon energy technology are nuclear power, hydropower, combined cycle gas turbines (CCGT) or coal fired power plants combined with carbon capture and sequestration technologies (CCS).

We find that a possible lock-in into inferior (non-learning) carbon-free energy technologies can be very costly compared to the costs of the innovation market failure alone (Sec. 3). Incomplete appropriation of the gains of innovation generally leads to higher prices. This is the same 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, the very good substitutability between energy from mature and learning generation technologies is the reason why energy 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 backstop technology; (ii) quotas (i.e. portfolio standards), (iii) feed-in-tariffs, (iv) taxes on the mature backstop 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 backstop 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

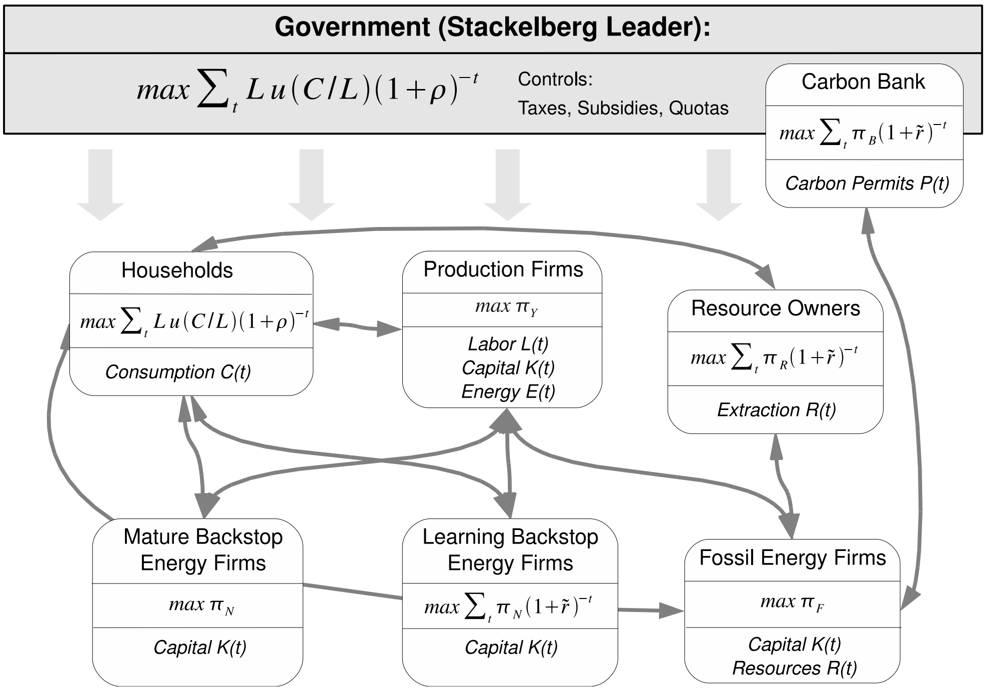


Figure 1: Overview of the modeling framework.

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. 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.

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 tech-

[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.

nology 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]

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

The factor Δ denotes the length of a time period in years and 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) backstop energy sector N, learning backstop 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] The household therefore faces the following constraints:

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

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

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

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 backstop 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 backstop (p_N) and learning backstop (p_L) energy (the price of consumption goods are set to one). Furthermore, the production sector may need to consider government intervention in form of a subsidy on the learning backstop energy τ_L or a feed-in tariff ς_F. The latter

[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.

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

takes the form of a subsidy but is cross-financed by a tax τ_F on energy from the fossil and the mature backstop technology energy sectors.

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

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 backstop energy are combined to final energy with the elasticity of substitution σ_3. Finally learning and mature backstop energy are combined to aggregate backstop 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 backstop technology: Quotas of the first kind, ψ_L^T, set a minimum share of energy from the learning backstop (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 backstop technology relative to total energy use.

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

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

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

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

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

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

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

$r_t - \delta$[6]:

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

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:

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

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

The learning backstop sector

The learning backstop sector maximizes profit π_L under capital input and with a fixed amount of land N. It considers interest rate and renewable energy prices 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).[7] Fossil energy and non-learning backstop firms can in each period adjust their factor endowment in order to achieve a profit-maximizing allocation to given carbon prices. In contrast, the learning backstop sector can only achieve the profit-maximum if the ancounced climate policy is actually implemented for the entire time horizon. If an anounced mitigation target will be relaxed at some future date, the competetiveness of the learning backstop with fossil fuels decreases and early investments with the aim to increase experience turn out to be partly unprofitable. Firms anticipating that the mitigation target could be relaxed therefore discount future profits at a higher rate.[8] The optimization problem of the sector reads:

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

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

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

[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]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. Additional risk premiums could be justified if capital or insurance markets are not perfect (i.e. due to asymmetric information) or investers are risk-averse.

