Carbon Capture and Storage, Wind and Nuclear Power, and Technology Learning

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Abstract

Limiting the carbon emissions of electricity generation will require significant investments in low-carbon technologies. Moreover, the phase-out of nuclear power generation induces the need for replacement investments. One of the replacement options is the carbon capture, transport and storage technology (CCTS). We analyze the impact of carbon restrictions on the diffusion of low-carbon technologies. All technologies are characterized by specific costs and CO_2 emissions, which need to be covered by constraint emission permits. The fossil fuel-based capacity can be replaced by low-carbon energy technologies which are associated with initially higher costs and, in the case of CCTS, with a lower thermal efficiency. Both parameters improve due to endogenous learning effects if the technology is applied. Using a numerical model for the European Union we show that CCTS plays an important role for the replacement of nuclear power capacities.

1 Introduction

The implementation of the European Union's emission trading system in 2005 increases the pressure on the electricity sector to apply initially expensive renewable or low-carbon energy technologies. Since carbon allowances can be traded across Europe a price for carbon emission is established. EU ETS affects the production of electricity from fossil-fuel generation.[1] Furthermore, given the aging power plant stock in the European Union (IEA, 2007a), major investments into capacity are needed within the next decade.

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[1]The cement and iron and steel manufacturing industries are also characterized by a high CO_2 intensity in production. hese emissions are produced by fossil fuel combustion and the necessary chemical processes.

Clearly, decisions made today to invest in reduced-carbon technologies and new plants will affect the EU's future generation mix. The welfare implications are obvious, e.g., dependence on coal might delay investment in innovative low-carbon alternatives, which in turn might lead to higher abatement costs in the future. This offers the question, which technologies will replace fossil fuel based generation in the future. However, as a switch to a 100% renewable energy system will require substantial redesign and rebuilding of the grid.

In this article we analyze the role of nuclear power and CCTS as bridging technologies towards a low carbon generation portfolio. We develop a dynamic, welfare-maximizing investment model, taking into account emission restriction, vintage capital, and endogenous learning. The model is used in a set of scenarios to analyze how each of these factors influences the decision to invest and how key figures, such as electricity price or welfare, change accordingly. We discuss the role of CCTS in phasing out nuclear generation as well as the impacts of learning effects for offshore wind.

Phasing out nuclear generation involves an unusual combination of political and economic challenges. Due to high investment costs for new plants, the high costs of nuclear waste storage and plant scrapping, only state owned or subsidized companies have invested into nuclear capacity in the last decade (Deutch et al., 2009). Although climate concerns have put nuclear back on the political agenda [2], the ongoing catastrophe in Japan has revived and strengthened the arguments about safety and storage. In reaction to the unfolding problems at the Fukushima plant, the German government ordered the shutdown of the country's seven oldest reactors in order to conduct a three-month safety review. If the shutdown is permanent, social rejection of nuclear will likely increase throughout Europe.

CCTS defines processes in which CO_2 from large point sources, such as fossil fuel power plants is captured, compressed, transported, and stored underground. Accordingly CCTS can be seen as an instrument to mitigate o mitigate the greenhouse gas (GHG) effect. The chemical industry has used CO_2 capture for decades on a small-scale, although the near-term technologies for the energy sector, such as post-combustion and pre-combustion capture or the oxyfuel technology, vary in maturity and thus have different time horizons for commercial availability. Three CCTS technologies are available: post-combustion chemical absorption technologies are commercially available but the technology is used only for the treatment of very clean gas mixtures in industries; pre-combustion capture technology treats CO_2 and H_2 after the gasification of coal, biomass, or the steam reformation of natural gas; and oxyfuel technology produces a pure CO_2 stream. However, all of these technologies are expected to enter the market with significantly higher capital costs and high energy losses in generation compared

[2] Up to 25 GW of nuclear power are planned in the UK until 2025

to standard plants. Table 1 shows recent industry and academic estimates of the costs and performance expected for the first CCTS power plants. In addition, investment in the transport network and carbon storage required (especially if storage is only allowed in offshore sinks) will be prohibitive (Mendelevitch et al., 2010).Therefore, high carbon will be needed to incentivize the proper amount of investment at least until the technology improves due to learning effects and economies of scale.

