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Relating R&D and investment policies to CCS market diffusion through two-factor learning

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Abstract

Carbon capture and storage (CCS) technologies have the potential to play a major role in the stabilization of anthropogenic greenhouse gases. To develop the capture technology from its current early pilot phase towards commercial maturity, significant public and private funding is directed towards R&D projects and pilot power plants. However, we know little about how this funding relates to the economics of CCS power plants and their market diffusion. This paper addresses that question. We initially review past learning effects from both capacity installations and R&D efforts for a similar technology, flue-gas desulfurization, using the concept of two-factor learning, and estimate the learning curve. We apply the obtained learning-by-doing rate of 7.1% and the learning-by-researching rate of 6.6% to CCS in the electricity market model HECTOR, which simulates 19 European countries hourly until 2040, to understand the impact of learning and associated policies on the market diffusion of CCS. Simulation results show that the individual impact of learning is similar for both learning rates, regardless of the CO_2 price. We then evaluate the effectiveness of policies subsidizing CCS investment costs (addressing learning-by-doing) and of policies providing R&D grants (addressing learning-by-researching) by relating the policy budget to the realized CCS capacity. We find that policies promoting diffusion through subsidies are, at lower policy cost, about equally effective as policies providing R&D funding. At higher spending levels, diffusion-promoting policies are more effective. Overall, policy effectiveness increases in low CO_2 price scenarios, but the CO_2 price still remains the key prerequisite for the economic competitiveness of CCS, even with major policy support.

Key words: Policy effectiveness, CCS, two-factor learning, electricity market

JEL classification: C63, O30, Q47

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1. Introduction and motivation

A prime challenge for the 21st century is the limiting of global warming to 2°C through the reduction of anthropogenic greenhouse gas emissions, formulated as a central result in the joint Accord of the Copenhagen Conference on Climate Change (2009). There are several CO_2 emission reduction targets addressing this challenge, such as the EU's commitment to a 20–30% target by 2020 (EU Commission, 2008) or the announced 17% target of the USA (US Congress, 2009).

As the main contributor to these emissions, the energy sector is especially impacted by this development and significant efforts are made to address this challenge. Carbon capture and storage (CCS) is widely seen as a major opportunity to continue fossil-fuel-based generation, while at the same time contributing to CO_2 abatement. The IEA's World Energy Outlook 2009 in its 450 ppm CO_{2e} scenario predicts that 150 GW of CCS coal capacity will be in operation by 2030 within OECD countries alone (IEA, 2009). Whereas the expectations placed on CCS are very high, the capture technology has still not been widely proven at full scale and technological progress has been limited in recent years, with only a few CCS pilot power plants being operational[1]. This presents a key obstacle to the anticipated large-scale CCS deployment. The solution lies in technological and managerial learning through extended R&D efforts as well as in the physical construction of an increasing number of (demonstration) CCS power plants.

Given the relatively high profile of CCS, we observe the need for additional CCS pilot plants and therefore investments, as foreseen for example in the EU's plan to have 12 plants operational by 2015 and to provide €1 billion of co-funding for CCS pilot plants (EU Commission, 2009a). The United Kingdom (UK)[2], Canada[3], and the State of Illinois, USA[4], have similar

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[1] Namely the Schwarze Pumpe coal-fired power plant in Brandenburg, Germany and the Lacq gas-fired power plant in Aquitaine, France. Additionally, two CCS power plant R&D efforts exist that operate on a small fraction of flue gases emitted from regular, non-CCS power plants (the Mountaineer station in West Virginia, USA and the Hazelwood station in Victoria, Australia).

[2] The UK in its 2010 Energy Act is planning to raise a CCS levy on households to subsidize up to four CCS demonstration plants (UK Parliament, 2010)

[3] Canadian CCEMA Act in Alberta, with the objective of a 50% reduction in greenhouse gas emissions intensity by 2020 (Canada, 2007). With this act, the Alberta Government alone plans to invest €2 billion into CCS (Deutsche Bank, 2009).

policies in place. On a corporate level, most major utilities have allocated significant funding towards CCS research, development and demonstration, with 24 CCS pilot and demonstration power plants announced to date (Wan and Chestney, 2009). This support is also needed, as stand-alone CCS power plant projects are only commercially viable in specific situations, such as in combination with enhanced oil recovery. Without this support, CCS runs the risk of being trapped in the "Valley of Death", the gap between public and private funding, especially due to the high up-front investment costs (Murphy and Edwards, 2003). A variety of support methods are available, such as R&D grants, subsidies for investment costs and others (Woerdman and Couwenberg, 2009). However, whereas the need to support CCS is accepted and continuously growing, we know little about the dynamics of how to optimally support this technology. This paper addresses these questions concerning R&D effectiveness, funding distribution, and funding level.

One method to estimate the relationship between R&D funding and technological improvement is “two-factor learning curves” (2FLC). This approach is based on "technological learning", the phenomenon that the cost of a specific technology decreases along with its cumulative deployment (initially Wright, 1936, and Arrow, 1962), but is extended by the additional consideration of cumulative R&D efforts (Kouvaritakis, 2000a,b; Jamasb, 2007). From a policy-analysis perspective, traditional learning-by-doing approaches only consider capacity deployment as the driving factor, thereby limiting any policy research to procurement policies that support investments in new capacity. However, policies supporting R&D, although a very popular method, cannot be analyzed with this approach, especially if the technology is at an early development stage.