[8]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. In our model, fossil resource rents become almost zero under the mitigation target. Introducing high risk premiums does not affect the resource extraction which is mainly detemined by the carbon price.

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). 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 present value of learning μ_t is given by $\mu_t - \mu_{t-1}(1 + (r_t + v - \delta))^{\Delta} = \Delta(1-\phi)\frac{\partial \mathbf{E_L}}{\partial H_t}\left(p_{L,t} - \mu_t + \frac{\mu_{t+1}}{(1+(r_{t+1}+v-\delta))^{\Delta}}\right)$ 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, 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 introduces an incentive problem.[9]

The mature backstop sector

The mature backstop sector sector maximizes profit π_N subject to capital input K_N with an AK-technology function:

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

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.

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. 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 $P = R$.

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

[9]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.

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

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

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. This approach allows us to decouple climate policy (the price on carbon) from technology policies.

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:

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

subject to Eqs. 2, 3, 10, 12, 15, 20–32

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:

$$\max_{\Theta} \quad \sum_{t=0}^{T} (1+\Delta\rho)^{-t} \Delta L_t \mathbf{U}\left(C_t/L_t\right) \tag{19}$$
$$\text{subject to Eqs. 1–15, 17–18 , 20–32, 33–52}$$

$\Theta = \{\tau_{L,t}, \tau_{N,t}, \tau_{R,t}, \varsigma_{F,t}, \psi^T_{L,t}, \psi^B_{L,t}, \psi^T_{B,t}\}$ 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 the 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 backstop technology refers to nuclear, gas or coal (with CCS) technologies 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-lerning backstop 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).[10] For the learning backstop energy we 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,

[10] We use a small negative external learning rate in Eq. 32 of $g_N = -0.4\%$ to obtain constant costs for the non-learning backstop energy because the interest rate falls over time. A negative learning rate can also be justified by increasing scarcities (uranium, gas, carbon dioxide storage capacities for CCS) 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.

however, i.e. learning spillovers and risk premiums, seems to be difficult to quantify. Several econometric studies about learning-by-doing spillovers in manufacturing and semiconductor industry suggest $0.2 \leq \phi \leq 0.6$ (Irwin and Klenow, 1994; Gruber, 1998; Barrios and Strobl, 2004).[11] Within related integrated assessment or policy assessment models, spillover rates usually range between 50 and 80 percent (Jones and Williams, 1998; Popp, 2006; Fischer and Newell, 2008). In the following, we set $\phi = 0.75$ for illustrative purpose, but we consider also lower and higher values. Due to the lack of empiric evidence, we assume that the risk premium is zero ($\upsilon = 0$). 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 backstop energy. As the backstop energy sector covers mainly electric energy, we assume a higher substitutability and set $\sigma_4 = 12$.[12]

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 C. Additional figures with several model results can also be found in the supplementary material.[13]

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 backstop generation (compared to the social optimum) is measured by the difference in years until the learning backstop achieves a share of 10% in the total energy.[14]

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

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

[11] These spillover rates refer to countries that already have a comprehensive patent legislation.

[12] 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.

[13] Supplementary material is available under: http://www.pik-potsdam.de/~kalkuhl/SM/tech-policy.pdf

[14] As we use a time-discrete model with a period length of $\Delta = 5$ years, we use a linear approximation in-between time steps.