Table 1 – Investment cost of different systems with and without CO_2 capture

Technology	Investment cost [€/MW]	Thermal efficiency [%]
Pulverized coal	1,478	46
Pulverized coal CCTS	2,500	35
IGCC-CCTS[a]	2,700	35
Oxyfuel[b]	2,900	35
CCGT-CCTS[c]	1,300	46

[a] Integrated gasification combined cycle [b] Oxyfuel [c] Combined cycle gas turbine
Source: Tzimas (2009)

Another way to meet the EU's GHG target is to expand onshore and offshore wind capacity. Europe for instance has experienced a rapid and massive expansion of onshore wind capacity, reaching already the capacity limit in some regions. Replacing first-generation turbines could increase onshore capacity by up to 250 GW until 2030 (DEWI, 2010). Offshore wind turbines generate more power than onshore turbines as wind speeds are generally higher and the wind is steadier offshore. New technologies are being developed (e.g., for strengthened tower foundations) to harness the wind in the harsher conditions associated with deeper waters. Difficult weather conditions, which can limit access for routine maintenance and the saline environment, create the need for more robust turbine parts. This in turn means higher costs, which, in the past, could not always be offset by higher productivity. But with more tailored subsidization[3], a better integration into the electricity grid and advanced technologies for the installment on sea, it is expect that offshore wind will take off within the next years.

Endogenous technical change has been incorporated in all types of energy system models analyzing transformation pathways of the energy sector and the impact of environmental and technology policies, e.g., linear activity analysis (MARKAL, Barreto, 2001) and non-linear partial equilibrium models (POLES, Russ and Criqui, 2007) and hybrid energy-macro models (MESSAGE, Rao et al., 2006; MERGE, Kypreos, 2005). All conclude that learning rates for environmental technologies result in a much earlier and

[3] In 2009, the German renewable energy legislation was adjusted to pay up to 150 €/MWh for offshore wind electricity (BMU, 2009).

more rapid reduction in GHG and reduce the social costs of climate change mitigation.

The remainder of this paper is organized as follows: Section 2 discusses the numerical model and its parametrization. Section 3 describes the scenarios and the results. Section 4 summarizes the findings and suggests topics for future research

2 Model Description

The model is designed to analyze the diffusion of CCTS and offshore wind technologies in a perfect competitive market. We incorporate vintage capital to account for plant efficiency and availability and the investment costs depending on the plants' installation dates.

2.1 Model without Learning Effects

The set of generation technologies is denoted by $g \in G$ and the model's time horizon is given by $t \in T := \{0, 1, ...T\}$. $f \in F$ denotes the set of fuels. The two-dimensional set $(g, f) \in M \subset G \times F$ indicates which plant g uses which fuel f.[4] Each generation technology g is characterized by a cost factor c_g [€/MWh] expressing the time invariant marginal cost. Furthermore, the heat efficiency $\eta_{g\tau}$ which depends on the installation date τ, together with the fuel cost pf_{ft} [€/MWh] determine the fuel cost. pi_{gt} [€/MW] denotes the cost of capacity investments. Demand in period t, D_t, is given by a linear demand function:

$$D(P_t) = a_t - b_t P_t \qquad \forall t \tag{1}$$

where a_t is strictly and b_t weakly positive. $P_t \in \mathbb{R}_0^+$ denotes the price in period t and $P_t(D_t)$ the inverse demand function.

The objective is to maximize welfare consisting of the integral over the demand function net of the generation and capacity investment cost. Denoting generation of technology g installed in period τ in period t by $X_{g\tau t} \in \mathbb{R}_0^+$ [MWh], capacity investment in period t by $I_{gt} \in \mathbb{R}_0^+$ [MW], and the discount factor by $\beta \in]0, 1]$ the objective function becomes:

$$\begin{aligned} \max \sum_t \beta^t \Bigg\{ & \int_0^{D_t(P_T)} P_t(D(t)) dD_t \\ & - \sum_{g,\tau \leq t} \left[c_g - s_{gt}^g + \sum_{f|_{(f,g)\in M}} \frac{pf_{ft}}{\eta_{g\tau}} \right] X_{g\tau t} \\ & - \sum_g (pi_{gt} - s_{gt}^i) I_{gt} \Bigg\} \end{aligned} \tag{2}$$

[4]We assume that each plant uses exactly one fuel as input.

The first line in the objective function (2) represents the consumer surplus. Generation and investment cost are expressed in the second and third line, respectively. s^g_{gt} [€/MWh] is a technology specific generation subsidy, i.e. a feed-in tariff. s^i_{gt} [€/MW] is a technology-specific investment subsidy. If the parameters become negative, they are interpreted as taxes.