In this paper, we estimate a 2FLC for CCS power plants through analogies, as no empirical data are available because CCS deployment has not yet started. We therefore empirically derive the 2FLC for the SO_2 scrubber technology, which is similar to the CO_2 scrubber technology used for CCS power plants[5], using cost, patents, and deployment data for the years 1970–2000. To validate the results, we compare them to already-published 2FLC estimates across the energy-generation industry as well as existing one-factor learning estimates for

[4] Illinois Clean Coal Portfolio Standard Act, requiring that all new plants put into operation after 2017 must capture and store 90% of CO_2 (Illinois, 2009).

[5] Specifically, post-combustion hard-coal-fired CCS power plants, the CCS plant technology closest to commercial readiness and the focus of this paper.

CCS, derived through the same SO_2 scrubber analogy (Riahi et al, 2004) or through expert panels (McKinsey, 2008).

Based on the 2FLC, we address the question of R&D and investment policy effectiveness for CCS power plants using a modified version of the HECTOR simulation model (Lohwasser and Madlener, 2009a,b). We provide an outlook for the European electricity market, including the diffusion of CCS technology under different policy scenarios until 2040 to explicitly consider the long-term effects of technological learning. The long time horizon is required due to the initial development stage of CCS, as early learning has a strong impact on the future. The analysis explicitly analyzes potential CCS policies considering the two effects mentioned: learning-by-doing (stimulation of deployment through investment cost subsidies) and learning-by-searching (promotion of R&D through grants).

The remainder of this paper is structured as follows. In Section 2, we discuss the concept of technological learning which, in Section 3, we then apply to CCS, using our own empirical analysis and comparisons to preexisting one- and two-factor learning curves. Section 4 focuses on the implementation of two-factor learning to the model used to simulate market diffusion as well as the description of the Base Case. In Section 5, we analyze the impact of learning-by-doing and learning-by-researching and, in Section 6, the impact of R&D and investment subsidy policies. Finally, Section 7 concludes with key takeaways and policy recommendations from our analysis.

2. Technological learning

The concept of technological learning is not new. Initially, flight pioneer Wright (1936) noticed the phenomenon that the labor hours required to construct an airframe (i.e. the plane without the engine) decreases with production experience for airplane manufacturing. Later, Arrow (1962) introduced the concept of learning-by-doing in his design of endogenous growth and related it to product manufacturing. Since then, a variety of studies have found empirical evidence for this relationship, known as the "learning curve", across different industries (BCG, 1968; Dutton and Thomas, 1984; Argote and Epple, 1990) and also specifically for power-generation technologies (McDonald and Schrattenholzer, 2001; Junginger et al, 2010). Within power generation, learning curves are frequently used for economic and policy analysis; Kahouli-Brahmi (2008), for example, provides a survey with 14 examples. The most common definition of a learning curve is:

$$C = C_0 \cdot Cap^{-\alpha} \,. \tag{1}$$

$$LR = 1 - 2^{-\alpha} \,. \tag{2}$$

with C as the specific costs of a technology per unit, in our case of electricity (€/MW or €/MWh), C_0 the initial investment cost at zero learning and α the learning elasticity. The learning elasticity can then be converted into a learning rate (LR) with eq. (2). This rate expresses the constant percentage of cost decline for every doubling of capacity. In the electricity supply industry, we observe a large range between about 2% for hydropower or supercritical coal plants and up to about 30% for wind and solar power plants (McDonald and Schrattenholzer, 2001; Köhler et al., 2006; Junginger et al, 2010). Technologies hereby often achieve a faster learning rate in their early deployment, such as coal power plants with a learning rate of 25% between 1948 and 1969 (Fisher, 1974), compared to the low value of supercritical coal plants mentioned earlier (see also Rose and Joskow, 1990, esp. p.357).

The concept of technological learning, especially its widely-used application for modeling energy-technology diffusion and policies (Kahouli-Brahmi, 2008), is not undisputed. For instance, Jamasb and Köhler (2007) mention that there is an overall need for more research to understand the nature of the real effects and processes that learning curves tend to capture. Furthermore, they state that single-factor curves are not suitable for the analysis of technologies that are in early stages of progress, as the effect of cumulative capacity on unit costs is only secondary in early development. Söderholm and Sundqvist (2007) further identify the problem of omitted variable bias, as cost reductions are not attributed towards R&D efforts. This leads to an overestimation of the learning-by-doing rate if R&D efforts are ignored (Jamasb, 2007). Another shortcoming of classic one-factor learning curves and the focus on capacity diffusion for technological learning only, is the limitation to diffusion-based policies (Klaassen et al., 2005).

Following these thoughts, the concept of explicitly considering R&D in technological learning as "two-factor learning curves" was introduced by Kouvaritakis (2000a,b). This adds R&D as an endogenous or control variable and addresses the omitted variable bias. The notion extends eq. (1) with the cumulatively-available knowledge stock KS and the learning-by-researching elasticity β:

$$C = C_0 \cdot Cap^{-\alpha} \cdot KS^{-\beta} . \tag{3}$$

The specific costs are therefore a direct consequence of cumulative capacity (*Cap*) as well as of accumulated knowledge (*KS*). The knowledge stock can either be represented through the sum of R&D expenses or, as a proxy, patents. A more complete overview of knowledge in this context is provided in Griliches (1995).