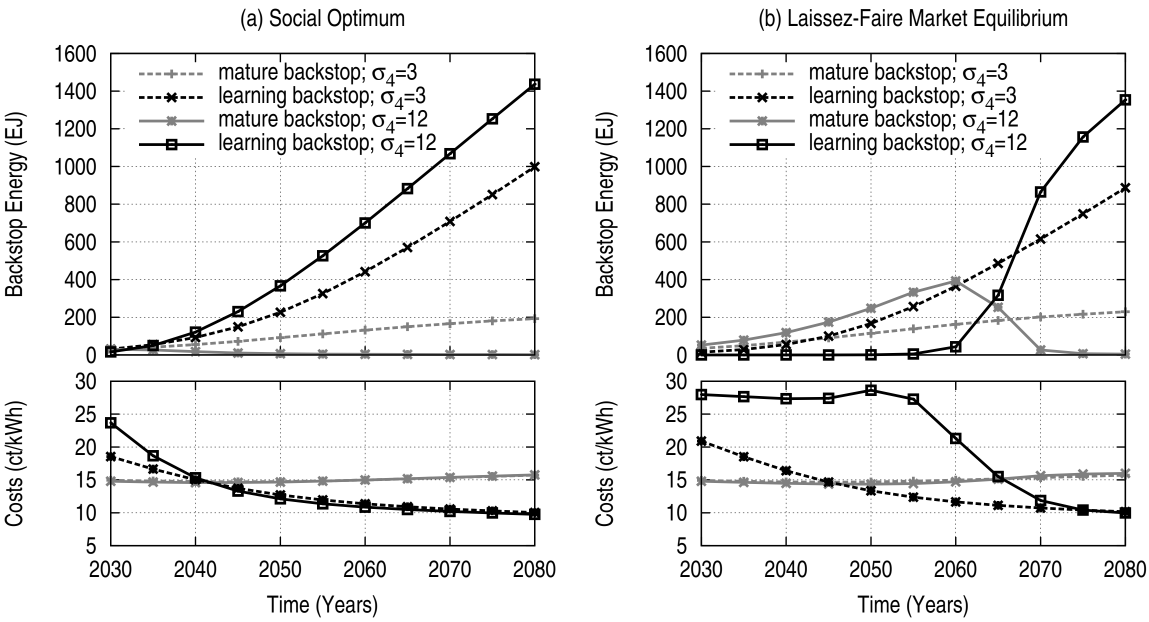
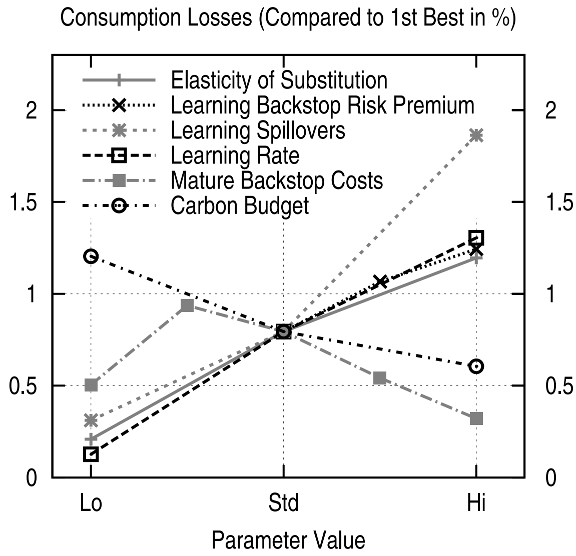


Figure 2: Backstop energy generation and costs (2030-2080) for two different elasticities of substitution ($\sigma_4 \in \{3, 12\}$) between learning and mature backstop energy: (a) optimal outcome and (b) laissez-faire equilibrium with 75 percent spillovers and no additional technology policy instruments.

curve and spillovers are internalized, future cost reductions for the learning technology are fully anticipated. Hence, the learning technology dominates the mature backstop 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 backstop technology is delayed significantly and energy demand is met by energy from the mature backstop technology. This has a clear and intuitive explanation: a low elasticity creates a niche demand for the learning backstop energy even when it is more expensive than the mature backstop. 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



Parameter		Lo	Std	Hi
Elasticity of Substitution	σ_4	3	12	21
Risk Premium	v		0.0	0.2
Spillover Rate	ϕ	0.5	0.75	1.0
Learning Rate	lr	0.1	0.17	0.25
	Ω	20000	200	60
	$A_{L,\text{max}}$	0.6	0.6	0.8
Mature Backstop 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.

considerable spillovers exist and market prices are distorted.

3.2 Economic impacts of lock-ins

In our standard parameterization the consumption losses due to the lock-in are 0.8%. 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 backstop 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 backstop 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 backstop 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 backstop energy causes consumption losses even if no competitive mature backstop technology is available (and no lock-in occurs). A doubling of the mature backstop production costs (i.e. $A_N = 0.1$) for example, makes the learning technology competitive even if spillovers exist. In this case the mature backstop generation is virtually zero. The resulting consumption losses due to spillovers are 0.3% for $3 \leq \sigma_4 \leq 21$ and there is almost no delay in learning backstop generation (< 5 years). In contrast, in case of lock-in, the delay of the learning backstop deployment increases to 25 years ($\sigma_4 = 12$) or 35 years ($\sigma_4 = 21$), respectively. Such a delay causes

	lr	ϕ	v	B_0	σ_4	Consumption losses [%]	Delay [years]	Initial carbon price [1=optimal]
1	17%	50%	15%	450	21	0.9	27	1.23
2	17%	50%	15%	200	21	1.4	35	1.17
3	17%	75%	10%	450	16	1.5	40	1.27
4	17%	75%	10%	200	16	2.2	50	1.18
5	25%	50%	15%	450	21	1.1	16	1.83
6	25%	50%	15%	200	21	1.3	17	1.77
7	25%	75%	15%	450	13	2.0	26	2.27
8	25%	75%	15%	200	13	3.4	37	2.09
9	25%	100%	0%	200	13	8.0	82	2.15

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

much higher consumption losses.