In each period t the demand for electricity D_t needs to be covered by the sum of the generation of all of the previously-installed technologies:

$$\sum_{g,\tau\leq t} X_{g\tau t} = D_t \qquad \forall t \tag{3}$$

The generation of power plants is restricted by the installed capacity:

$$X_{g\tau t} \leq fl_{g\tau t}\Delta t\, CAP_{g\tau} + fl^{ex}_{g\tau t}\Delta t\, cap^{ex}_{g\tau} \qquad \forall g, t, \tau \tag{4}$$

$CAP_{g\tau}$ [MW] denotes the capacity endogenously installed in period τ. In contrast, $cap^{ex}_{g\tau}$ [MW] is exogenously-imposed capacity. Similarly, $fl_{g\tau t}$ [hours/year] are the full-load hours of endogenously installed and $fl^{ex}_{g\tau t}$ [hours/year] those of the exogenously given capacity. $\Delta\, t$ [years] is the exogenously given length of periods. We introduce the differentiation of endog- and exogenously-installed capacity in order to cope with the existing capacity prior to our model's start-time, i.e. imposing initial capacities. The full-load hours indicate how many hours in a year a plant is available. Relating the full-load hours to the installation date of the capacity allows us to introduce the plants' decreasing availability as the time increases for maintenance and repair. If the age of the plant exceeds the exogenously-given lifetime, the plant will be scrapped and, and the full-load hours become zero. A simplified example for a plant with a lifetime of three years is:

$$fl_{\tau t} = \begin{pmatrix} 8320 & 7880 & 7620 & 0 & 0 \\ 0 & 8320 & 7880 & 7620 & 0 \\ 0 & 0 & 8320 & 7880 & 7620 \\ 0 & 0 & 0 & 8320 & 7880 \\ 0 & 0 & 0 & 0 & 8320 \end{pmatrix}$$

The installed capacity CAP_{gt} is the result of the capacity investment $ICAP_{gt}$. Depending on the technology, investment will need i^{lag}_g periods to become effective:

$$CAP_{g(t+i^{lag}_g)} = I_{gt} \qquad \forall t \tag{5}$$

The total amount of capacity that can be invested in one period is constraint by the technology-specific parameter i^{max}_g [MW]:

$$I_{gt} \leq i^{max}_g \qquad \forall g, t \tag{6}$$

and is a combination of a fix value for each technology's fixed value $icap_{fix}$ plus a percentage of the available capacity $icap_{var}$. This results in a dynamic investment cap and accounts e.g., for the upscaling of production capacity for a new technology entering the market (Table 3).

We compute the carbon emission of each plant using their age-dependent heat efficiency of plants ($\eta_{g\tau t}$) and the fuel specific carbon content θ_f [t_{CO_2}/MWh]. Accounting for the possibility of CCTS, we introduce the carbon capture rate $cpr_{g\tau}$ which depends on the installation date of the plant. In every period, the total amount of carbon emissions is restricted by e_t^{max} [tCO_2]:

$$\sum_{\tau \leq t, f|_{(g,f)\in M}} (1 - cpr_{g\tau}) \frac{\theta_f}{\eta_{g\tau}} X_{g\tau t} \leq e_t^{max} \qquad \forall t \tag{7}$$

2.2 Learning Effects

Our model incorporates two learning effects: 1. the decreasing investment costs in previously-taken capacity investments, i.e. a learning-by-doing effect for investment cost, and 2. a learning-by-experience effect for the heat efficiency.[5] Both effects are incorporated using one-factor learning curves for investment and generation.

The learning curve for investment describes the relationship between cumulative capacity investments and the cost of capacity investments. Denoting the endogenous investment price by PI_{gt}, the one factor learning curve becomes:

$$PI_{gt} = pi_g^0 \left[\frac{cap_g^0}{cap_g^0 + \sum_{\tau<t} (I_{g\tau} + cap_{g\tau}^g)} \right]^{-\alpha_g} \qquad \forall g, t \tag{8}$$

where pi_g^0 [€/MW] is the initial capacity price of technology g, cap_g^0 the initially installed capacity, and α_g the learning elasticity. $cap_{g\tau}^g$ denotes the exogenously imposed capacity. However, in contrast to $cap_{g\tau}^{ex}$ this capacity cannot be used for generation. We include this kind of exogenous capacity to account for possible learning spill-overs from capacity investments outside the regional scope of the model.

The learning-by-experience learning curves determines the heat efficiency depending on cumulative generation. We denote the endogenously determined heat efficiency by H_{gt}. Consequently, the respective equation becomes:

$$H_{gt} = \eta_g^0 \left[\frac{x_g^0}{x_g^0 + \sum_{\tilde{\tau}<t, \tau<\tilde{\tau}} X_{g\tau\tilde{\tau}}} \right]^{-\gamma_g} \qquad \forall g, t \tag{9}$$

η_g^0 denoted the initial heat efficiency, x_g^0 the initial cumulative capacity, and γ_g the learning elasticity.

[5] A third aspect which is not covered in the model would relate to learning-by-researching. It is sometimes used in top-down models where a stock of knowledge accumulates over time based on R&D spending.