Compared to one-factor learning, there are comparably few empirical studies applying this concept to the energy domain, specifically Criqui et al. (2000) and Miketa and Schrattenholzer (2004), both for wind and photovoltaic generation, Klaassen et al. (2005) for wind generation in Germany, Denmark, and the UK, Watanabe et al. (2000) for photovoltaics in Japan as well as Kouvaritakis (2000a,b) and Jamasb (2007) for a variety of electricity generation technologies. One reason lies in the greater difficulty of obtaining sufficient and robust data points compared to regular learning curves. Furthermore, statistical collinearity biases between R&D expenses and capacity addition can pose a problem, leading to the need to use appropriate statistical methods, such as 2SLS or 3SLS estimates, as used for instance in Jamasb (2007).

The concept has also been adopted for electricity modeling, both for top-down (e.g. Buonanno et al., 2000; Kypreos, 2007) and bottom-up models (e.g. Grübler and Gritsevskyi, 1997; Barreto and Kypreos, 2004; Miketa and Schrattenholzer, 2004).

3. Two-factor learning for CCS power plants

3.1. Estimation through the analogy with flue-gas desulfurization

Flue-gas desulfurization (FGD) technologies remove SO_2 with scrubbers from a coal-fired power plant's flue gases through the reaction with an alkaline sorbent[6], a similar approach to the CO_2 scrubbers that use an amine solvent[7] to (reversibly) react with the CO_2 of the coal-fired power plant's flue gas. For the purpose of this study, we use the learning curve of FGD systems as a proxy[8] for the learning curve of post-combustion CCS coal-fired power plants.

[6] For wet SO_2 scrubbers, which represent the large majority of all SO_2 scrubbers (Nolan, 2000), and are used for the analogy analysis in this paper.

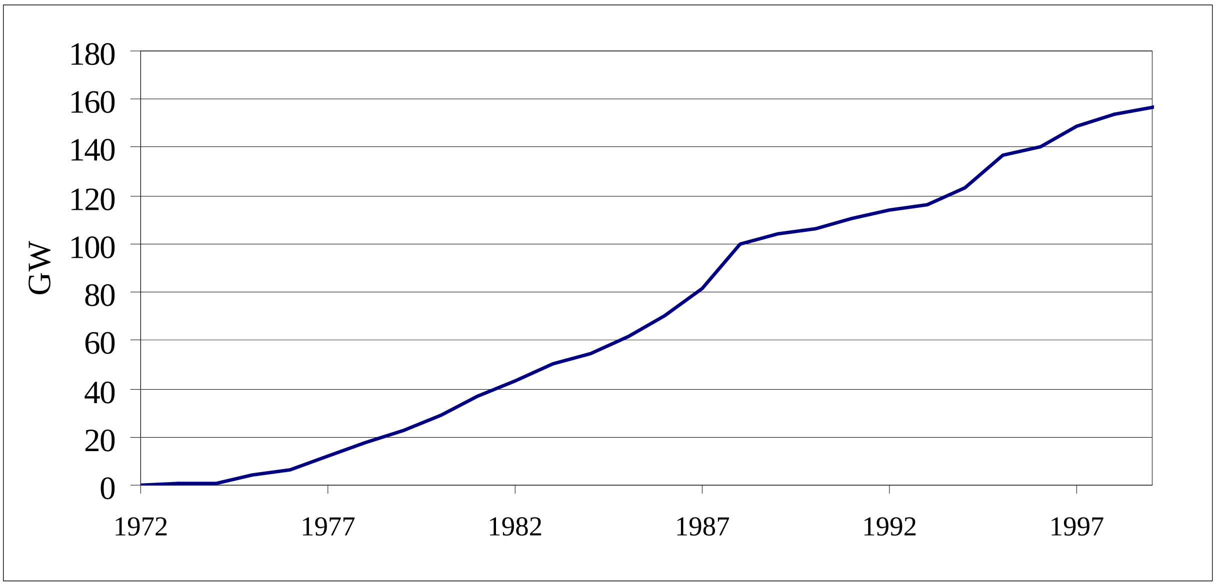
[7] Specifically, most post-combustion capture approaches use MEA (monoethanolamine) as a solvent for CO_2 scrubbing.

[8] This is the same approach as in Riahi et al. (2004), who also applied the FGD learning curve to CCS. However, their approach relied on a single-factor learning curve, which does not allow for an analysis of R&D-based policies.

As learning rates are not always constant over time, we try to align the FGD learning curve time horizon (the first 30 years after the initial commercial application of utility boilers, 1970–2000) with our CCS learning time horizon (first 25 years right after demonstration-scale deployment begins, 2015–2040). Using historical FGD capacity diffusion and R&D progress, we apply the ordinary least squares method (OLS) to eq. (3) in order to estimate the regression coefficients for learning-by-doing (α) and learning-by-researching (β), respectively. After checking for statistical significance (t-test with confidence levels), we obtain the learning rate from the regression coefficient α with eq. (2).

The history of FGD begins in the UK, where the technology was first deployed in the 1930s to address land damage from acid rain caused by SO_2 emissions from nearby power plants. However, it took until the 1970s for SO_2 scrubbers to be widely installed in commercial-scale power plants, mainly in the USA and Japan (Biondo and Marten, 1977). In the following years, a continuously-growing number of power plants were equipped with the technology, and the capacity development for the USA, Germany, and Japan, which represent over 80% of worldwide installations (Rubin et al., 2004), is depicted in Figure 1. Nowadays, we find this technology in almost all new coal-fired power plants coming online.