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 further parameter sets that cause particularly severe lock-ins with consumption losses greater than one percent. Even if spillovers are only 50 percent, the existence of an additional high risk premium postpones learning energy generation and provokes consumption losses of 1.4% 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 backstop 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 77–127 percent compared to the case where no market failures exist.

3.3 The role of energy subsidies

Besides technological parameters, existing energy subsidies may also exacerbate lock-ins if they favor non-learning technologies against learning ones. The limited liability of nuclear reactor operators for accidents, for example, exhibits an implicit subsidy on nuclear energy. Heyes and Heyes (2000) estimate the magnitute of this implicit subsidy to be 0.01–3.58 ct/kWh for nuclear reactor operators in Canada.[15] Government grants, rebates, loans or guarantees for investments into nuclear power plants provide further implicit subsidies as well as non-internalized environmental costs for the safe storage

[15]The low subsidy value results from a worst off-site damage scenario of \$1 bn and an accident probability of 10^{-6} per reactor-year while the high value results from a worst off-site damage scenario of \$100 bn and an accident probability of 10^{-5}.

Learning rate lr	Spillovers ϕ	Non-learning subsidy [ct/kWh]				
		0	1	2	3	4
17%	0%	0.0	0.0	0.0	0.0	0.2
17%	75%	0.8	1.0	1.3	1.7	2.1
25%	0%	0.0	0.0	0.0	0.0	–
25%	75%	1.3	1.5	1.8	2.1	–

Table 2: Consumption losses (in %) due to energy subsidies for non-learning backstop energy relative to the reference case with zero spillovers and subsidies.

of nuclear waste. Goldberg (2000) calculates the average direct subsidies to nuclear electricity generation within 1947–1999 by 1.2 ct/kWh.

In order to analyse the impact of distortionary subsidies on the magnitude of lock-ins, we integrate in the laissez-faire economy a constant ad-hoc subsidy for the non-learning backstop energy ranging from 1 to 4 ct/kWh. Tab. 2 shows the resulting consumption losses for different learning and spillover rates against the reference case of zero spillovers and zero subsidies. In the case where learning-by-doing is perfectly anticipated ($\phi = 0\%$), subsidies in the range of 1–4 ct/kWh have only a marginal effect on consumption and learning backstop deployment. However, if learning is not anticipated appropriately ($\phi = 75\%$), the consumption losses increase significantly due to an extended lock-in into the non-learning technology. For example, a 3 ct/kWh subsidy doubles the costs of technology lock-ins in the mdium learning-rate scenario. Even small distortionary subsidies can delay the deployment of the learning backstop technology by more than one decade and decrease therefore consumption.

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 percent learning rate) and a medium learning case (17 percent learning rate). We calculate optimal policies for a 75% spillover rate; considering cases with 50% spillover rate, high substitutability between E_N and E_L or additional risk premium leads to similar results.[16]

In the Stackelberg equilibrium, we calculate the welfare maximizing time paths of (i) learning backstop subsidies, (ii) feed-in-tariffs, (iii) backstop energy quotas, (iv) mature backstop taxes, and (v) a modified carbon price. The performance of each of these instruments with respect to consumption losses and delay of learning backstop deployment is shown in Fig. 4. In the following we discuss these instruments in detail.

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

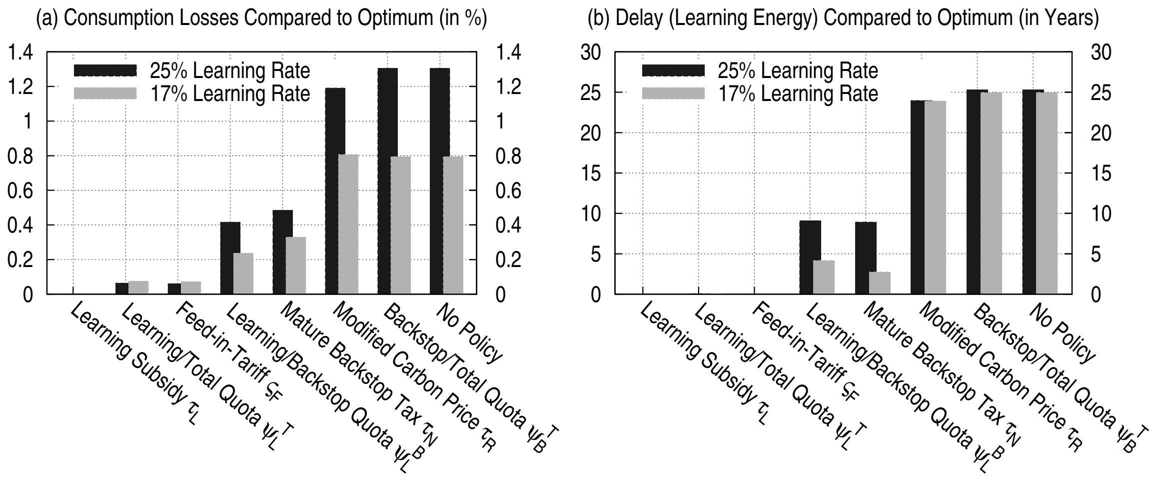


Figure 4: Performance of several policy instruments under the Stackelberg equilibrium: (a) Consumption losses relative to the optimal solution; (b) delay to achieve a share of 10% learning backstop energy.