The model with learning effects is obtained by adding equations (8) and (9) and substituting the exogenous investment price pi_{gt} (heat efficiency η_{gt}) by its endogenous equivalent PI_{gt} (H_{gt}) in equation (2) and (7).

The full model without learning effects maximizes equation (2) under the constraints (1) and (3) to (7). Evaluating the integral in the objective function under the given linear demand function, the objective function becomes quadratic. The model with learning effects add further non-linearities through equation (8) and (9). We implement the model in the General Algebraic Modeling System GAMS (Brooke et al., 2005) using CONOPT (Drud, 1994) as solver.

2.3 Parameterization

We consider base-load capacities in our model. The initial share of generation technologies is based on the world energy technology outlook (WETO-H2, 2007) for Europe. The initial capacities are scaled to meet a demand of 2500 TWh which is supplied by the exogenous starting capacities of 170 GW coal, 50 GW CCGT, 105 GW nuclear, 75 GW onshore wind and 2 GW offshore wind (DEWI, 2010). This generation mix results in emission of 1.135 Gt CO_2. We do not include hydro generation because it has already reached its maximum potential (Hartmut et al., 2003) and the share of hydro is assumed to increase only by a small amount due to future efficiency improvements. Elasticity of demand is set to 0.3%.

Table 2 shows the cost and performance data for the technologies. Capital costs are assumed to remain constant for all technologies as long as no learning takes place. For mature technologies, subsequent improvements are rather incremental and might be offset by increasing prices for raw materials or labor, resulting in a stable price instead of further cost reduction. With respect to the thermal efficiency, the situation looks different. Even for mature technologies like hard coal or lignite power plants, efficiency has been improving, albeit at a decreased rate due to physical and materials limitations (Fischedick et al., 2008). This advance for the standard technologies is included as thermal efficiency improvement (see Figure 2 in the Appendix).

Table 2 – Technology Data

Technology	Capital costs [€/MW]	Build time [yr]	Full load [h]	OM costs [€/MWh_{el}]	Lifetime [yr]
Coal[b]	1478	4	7500	3	40
Nuclear[a]	3000	4	8000	3	40
CCGT[a]	750	2	7000	2	30
Coal CCTS[b]	2700	4	7000	5	40
Wind onshore[c]	1500	1	2100	1	25
Wind offshore[c]	3000	2	3500	1	25

[a] Wissel et al. (2008) [b] Tzimas (2009) [c] Jeske (2009), including grid connection

Table 3 – Investment Cap

Technology	Fixed cap [GW]	Variable cap [%]	i_g^{max} [GW] in 2010
Coal	2	2	5.4
Nuclear	2	2	4.1
CCGT	2	2	3
CCTS	2	2	2
Wind onshore	2	4	5
Wind offshore	2	6	2.1

The capture rate for the CCTS technology is set at 90% (Fischedick et al., 2008) and the additional variable cost for transport and storage are set to 7 €/tCO_2. Table 4 gives data on the carbon content and fuel prices . Fuel prices are assumed to increase over time: 1 % per annum for coal, natural gas and uranium.

Table 4 – Fuel Data

Fuel	Price [€/MWh_{th}]	CO_2 emission factor [CO_2/MWh_{th}]
Coal	6	0.37
Uranium	6	0
Natural Gas	20	0.2

Table 5 gives the parameters for the one factor learning curves. The learning curves for the investment costs are calibrated by the learning elasticity α, which gives the percentage drop in price each time the cumulative installed capacity doubles. Further, the initial capacity $cap_{g,0}$ defines after which installed capacity the learning starts. Thermal efficiency for the

CCTS technology increases in two ways. First, as the efficiency for the standard plant increases overtime, it also applies to the CCTS technology even if no investment is undertaken. Second, the endogenous learning curve for the thermal efficiency improvement of CCTS is calibrated by applying the learning elasticity η and the minimum generation $gen_{g,0}$. Having found no estimation for η in the literature, we therefore calibrate the learning curve so that the thermal efficiency of the CCTS technology starting at 32% is assumed to approach 48% in 2050, thus staying 5% below the efficiency of a standards plant in 2050.