Figure 1: Cumulative wet FGD capacity in the USA, Germany, and Japan

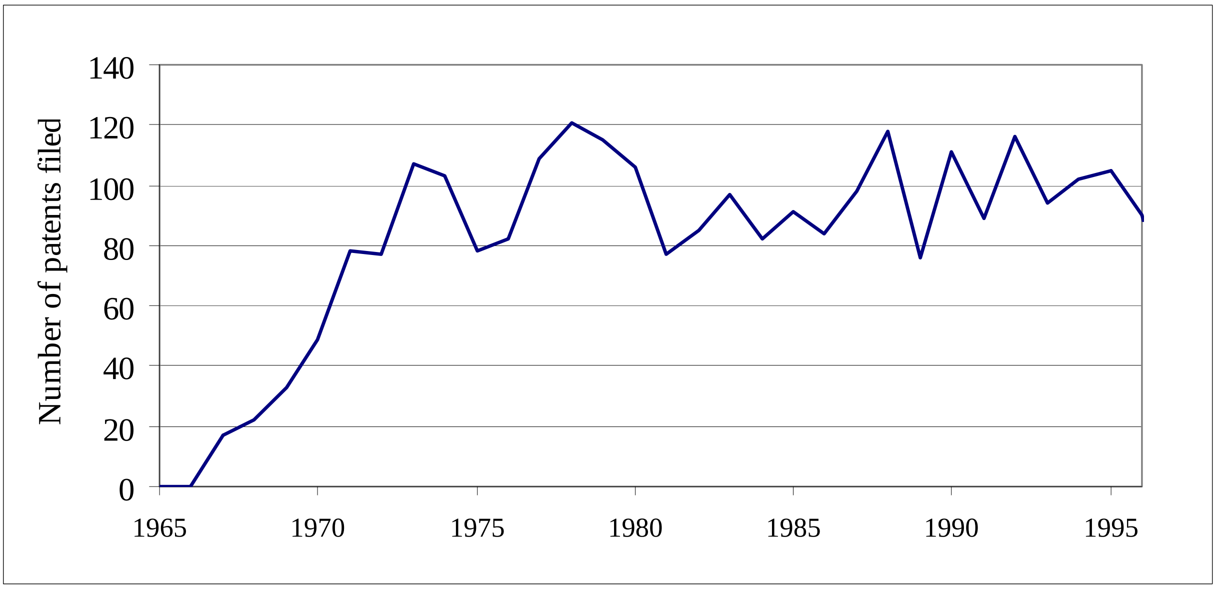


Sources: Soud (1994) and Rubin (2004)

Along with the introduction of the FGD technology, research efforts in this area increased in the late 1960s and early 1970s. A PhD thesis on SO_2 control by Taylor (2001) analyzed this development and identified FGD-related patents through patent subclasses filed in the US Patent and Trademark Office[9]. The number of patents filed per year in these subclasses is depicted in Figure 2. We see the strongest growth during the years 1967–1971, which is about four years before noticeable commercial deployment started.

We use this development as a proxy for the accumulated knowledge stock (*KS* in eq. (3)), as technology patents, especially their relative development, strongly correlate with R&D spending (Margolis and Kammen, 1999). Furthermore, filed patents do not immediately materialize into lowered production costs; we observe a time-lag for this development. Griliches (1998) proposes a range for the time-lag of 3–5 years, so we use the average value of four years for our analysis, which is also consistent with the lag observed between the patent filing and commercial deployment of FGD mentioned in the previous paragraph.

Figure 2: FGD-related patents by filing date



Source: US Patent and Trademark office, compiled by Taylor (2001)

[9] Namely 423/242.1-244.11, 095/137, 110/345 and 44/622-5.

The third and last empirical development needed to estimate a 2FLC is the decline in costs, in our case specific investment costs for wet FGD units. To measure exclusively the cost of FGD and exclude any potential cost improvements for the underlying coal-fired power plant, we use the cost of retrofit FGD units. As the source, we use an evaluation from Boward and Brinkmann (1998) that reveals the cost development for the USA, depicted in Figure 3. Starting at 400 US$/kW, investment costs significantly and linearly (R^2 = 99%) drop to eventually only 100 US$/kW in real terms. As this development is critical for the learning curve, and since the market for retrofit FGD units is neither transparent nor standardized, we test for robustness using a second source (Rubin et al., 2004). This source also reports a cost development for wet FGD scrubbers in the USA, i.e. data corresponding to the R&D and capacity deployment figures in use, and was also used by Riahi et al. (2004) to estimate the CCS learning rate referenced in Section 3.2 of this paper. The development starts at about 250 US$/kW in 1976 and eventually drops to about 125 USD$/kW in 1995, values that are lower than the figures mentioned by Boward and Brinkmann (1998). However, as the proposed principle of learning focuses on the relative development and the slope is relatively similar, we also observe very similar learning rates for learning-by-doing and learning-by-researching, with a difference of only about one percentage point[10]. We can therefore conclude that, despite uncertainty in the absolute level of cost reduction for FGD units, the impact on the resulting learning rates should be limited.

Before undertaking the regression analysis, we fill in any missing values through statistical imputation[11] and, as a final step, convert eq. (3) to a logarithmic scale. This transforms the multiplicative relationship between initial costs, capacity and knowledge stock to an additive relationship[12], simplifying the statistical analysis while not altering any results. We then fit the dataset into the equation, minimizing the error term by using the ordinary least squares method (OLS). The results are summarized in Table 1, and we can see that the historical FGD learning-by-doing rate is 7.1% and the learning-by-searching rate 6.6%.