4.1 Subsidy for learning backstop energy

Economic intuition suggests that a subsidy would be the appropriate instrument to internalize spillovers and achieve an optimal energy generation. As the social value of the learning technology is higher than its private value, an instrument is needed to correct for this positive externality. A subsidy is the most obvious way to implement this. Here, the subsidy τ_L is lump-sum financed and changes the energy allocation via an impact on the first-order conditions of the production sector (see Eq. 38 in the appendix).

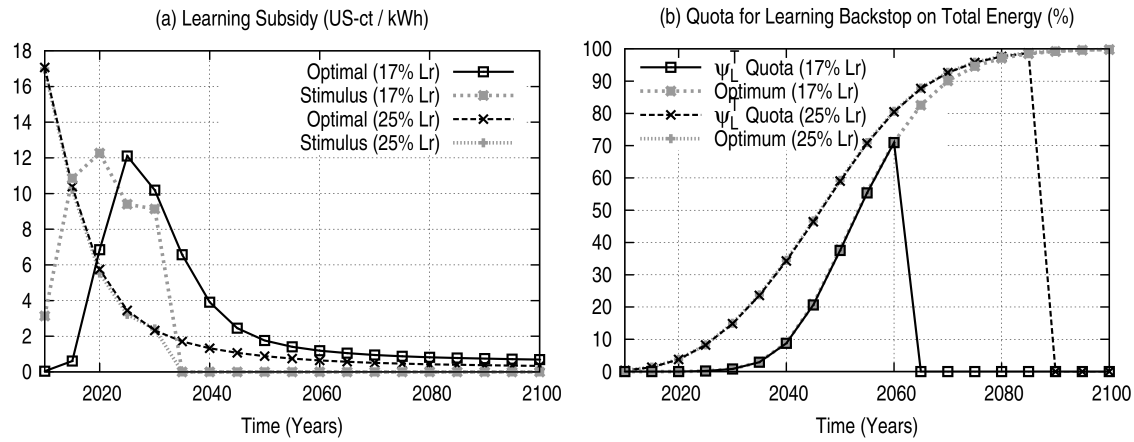


Figure 5: (a) Optimal subsidy and subsidy stimulus (2010-2030 only) and (b) optimal quota for learning backstop on total energy and share of learning backstop on total energy in the social optimum.

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 backstop 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 scarcely 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 backstop energy that is cross-financed by a tax on fossil and mature backstop 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 displayed in Fig. 5a. As the cross-financing mechanism causes small distortions for fossil and mature backstop energy prices,[17] the feed-in-tariff converges faster to zero. Consumption losses, however, are small ($< 0.1\%$) and there is no delay in learning backstop 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. (5–7), we introduced three different quota designs: (i) a minimum quota for the backstop 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 backstop generation (ψ_L^B).

Quota for (total) backstop 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 backstop technology relative to the fossil energy technology. However, this is too unspecific to prevent the lock-in into the mature backstop. A positive quota requirement would be met primarily by the mature backstop.

Quotas for learning backstop energy

This instrument is more specific. It can indeed increase the generation of learning backstop energy. However, we find that the reference point of the quota matters: if

[17] The difference between lump-sum subsidy τ_L and feed-in-tariff ς_F becomes apparent in the first-order conditions (37–39) in Appendix B.

the quota is chosen relative to the shares of the two backstop energies (ψ_L^B), it can discriminate mature against 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). Similar 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.[18] This explains why the quota is set to zero in the second half of the century: the consumption losses due to the distortion outweigh the gains due to higher learning backstop generation. Overall consumption losses are small and of the same magnitude as for the feed-in-tariff.

4.4 Tax on the mature backstop

Instead of promoting the learning technology, the lock-in can alternatively be addressed by taxing the mature backstop 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 backstop 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 backstop technology are made. Nevertheless, the modified carbon tax cannot prepone this transition phase. A higher carbon price would primarily encourage the mature backstop technology. Hence, the delay and consumption losses remain almost unchanged compared to the laissez-faire outcome.

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.

[18] See the marginal conditions (37–39) in Appendix B for mathematical details.