Table 5 – Learning Parameters

Technology	Elasticity η	$gen_{g,0}$ [TWh]	Elasticity α	$cap_{g,0}$
CCTS	0.025	10	0.1[a]	4
Wind onshore	0	0	0.05[b]	1
Wind offshore	0	0	0.10[b]	4

[a] Rubin et al. (2006) [b] IEA (2009)

3 Results

3.1 Scenario Description

In the reference scenario *REF* we impose the restriction that emissions cannot increase in the future, i.e. the emission scenario of every period is the base year value of 1.135 Gt. All counterfactual scenarios are characterized by an emission reduction path reducing emissions by 2% per year. This leads to an emission reduction of 55% until 2050. However, the six counterfactuals differ by their restrictions on the technology portfolio. In the *CCTS&NUC* scenario CCTS as well as nuclear power plants are available options. In contrast, the *NO CCTS* does not allow for the implementation of CCTS plants. This scenario reflects the rather slow CCTS development observed so far as well as the uncertainty that the tech may never contribute to decarbonization of Europe's electricity sector. NEXT SENTENCE: Similarly, in the *NO NUC* scenario the use of nuclear power is phased out over the next 30 years but CCTS plants are available. We test the influence of learning effects on each of the counterfactual scenarios. The learning scenarios are denoted by *CCTS&NUC-L*, *NO CCTS-L*, *NO NUC-L*, respectively. We evaluate the results in terms of the generation mix shown in Figure 1, the average electricity price, and the welfare changes which are both given in Table 6.

3.2 Reference Scenario

In the reference scenario *REF* emissions are not allowed to further increase from the benchmark year. Given the initial generation capacity and the lowest marginal costs of all thermal generation technologies, coal retains its high share in electricity production until 2050 (see Figure 1). The increase until 2030 is driven by the exogenous efficiency improvement which allows capacity built in later periods to increase output but still emit the same amount of CO_2/MWh_{el}.

The requirement for replacements due to aging capacity, the investment lag i_g^{lag}, and the shadow price on the emission constraint generally result in a complex investment pattern: investment in coal generation for instance lessens the capacity restriction in Equation 4 due to the high capacity factor and the long life of the installed capacity. However, coal emits the highest amount of CO_2 per MWh, raising the shadow price on the emission price given by Equation 7. This causes more investment in natural gas, nuclear and onshore wind in subsequent periods.

In summary, absent a climate policy aiming at further reducing today‘s CO_2 emissions, we cannot expect significant changes in the EU's generation mix. As a result of missing incentives to pay for the learning investment in the form of a persistently high shadow price on emissions, environmentally desirable but expensive technologies will not come to market. This continuation of the status quo can also be observed in the projected electricity price (see Table 6). With an average of 52 €/MWh, the prices are the lowest of all of the scenarios.

Table 6 – Average Electricity Prices and Change in Producer and Consumer Rents until 2050

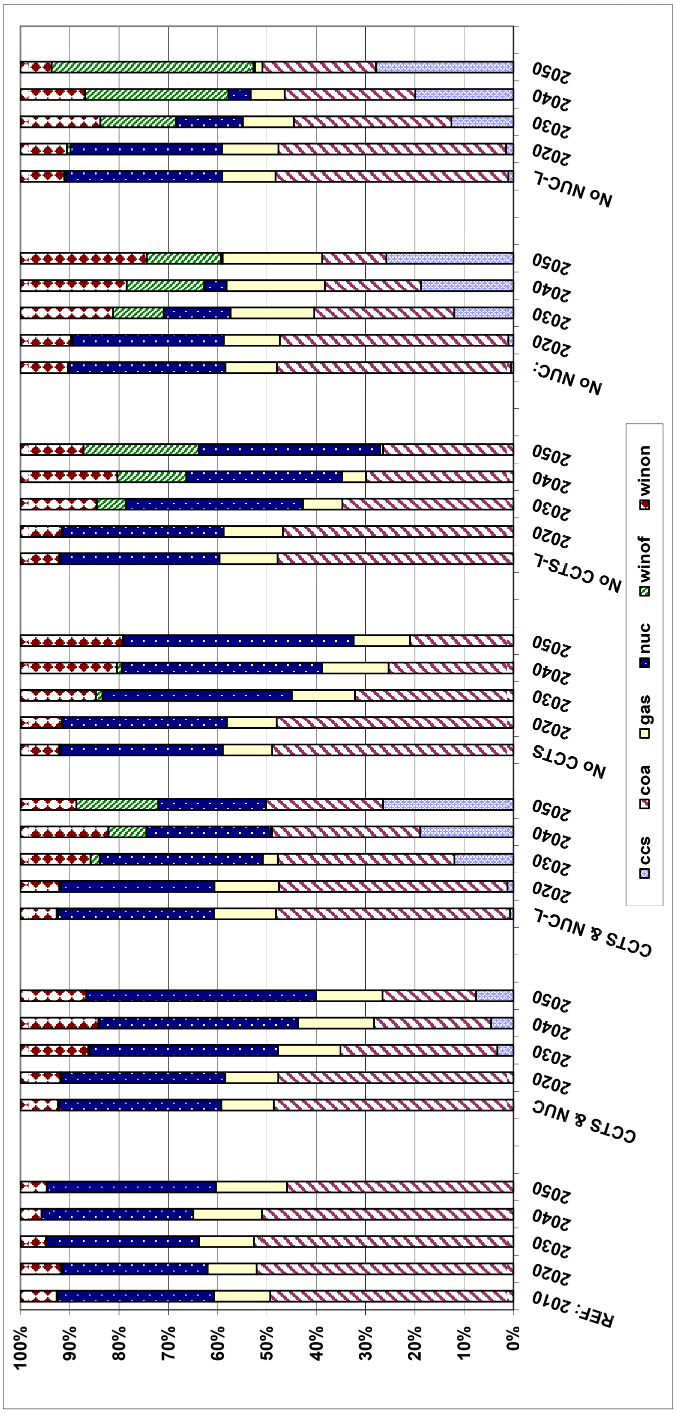
	REF	CCTS &NUC	CCTS &NUC L	NO CCTS	NO CCTS-L	NO NUC	NO NUC-L
Electricity price [€/MW]	52	57	53	59	54	66	56
Δ producer rent [bn€]	0	202	-124	435	-115	904	172
Δ consumer rent [bn€]	0	-533	-52	-152	-60	-333	-79
Δ PR + Δ CR [bn€]	0	-65	-51	-96	-67	-206	-51