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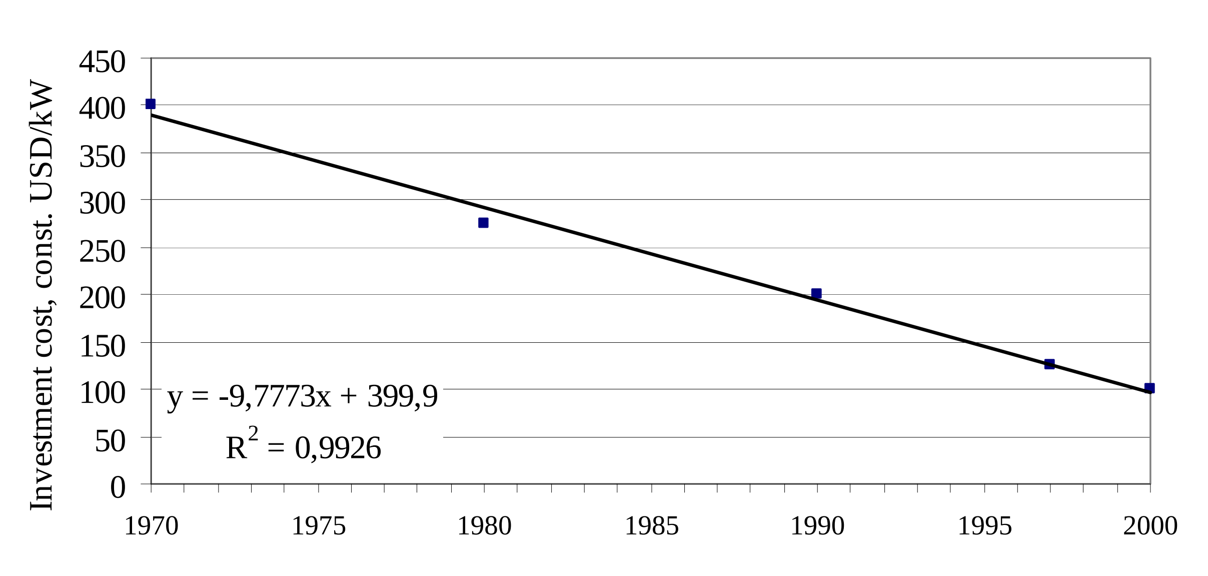
[10] The learning rates with the cost development of Rubin et al. (2004) produced a learning-by-doing rate of 6.3% compared to 7.1% with the Boward and Brinkman (1998) dataset and a learning-by-researching rate of 5.7% compared to 6.6%, both with comparable significance with the *t*-statistic.

[11] This step is needed, as not all input data are available throughout the analyzed time horizon of 1970–2000. Specifically, we impute one missing year (2000) for capacity data and the linear extrapolation of costs shown in Figure 3.

[12] Specifically, eq. (3) in log-linear form is $\log(C) = \log(C_0) - \alpha \cdot \log(Cap) - \beta \cdot \log(KS)$.

Figure 3: Specific investment costs for the retrofit of wet FGD units



Source: Boward and Brinkmann (1998)

Table 1: Results of 2FLC estimation for wet FGD units

Variable	Value	*t*-statistic
Capacity coefficient (α)	-0.099	-1.919*
Knowledge stock coefficient (β)	-0.093	-1.944*
Initial cost (A)	585.1	35.950**
Learning-by-doing rate	7.1%	
Learning-by-researching rate	6.6%	
Regression fit R	0.86	
Regression fit R^2 (adjusted)	0.73 (0.71)	

Null hypothesis of the coefficient being 0 rejected at a significance level below 10% (*) and 1% (**)

These values are relatively similar, implying a comparable impact of capacity deployment and R&D. This hypothesis is confirmed if we individually estimate the learning-by-doing rate by fitting the dataset to a regular one-factor learning curve as shown in eq. (1) and then, separately, the one-factor learning curve for learning-by-researching[13]. This leads to a (one-factor, or “joint”) learning-by-researching rate of 11.2% and learning-by-doing rate of 12.2%. Whereas both values are, in concurrence with the 2FLC results, quite similar, we also see that the

[13] Effectively, this is eq. (1) with KS as independent variable, namely $Cost = A \cdot KS^{-\beta}$.

impact of R&D is slightly below capacity development – just as in the 2FLC, with the learning-by-researching rate of 6.6% being just below the learning-by-doing rate of 7.1%.

3.2. Comparison with previously-published learning curves

To increase the confidence in the obtained learning curves for FGD and thus CCS, we compare the results to various previous publications. However, to date only one-factor learning curves (i.e., using capacity development as an independent variable) have been published for FGD and CCS. We therefore initially compare the one-factor learning curve resulting from our dataset with these publications by fitting it to eq. (1). The resulting learning-by-doing rate is 12.2% with strong statistical significance[14]. If we compare this value to existing publications, we find that Rubin et al. (2004) estimated the learning rate at 11%, Al-Juaied and Whitmore (2009) at 10-12%, Riahi et al. (2004) at 13% and McKinsey (2008) at 12%. The latter two also apply their FGD curve to CCS, following the same rationale of technical similarity that we use; McKinsey (2008) additionally uses the learning rate of LNG (13%) and renewables (3–23%) as an additional input, but their concluded CCS learning rate is still 12%. Al-Juaied and Whitmore (2009) derive the CCS learning rate through the difference between their current (first of a kind) and future (next of a kind) costs with a specific capacity deployment assumed. We can therefore conclude that our value of 12.2% is well in line with existing FGD and CCS estimates.