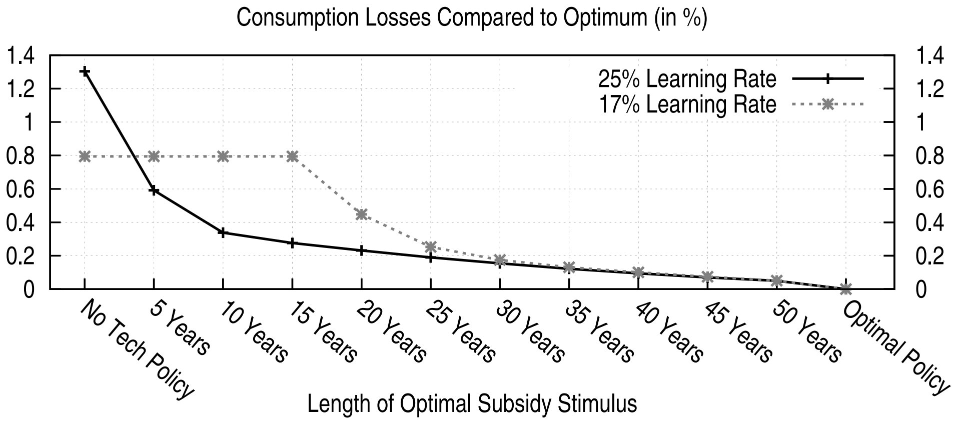


Figure 6: Consumption losses with respect to the length of optimal temporary subsidies (starting in 2010).

The consumption losses of these policy stimuli are shown in Fig. 6. A policy stimulus of 30 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 parameterization, this is immediately in 2010). The optimal stimulus subsidy may differ substantially from the optimal permanent subsidy as indicated exemplarily by Fig. 5a. For the moderate (17%) learning case, the 25-year-subsidy (and thus, learning backstop deployment) is preponed because the subsidy is not available in later periods.

6 Robustness of optimal policy instruments

This section provides some elementary considerations about the robustness of optimal policies by introducing small perturbations. For the three most efficient instruments 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 except when the subsidy is set too low. In this case 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 backstop technology because the subsidy is too low to make the learning backstop competitive. This does not occur for the other instruments. Even the 1%-lower-than-optimal feed-in-subsidy makes the learning technology early competitive because it additionally implies a taxation of fossil and mature backstop energy. For the quota, small perturbations translate directly to small deviations in production if the quota is binding. Thus, a lock-in cannot occur.

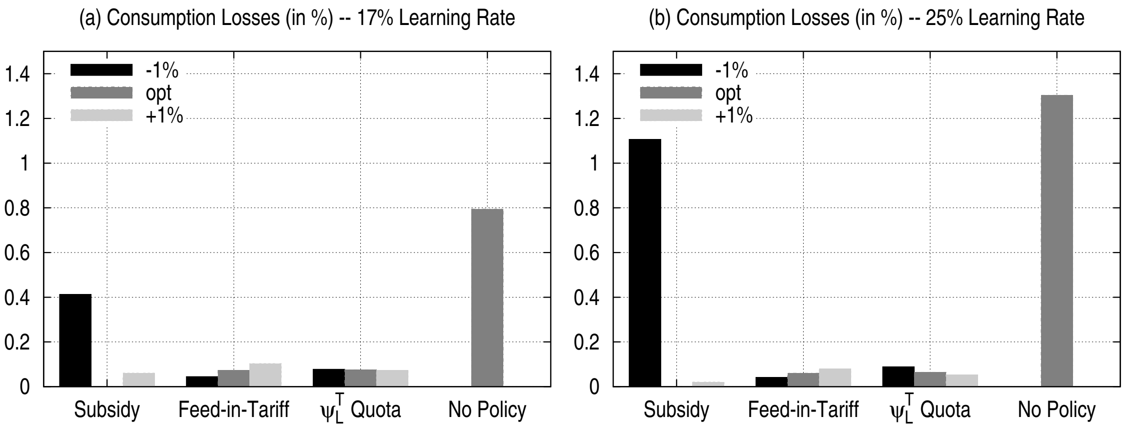


Figure 7: Consumption losses relative to the 1st-best optimum of optimal and 'close-to-be-optimal' (±1%) instruments.

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) high learning spillovers (and/or imperfect commitment to climate policy), (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 backstop 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 0.8% to 3.4% and carbon price increases by 17–127 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.[19] Thus, while in many economic sectors condition (i) and (iii) hold, condition (ii) is violated. Spillovers and discount rate mark-ups have

[19]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.

only small impact on welfare and may not justify (technology-specific) policy intervention. In contrast, energy from several technologies is an almost perfect substitute which leads to a strong competition in prices. Thus, the energy sector is at high risk of lock-ins into dynamically inferior technologies which exacerbates consumption losses.