Source: own calculation

3.3 Emission Reduction

In all scenarios except for the Reference Case, an annual reduction in the initial CO_2 restriction of 2 % is implemented. This leads to an emission reduction of 55% until 2050. In the absence of technological learning, scenario *CCTS&NUC*, the emission reduction is mainly achieved by extending

Figure 1 – Share in Electricity Production from 2010 to 2050



nuclear and onshore wind. Its installed capacity increases from 75 GW to 192 GW in 2040, but is partly replaced by nuclear in later periods which supplies almost 47 % of the demand in 2050. Natural gas capacity expands only slightly, since the shadow price on emissions favors investment into zero-carbon technologies (see Figure 1). The CCTS technology is used only to a small extend, as costs are too high compared to the low-carbon alternatives, nuclear power and onshore wind. For offshore wind the low full-load hours compared to nuclear and CCTS and the high investment costs, prevent the technology from becoming competitive at all. The model shows that an ambitious emission reduction with current technologies is possible, but at a high social cost. With 57 €/MWh, the average electricity price is 5 €/MWh higher compared to the Reference Case. The higher price and the extension of nuclear capacity translate into a higher producer rent of 202 bn€. However, the consumer's rent decreases by -533 bn€ over the modeling horizon. In total, this scenario results in a loss in welfare of -331 bn€ (see Table 6).

The incorporation of learning effects, scenario *CCTS&NUC-L*, changes the figure. For CCTS, the implementation of the learning curve leads to an endogenous reduction in capital costs of 750 to 2250 €/kW during the first 10 years and to 1810 €/kW until 2050. Also, the efficiency penalty to coal drops from 12% to 10% during the first 10 years and to 5% as CCTS efficiency reaches 48% in 2050. After 2020, prices and thermal efficiency reach a level where competition with nuclear power and natural gas is possible. We therefore observe a rapid increase in the installed capacity until 2050. For offshore wind, investment and therefore the leaning process is delayed for 10 years. The calibration of the learning curve results in a reduced investment cost of 1850 €/kW in 2050. Compared to onshore wind (1400 €/kW in 2050), offshore technology remains more expensive, however the higher full-load hours overcompensate for the investment cost's penalty. This explains why onshore wind capacity is partly replaced after 2040 (see Figure 1). The implications of technological learning for the change in welfare are significant. As the average electricity price rises to 53 €/MWh, consumer rent decreases by -52 bn€, which is 481 bn€ lower compared to the no-learning scenario S2a. For the producers, the learning investment results in much higher costs in earlier periods which cannot be offset by the savings in fuel cost of 127 bn€over the modeling period. This and the lower electricity price lead to a reduction in the producer's rent of -124 bn€. In opposition to the no-learning scenario, the cost burden for the emission reduction shifts from consumers to producers. In total, this leads to a reduction in welfare of -175 bn€, which is 156 bn€ lower compared to the no-learning scenario.

3.4 Emission Reduction without CCTS

The scenario without investment opportunities in CCTS and no learning is similar to the scenario with all investment opportunities. The share of nuclear again increases to almost 47%. The remaining gap is supplied by onshore wind, which increases to 21% in 2050, equal to 246 GW (see Figure 1). As a result, the average electricity price rises to 59 €/MWh, a minor impact compared to the scenario with CCTS. However, we observe a significant impact in producer rent, which is 435 bn€ higher compared to the Reference Case. The drop in consumer rent of -756 bn€ is the second highest of all scenarios. Total welfare drops by -321 bn€, which shows that the CCTS technology, due to the high capacity factor, low CO_2 emissions and long life, should be used in a generation portfolio aiming at maximizing total welfare.