Based on the results of the one-factor learning curve, we now compare the values obtained to the 2FLC of other electricity-generation technologies, as no sources are available for FGD (or similar technologies such as NO_x capture systems). Jamasb (2007) provides an overview of 13 2FLC and groups technologies into the categories *mature* (e.g. hydro or coal-fired power plants), *reviving* (e.g. CCGTs), *evolving* (e.g. nuclear) and *emerging* (e.g. thermal solar power). Mature technologies, at the time of reporting, "are developed and utilized over a long period of time and have had a major share of the expansion", which describes the situation of FGD in the 21st century rather well. The reported range is between 2% and 6%, with one outlier at 12% for learning-by-doing and between 1% and 6% for learning-by-researching. Our obtained values for FGD were 7% and 6%, respectively, and therefore fall into this range,

[14] Result of the *t*-test is -8.122 and the null hypothesis of the coefficient being zero is rejected at the 1% level of significance.

but at the higher end. However, as the level of maturity for FGD is also at the lower end of the included technologies, such as hydro or conventional hard coal and lignite, we can expect stronger learning, explaining the observed values. The learning rates are still far below the values observed for evolving technologies, with learning-by-doing rates between 13% and 42% and learning-by-researching rates between 24% and 44%. The remaining two groups are far below our observed FGD learning-by-doing rates, with reviving technologies between 0% and 1%, and emerging technologies between 1% and 2%.

In a direct comparison with other currently-promoted technologies contributing to global greenhouse gas (GHG) abatement, namely wind generation and solar, we see that their learning-by-researching rates are 2–5 times greater than the learning-by-doing rates. Specifically, for solar power Jamasb (2007) reports a 2.2% learning-by-doing and 5.3% learning-by-researching rate and for wind 1.0% and 4.9%, respectively.

In summary, we can therefore conclude that the observed learning rates for FGD are in line with expectations based on existing publications, both for one-factor and for two-factor learning. In the following sections, we apply the obtained learning-by-doing rate and the learning-by-researching rate of 7% (rounded) in both cases to CCS technology as our Base Case for the purpose of electricity market simulation in order to understand their relevance.

4. Endogenizing the effect of R&D and market experience in the HECTOR model

To analyze market deployment of CCS in dependence on various learning rates and stimulation policies, we use HECTOR, a model that simulates the European electricity market bottom-up (Lohwasser and Madlener, 2009a). It matches variable-cost-based supply bids from power plants with national electricity demand on an hourly level until 2040 for 19 individual European countries[15]. In every hourly time step, the model considers the wind patterns, electrical energy demand patterns, and import/export transmission capacities to other countries. It also individually considers each power plant, aggregated into about 400 groups with similar technical and economic characteristics, and calculates a bid for its full or partial capacity at a bid price based on its variable and opportunity costs for the local energy market (e.g. EEX),

[15] Specifically, the simulated countries are the EU-15 excluding Luxembourg and Ireland and including Norway, Switzerland, Czechia, Hungary, Poland, and Slovakia, grouped into 14 regions.

which matches demand and supply hourly. The model further incorporates opportunistic behavior of power-plant operators through a mechanism that increases bid prices when the expected regional reserve margins become low. Renewables do not participate in the endogenous bidding process, but are assumed to bid at zero price at a quantity defined primarily by historic production patterns. The model decides on investments through continuous NPV calculations for constructible plants (like CCS-equipped coal-fired power plants) considering expected future revenues[16]. The ability of the model to closely approximate historic wholesale electricity prices is relatively accurate, providing a certain degree of trust. As a price across Europe's main regions[17] between 2006 and 2008, the simulation results achieved an average of €54.5/MWh compared to €54.8/MWh in reality. A detailed overview of the HECTOR model, including further explanations of its structure, source data as well as comparisons with historic electricity prices, is provided in Lohwasser and Madlener (2009a).

In our simulation setup, we use an integrated outlook for the energy and transport sector published by the EU Commission's DG-TREN (2008)[18], which incorporates the EU's current 20% renewables and 20% CO_2-emission reduction targets (EU Commission, 2008). For fuel prices, DG-TREN expects rather flat coal prices at €10–11/boe[19] and increasing natural gas prices, starting at €33/boe in 2010 and increasing to €38/boe in 2030. Oil prices follow the same trend as gas prices and all reported prices are inflation-adjusted to real 2005 terms. For electricity demand growth between 2010 and 2030, DG-TREN expects on average 1.2% for the EU countries contained in the model. To limit complexity within the scenarios and to sharpen the analysis, we only consider CCS for hard-coal plants, as they are the largest user of this technology and therefore do not include CCS for lignite, biomass or natural gas plants. We also treat CCS for hard-coal plants as one technology, i.e. we do not explicitly distinguish between specific CCS methods (post-combustion capture, pre-combustion capture and oxyfuel), as the winning technology is still unclear. Post-combustion capture methods, however, are the closest to commercial readiness and we therefore use the power-plant

16 Capacity investments for renewables and nuclear plants follow an externally predefined path instead to match policy targets (e.g. the EU's 20% target for renewables or national nuclear phase-out policies).

17 Germany (EEX), Italy (IPEX), France (PowerNext), Spain (OMEL) and Scandinavia (NordPool).

18 Scenario IV from DG-TREN (2008).

19 boe = barrels of oil equivalent is the approximate amount of energy released by burning a barrel of crude oil (1 boe = 6.12 GJ).

economics published in IPCC (2005) for these plants as the model input. This report quotes today's investment CCS costs at around 2000 €/kW based on eight design studies, a value approximately in line with a report by MIT (2007). However, as no demonstration-scale CCS power plant exists to date, there is uncertainty around this value and some authors quote up to 5500 €/kW (Al-Juaied and Whitmore, 2009).