Our parameter analysis showed that ambitious mitigation targets, high learning rates and high risk premiums (due to imperfect commitment to climate policy) particularly delay innovation and raise consumption losses. Even a 50 percent spillover can cause a severe lock-in with 1.4% consumption loss if risk premiums are high (15 percent) and the mitigation goal is ambitious (200 GtC). Furthermore, existing distortionary subsidies – albeit beeing small – can substantially exabercate the lock-in if they favor non-learning technologies agains learning ones.

An optimal policy has to internalize spillovers. This can be done by a subsidy on learning backstop energy which is lump-sum financed (Sec. 4). Feed-in-tariffs and minimum quotas on learning backstop energy also provide a way to promote a technology. However, these are cross-financed by an implicit tax on mature backstop 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, 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. While such a policy prevents lock-in, it cannot achieve the optimal timing of innovation leading to consumption losses of 0.3–0.5 percent. Technology-unspecific backstop quotas and modified carbon pricing are poor instruments resulting in negligible or zero welfare gains.

Finally, we analyzed the performance of subsidies which are only available for a certain time (Sec. 5). It turned out that a policy stimulus of 30 years is sufficient to decrease consumption losses below 0.2%.

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. A concluding evaluation of these risks requires a comprehensive robustness analysis which considers uncertainties in several economic parameters. While this is beyond the scope of this paper, it indicates an important question for future research.

A Technology

The following functional forms for utility and production are used:

$$\mathbf{U}(C/L) = \frac{\left(\frac{C}{L}\right)^{1-\eta}}{1-\eta} \tag{20}$$

$$\mathbf{Y}(Z,E) = \left(a_1 Z^{\frac{\sigma_1-1}{\sigma_1}} + b_1 E^{\frac{\sigma_1-1}{\sigma_1}}\right)^{\frac{\sigma_1}{\sigma_1-1}} \tag{21}$$

$$\mathbf{Z}(K_Y, L) = \left(a_2 K_Y^{\frac{\sigma_2-1}{\sigma_2}} + b_2 (A_Y L)^{\frac{\sigma_2-1}{\sigma_2}}\right)^{\frac{\sigma_2}{\sigma_2-1}} \tag{22}$$

$$\mathbf{E}(E_F, E_B) = \left(a_3 E_F^{\frac{\sigma_3-1}{\sigma_3}} + b_3 E_B^{\frac{\sigma_3-1}{\sigma_3}}\right)^{\frac{\sigma_3}{\sigma_3-1}} \tag{23}$$

$$\mathbf{E_B}(E_L, E_N) = \left(a_4 E_L^{\frac{\sigma_4-1}{\sigma_4}} + b_4 E_N^{\frac{\sigma_4-1}{\sigma_4}}\right)^{\frac{\sigma_4}{\sigma_4-1}} \tag{24}$$

$$A_{Y,t+1} = A_{Y,t}\left(1 - \Delta + \frac{\Delta}{1 - g_0 e^{-\zeta \Delta t}}\right) \tag{25}$$

$$L_t = L_0(1-q_t) + q_t L^{max}, \qquad q_t = \frac{e^{\Delta f t} - 1}{e^{\Delta f t}} \tag{26}$$

$$\mathbf{E_F}(K_F, R) = \left(a K_F^{\frac{\sigma-1}{\sigma}} + b R^{\frac{\sigma-1}{\sigma}}\right)^{\left(\frac{\sigma}{\sigma-1}\right)} \tag{27}$$

$$\mathbf{R}(S, K_R) = \kappa(S) K_R \tag{28}$$

$$\kappa(S) = \frac{\chi_1}{\chi_1 + \chi_2\left(\frac{S_0 - S}{\chi_3}\right)^{\chi_4}} \tag{29}$$

$$\mathbf{E_L}(A_L, K_L, N) = A_L K_L^{\nu} N^{\nu-1} \tag{30}$$

$$\mathbf{A_L}(H) = \frac{A_{L,max}}{1 + \left(\frac{\Omega}{H}\right)^{\gamma}} \tag{31}$$

$$\mathbf{E_N}(K_N) = A_N e^{\Delta g_N t} K_N \tag{32}$$

B First-order conditions of decentralized agents

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

$$L_t \frac{\partial \mathbf{U}}{\partial C_t} = \lambda_{H,t} \tag{33}$$

$$\lambda_{H,t} - \lambda_{H,t-1}(1+\rho)^{\Delta} = -\Delta \lambda_{H,t}(r_t - \delta) \tag{34}$$

$$0 = \lambda_{H,T} K_{T+1} \tag{35}$$

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 (21–24) leads to the first-order conditions:

$$r_t = \frac{\partial \mathbf{Y}(\mathbf{Z},\mathbf{E})}{\partial K_{Y,t}}, \qquad w_t = \frac{\partial \mathbf{Y}(\mathbf{Z},\mathbf{E})}{\partial L_t} \tag{36}$$