In contrast to the no-learning scenario, the CCTS technology plays a an important role in the scenario *NO CCS-L*. Absent an investment alternative in the technology, this capacity must be replaced by alternatives. The model starts investment in offshore wind capacity from the first period, which results in a higher cost reduction of 22 €/kW and an increased use of the technology compared to scenario S2a. In 2050, the capacity reached 86 GW offshore and 209 GW onshore. Both technologies represent 35 % of total electricity generation. In general, the results show that absent the CCTS technology, the emission reduction is compensated by hin wind capacity as well as more nuclear consumption compared to the case when all investment opportunities are available *CCTS&NUC-L*. The change in total welfare of -287 bn€and the allocation of losses are comparable to Scenario *CCTS&NUC-L*. Due to the learning investment, producer rent decreases by -115 bn€. Since the learning investment is only spent for offshore wind technology, the loss in producer rent is 10 bn€less than in scenario S2b. The consumer rent decreases significantly by -172 bn€compared to the reference scenario. We note that the results should not be generalized to other markets e.g., where electricity prices or the potential for renewables are lower. Scenario *CCTS&NUC-L* has shown, that the model prefers paying the learning investment for CCTS prior to offshore wind as the benefits for generation are higher in the long-term. This is explained by the low fuel costs for coal, the high capacity factor, and the long life of the CCTS plants.

3.5 No Nuclear

This scenario restricts nuclear power under the imposed emission restriction. Consequently, no new investment in the technology is allowed while the environmental target of an annual emission reduction of 2 % remains in place. In the non-learning case, *NO NUC*, the opening gap of low carbon electricity generation is replaced by almost 26% of CCTS (see Figure 1).

Onshore wind, as the most mature of all innovative low-carbon energy technologies, experiences a significant growth to almost 27 %. However, onshore wind and CCTS cannot entirely compensate for the nuclear phase out. We therefore observe a shift from coal to natural gas, leading to the least share of coal and the highest share of natural gas of all scenarios. The large-scale application of immature, thus costly technologies, has the strongest impact on electricity prices which increase to 67 €. The high prices are also shown in the increase of producer rent: with an added 904 bn€ producers will strongly benefit under a welfare maximizing generation portfolio in this scenario. Previous scenarios without technology learning have shown that consumers bear the majority of the welfare losses due to the emission reduction is borne by the consumers. In this scenario, the highest electricity price also means that the loss in consumer rent reaches -1515 bn€ and the highest loss in total welfare of -610 bn€.

When considering technology learning, scenario *NO NUC-L*, the phase-out of nuclear technology again is fully compensated by CCTS and wind capacity. The boost in electricity prices to 56 €/MWh becomes much lower than the 67 €/MWh observed in the no-learning scenario, but still results in an higher producer rent of 172 bn€. Consumer rent decreases by -422 bn€. In total, this scenario shows a decrease in welfare of 249 bn€.

4 Conclusion

This paper developed a dynamic model to analyze the diffusion process of innovative, large-scale energy technologies under different assumptions. The model was applied to a generation mix based on today's European electricity market. Absent a CO_2 emission reduction, CCS and offshore wind were not implemented. If emissions have to be reduced, CCTS power plants only play a minor role. However, if learning effects are taken into account, the future increase in the efficiency of power plants and the decrease in the investment cost triggers the use of CCTS as well as offshore wind generation. Furthermore, the results show that if an accelerated nuclear phase out is implemented, the CCTS technology as well as offshore wind generation are necessary to replace the low-carbon nuclear capacity even without learning effects. The welfare implications, and more specifically the distribution of losses under technological learning, are important. Generally, losses in the electricity sector due to the emission reduction are lower in the learning scenarios. Those losses are borne by the producers due to the investment in initially expensive technologies which pay of in later periods. Further, the high price increase observed in the no-learning scenarios is absorbed by the learning effect.

Support instruments such as investment subsidies or feed-in tariffs may change the results and an emission tax lead to results different than those under a quantity constraint. For instance Germany implemented a feed-in tariff for renewable electricity, which is passed through to the end-users. This would have strong implications for the distribution of rents. The implications for the distribution of rents is the subject will be the subject of a future paper.