To focus the analysis on learning for CCS hard-coal power plants, we exclusively apply technological learning for this technology[20]. Given the fact that the other technologies available for endogenous investment decisions, primarily various non-CCS coal- and gas-based power plants, are already very mature, i.e. far along in their learning progress, the expected impact from learning for these technologies is in any case limited. Finally, as only learning effects for investment costs are available, we limit endogenous technological learning to this factor. Improvements in conversion efficiency are treated exogenously; we assume a continuation of the IPCC's reported initial level of 33% until 2020 and then gradually increase to 40% by 2025. As investment costs have far more influence on the economics of a CCS power plant, compared to energy efficiency (Lohwasser and Madlener, 2009b), the overall impact should be limited.

As the overall price for CO_2 emissions will be the key driving factor for CCS profitability and therefore its success (IEA, 2008), special attention is needed for this assumption. As a consequence, we consider this development with two scenarios. The first is named "CO_2-38" with a CO_2 price development as reported in the DG-TREN scenario (DG-TREN, 2008), that we used for all other assumptions, in which the average CO_2 price is €38/t between 2015 and 2020. The prices start at €20/t in 2010, increase to €43/t in 2020 and reach €49/t in 2030. As these values are, especially in light of the results of the Copenhagen conference on climate change in 2009, relatively high, we simulate a second scenario with a lower price, named "CO_2-25", where the CO_2 price development is lowered by a constant value of €13/t to achieve an average price of €25/t between 2015 and 2020.

We further extend the HECTOR model by adding functionality on technological learning through exogenous R&D expenses and endogenous capacity development. Cumulative R&D

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[20] The learning effects exclusively apply to the CCS portion of the power plant, representing about 39% of the overall investments power plant costs (IPCC, 2005). Parts of the CCS value chain that are not part of the power plant – transport and storage – are kept at constant levels, as described in the model documentation (Lohwasser and Madlener, 2009a)

expenses and capacity deployment are updated every time step, and the resulting progress ratio in cost decline is updated according to eq. (3), along with the learning rate to elasticity conversion in eq. (2). This progress ratio is then considered for the calculation of investment costs as part of the NPV calculation within the capacity investment module of HECTOR. Lowered investment costs result in an NPV increase, which again represents an increased attractiveness of the technology and, finally, increased deployment in the market – the variable we use to measure policy effectiveness.

The model input for R&D expenses is taken from the IEA R&D statistics database that reports annual CCS R&D spending for the years 2000–2008 for most countries covered by the model (IEA, 2010). The reported annual spending level across the modeled countries was relatively stable for the years 2005–2008 at around €30 million, and we assume a continuation of this level throughout the model horizon and the years before availability of CCS, to obtain the starting level for technological learning. Additionally, we also include the already-announced EU program to "aid economic recovery by granting community financial assistance in the field of energy" (EU Commission, 2009a) with an overall value of €1.05 billion, which requires the projects to be completed by 2015. We therefore also distribute the budget over this period, which leads to an assumed R&D spending of €230 million annually. Any spending beyond or below this level is simulated through sensitivities as part of the R&D policy effectiveness analysis presented in Section 6.

As CCS is still at its infant stage, a clear distinction between learning-by-researching and learning-by-doing is hardly possible. Existing power plants, such as Vattenfall's CCS plant in Schwarze Pumpe, Germany, cannot be exclusively attributed towards either learning-by-researching or learning-by-doing, especially given its pilot scale of 30 MW_{th}. This, however, is likely to change once CCS research comes into a more mature phase and larger-scale demonstration plants of several hundred MW_{el} come online, expected around 2015 (McKinsey, 2008). We therefore take 2015 as the starting year for any learning effects (i.e., learning progress is at 100% in 2015) and use already-announced CCS capacity additions (Wan and Chestney, 2009) and R&D efforts for the development until 2015. This also provides the starting point for learning-by-doing and learning-by-researching[21].

[21] By 2015, this will lead to a cumulative CCS pilot capacity of 10.5 GW and R&D expenses of €1.3 billion, which are not included in the CCS demonstration and commercial-scale capacity figures reported in Sections 5 and 6.

5. The impact of technological learning on CCS diffusion

To understand the relevance of different learning curves, we simulate the electricity market development in the HECTOR model for the years 2005–2040, using the assumptions defined in the previous section for the two CO_2 price scenarios. In particular, we define our Base Case with the learning rates obtained through regression analysis, i.e. 7% for both learning-by-doing and learning-by-researching, but now apply a sensitivity for learning rates of 0%, 5%, and 10%, both as learning-by-doing and learning-by-researching rates. The sensitivity range is derived from the values of similar electricity generation technologies outlined in Section 3.2, which spans across most values expected for this technology. Based on the sensitivity analysis, we can now observe how relevant the actual CCS learning rate will be for the diffusion of the technology. The simulation results for overall CCS capacity are depicted in Figure 4, and the breakdown at country level for the different power generation technologies in Table 2.