$$p_{F,t} = \frac{\partial \mathbf{Y}(\mathbf{Z},\mathbf{E}(\mathbf{E_F},\mathbf{E_B}))}{\partial E_{F,t}} - \tau_{F,t} - \psi_{1,t}\psi_{2,t}\phi_{L,t} - \psi_{3,t}\phi_{B,t}, \tag{37}$$

$$p_{L,t} = \frac{\partial \mathbf{Y}(\mathbf{Z},\mathbf{E}(\mathbf{E_F},\mathbf{E_B}(\mathbf{E_L},\mathbf{E_N})))}{\partial E_{L,t}} + \varsigma_{F,t} + \phi_{L,t}(1-\psi_{1,t}) + (1-\psi_{3,t})\phi_{B,t}, + \tau_{L,t} \tag{38}$$

$$p_{N,t} = \frac{\partial \mathbf{Y}(\mathbf{Z},\mathbf{E}(\mathbf{E_F},\mathbf{E_B}(\mathbf{E_L},\mathbf{E_N})))}{\partial E_{N,t}} - \tau_{F,t} - \phi_{L,t}\psi_{1,t} + (1-\psi_{3,t})\phi_{B,t} \tag{39}$$

With the KKT conditions for the inequaltiy constraints (5–6):

$$0 = \phi^T_{L,t}(E_{L,t} - \psi^T_{L,t}(E_{F,t} + E_{N,t} + E_{L,t})) \tag{40}$$

$$0 = \phi^B_{L,t}(E_{L,t} - \psi^B_{L,t}(E_{N,t} + E_{L,t})) \tag{41}$$

$$0 = \phi^T_{B,t}(E_{L,t} + E_{N,t} - \psi^T_{B,t}(E_{F,t} + E_{N,t} + E_{L,t})) \tag{42}$$

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

$$p_{R,t} + \tau_{R,t} + p_{C,t} = p_{F,t}\frac{\partial \mathbf{E_F}}{\partial R_t}, \qquad r_t = p_{F,t}\frac{\partial \mathbf{E_F}}{\partial K_{F,t}} \tag{43}$$

Fossil resource extraction sector Maximizing the Lagrangian $\mathcal{L}_R = \sum_{t=0}^{T}\left(\Delta\pi_{R,t}\Pi_{s=0}^{t}\left[1+r_s-\delta\right]^{-\Delta} + \lambda_{R,t}(S_{t+1} - S_t + \Delta R_t)\right)$ with respect to R_t and S_t and the substitutions (9) and (28–29) leads to the first-order conditions:

$$\lambda_{R,t} = p_{R,t} - r_t/\kappa_t \tag{44}$$

$$\lambda_{R,t} - \lambda_{R,t-1}(1 + (r_t - \delta))^{\Delta} = -\Delta(p_{R,t} - \lambda_{R,t})\frac{\partial \mathbf{R}}{\partial S_t} \tag{45}$$

$$\lambda_{R,T}S_{T+1} = 0 \tag{46}$$

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

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

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

$$0 = \lambda_T$$

With $\mu_t := \lambda_t \Pi_{s=0}^{t} \left[1 + \Delta(r_s + v - \delta)\right]$ we can transform this into:

$$r_t = \left(p_{L,t} - \mu_t + \frac{\mu_{t+1}}{(1 + r_{t+1} + v - \delta)^{\Delta}}\right) \frac{\partial \mathbf{E_L}}{\partial K_{L,t}} \tag{47}$$

$$\mu_t - \mu_{t-1}(1 + r_t + v - \delta)^{\Delta} = \Delta(1 - \phi) \frac{\partial \mathbf{E_L}}{\partial H_t} \left(p_{L,t} - \mu_t + \frac{\mu_{t+1}}{(1 + r_{t+1} + v - \delta)^{\Delta}}\right) \tag{48}$$

$$\mu_T = 0 \tag{49}$$

Mature backstop energy sector The common static condition applies:

$$A_N e^{\Delta g_N t}(p_{N,t} - \tau_{N,t}) = r_t \tag{50}$$

Carbon bank Intertemporal optimization results in a Hotelling price:

$$p_{C,t} = (1 + r_t - \delta)^{\Delta} p_{C,t-1} \tag{51}$$

$$p_{C,T} B_{T+1} = 0 \tag{52}$$

C 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–backstop energy	3
σ_4	elasticity of substitution learning–mature backstop	12
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
ν	share parameter learning backstop generation	0.95
$A_{L,max}$	maximum productivity learning backstop	0.6
Ω	scaling parameter	200
γ	learning exponent	0.27
N	land	1
υ	risk premium (learning backstop)	0.0
ϕ	spillover rate (learning backstop)	0.75
A_N	productivity mature backstop	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
Δ	length of time period (years)	5
T	time horizon (in Δ years)	30

Table 3: Parameters used for the numerical model.

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