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5 Appendix

Figure 2 – Exogenous Efficiency Improvement

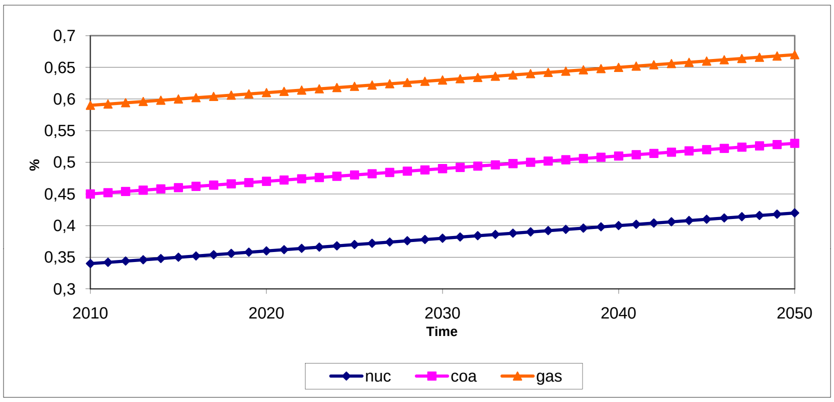

Table 7 – Share in electricity generation, REF [%]

Technology	2010	2020	2030	2040	2050
Coal	49.3	52.1	52.6	51.0	45.9
Nuclear	31.6	29.4	30.8	30.8	34.3
Natural gas	11.4	9.9	11.1	13.9	14.4
CCTS	0	0	0	0	0
Wind onshore	7.3	8.3	5.1	4.3	5.3
Wind offshore	0.3	0.3	0.3	0.0	0.0

Source: own calculation

Table 8 – Share in electricity generation, NUC&CCTS [%]

Technology	2010	2020	2030	2040	2050
Coal	48.6	39.6	31.8	23.7	19.0
Nuclear	32.9	33.2	38.3	40.5	46.7
Natural gas	10.6	10.7	12.6	15.4	13.4
CCTS	0.0	0.0	3.3	4.6	7.6
Wind onshore	7.6	8.1	13.7	15.8	13.3
Wind offshore	0	0	0	0	0

Source: own calculation

Table 9 – Share in electricity generation, NUC&CCTS-L [%]

Technology	2010	2020	2030	2040	2050
Coal	47.4	46.3	35.8	30.1	23.7
Nuclear	31.6	31.2	33.1	25.2	21.8
Natural gas	12.6	13.1	3.1	0.0	0.0
CCTS	0.7	1.2	12.0	18.9	26.5
Wind onshore	7.3	7.8	14.2	17.8	11.3
Wind offshore	0.3	0.3	1.9	7.7	16.6

Source: own calculation

Table 10 – Share in electricity generation, No CCTS [%]

Technology	2010	2020	2030	2040	2050
Coal	49.0	48.0	32.2	25.3	21.0
Nuclear	32.9	33.2	38.4	40.6	46.7
Natural gas	10.0	10.1	12.8	13.5	11.4
CCTS	0.0	0.0	0.0	0.0	0.0
Wind onshore	7.9	8.4	15.3	19.6	20.8
Wind offshore	0.3	0.3	1.3	1.0	0.1

Source: own calculation

Table 11 – Share in electricity generation, No CCTS-L [%]

Technology	2010	2020	2030	2040	2050
Coal	47.9	46.7	34.7	29.9	26.4
Nuclear	32.2	32.5	35.9	31.6	36.9
Natural gas	11.8	12.1	8.0	4.8	0.6
CCTS	0.0	0.0	0.0	0.0	0.0
Wind onshore	7.9	8.4	15.5	19.6	12.8
Wind offshore	0.3	0.3	5.9	14.0	23.4

Source: own calculation

Table 12 – Share in electricity generation, No NUC [%]

Technology	2010	2020	2030	2040	2050
Coal	47.5	46.4	28.4	19.5	13.0
Nuclear	31.6	30.7	13.6	4.5	0.3
Natural gas	10.5	11.4	17.0	19.9	20.2
CCTS	0.5	1.0	12.0	18.8	25.8
Wind onshore	9.6	10.2	18.8	21.6	25.6
Wind offshore	0.3	0.3	10.3	15.7	15.0

Source: own calculation

Table 13 – Share in electricity generation, No NUC-L [%]

Technology	2010	2020	2030	2040	2050
Coal	47.2	46.1	32.0	26.5	23.1
Nuclear	31.6	30.7	13.6	4.5	0.3
Natural gas	10.8	11.5	10.4	6.9	1.5
CCTS	1.0	1.5	12.6	19.9	27.9
Wind onshore	8.9	9.4	16.2	13.1	6.3
Wind offshore	0.4	0.7	15.3	29.0	40.9

Source: own calculation