Figure 4: CCS capacity development across all model regions over time as a function of the learning rate

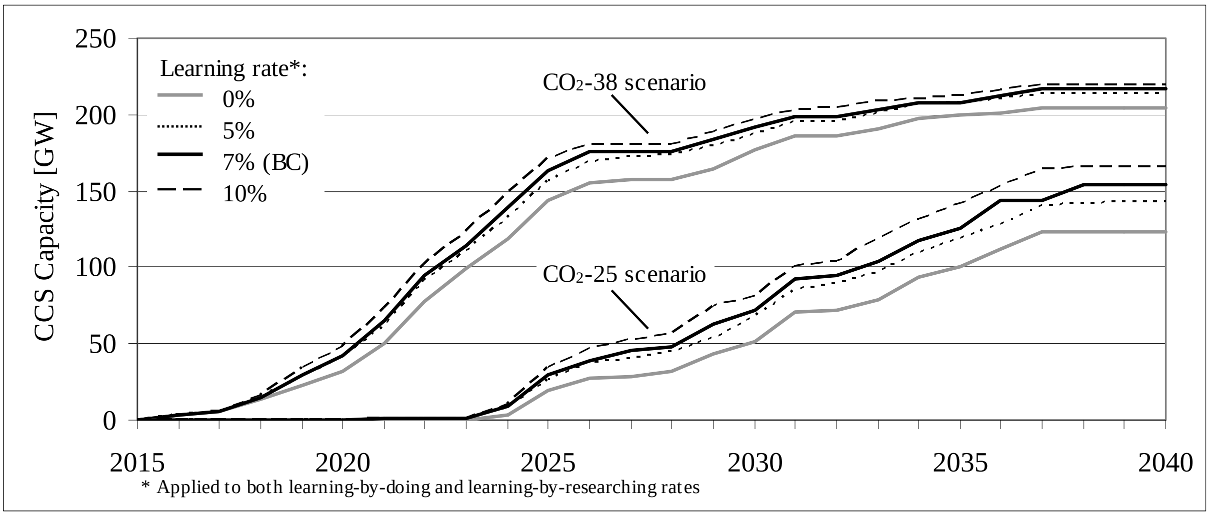


Table 2: Installed capacity in 2040 for different learning rates in both scenarios [GW]

	CO_2-38 scenario						CO_2-25 scenario						Scenario-independent	
Country	**7% learning[a]**			**0% learning**			**7% learning**			**0% learning**				
	CCS	Coal[b]	Gas[b]	CCS	Coal	Gas	CCS	Coal	Gas	CCS	Coal	Gas	RES[c]	Other[d]
Belgium	4	5	4	4	5	4	4	7	5	4	8	5	8	0
Germany/Austria/Switzerland	45	26	9	45	27	9	26	66	9	23	66	9	93	3
Czechia	9	5	0	9	6	0	5	8	1	3	8	1	8	3
Denmark	0	3	1	0	3	1	0	5	2	0	5	2	8	0
France	45	14	3	41	15	5	27	14	3	23	15	3	62	58
Greece	6	3	4	6	3	4	6	5	4	4	6	4	9	0
Hungary	2	1	2	1	1	2	1	1	2	1	2	2	4	4
Italy	12	13	51	12	12	53	12	26	35	12	26	36	45	1
Iberia	20	17	9	15	18	12	12	19	13	8	21	14	97	6
Netherlands	10	8	13	10	8	13	8	18	11	5	18	13	11	0
Poland	11	19	0	11	17	2	11	21	0	9	25	0	30	5
Finland/Norway/Sweden	4	6	16	2	6	18	3	14	6	4	13	6	75	14
Slovakia	5	0	1	4	0	1	3	2	2	2	2	2	5	2
UK	45	39	6	45	39	6	36	49	11	27	50	21	60	9
Total	217	160	120	205	161	129	154	256	102	123	265	118	516	106

a) Applied to both learning-by-doing and learning-by-researching rates

b) Excluding CCS-enabled capacity

c) Renewable Energy Sources (RES): Wind, biomass, hydro, solar, geothermal, and other renewables

d) Oil and nuclear capacity

As a result for the CO_2-38 scenario, we observe highly-similar capacity diffusion paths for the learning rates 5%, 7% and 10%, i.e. there is relatively little impact of the learning rate on the success of CCS. Even in the 5% learning rate scenario, the CCS diffusion is only 3 GW or 1.4% below the Base Case with 7% learning by 2040. Likewise, the 10% learning rate scenario achieves 2 GW of additional capacity compared to the Base Case by 2040. The reason lies in the "progress rate", i.e. the investment costs after learning relative to initial costs without learning (C_0). In the Base Case, CCS-equipped hard-coal-fired power plants have a progress rate of 85% by 2040. This corresponds to about 2000 €/kW at their availability in 2015 and about 1700 €/kW in 2040 (in real terms). The 5% learning sensitivity, in contrast, reaches a progress rate of 89% (1780 €/kW) and the 10% learning sensitivity reaches a progress rate of 80% (1600 €/kW) by 2040. These slight variations in investment costs do enhance profitability of the technology and, in turn, their market diffusion, but the overall impact is not significant enough to severely alter the generation landscape in a "make-or-break" style for CCS. A reason for this lies in the relatively low portion addressed through learning. Unlike the typical learning curves for power generation technologies, which address 100% of the cost base, the CCS equipment only makes up for 39% of the cost base of the overall pulverized coal-fired CCS power plant (IPCC, 2005). Therefore, technological learning effects only apply to this portion; the remainder is the underlying pulverized coal-fired power plant, which only marginally participates in learning effects due to its low learning-by-doing rate of 3.8%[22], in conjunction with the huge deployment that the technology has already experienced, making any additional doubling of capacity needed for the cost reduction a large step. For the Base Case, we achieve a learning-by-doing progress rate of 72% and a learning-by-researching progress rate of 84%, jointly reducing the cost of the CCS portion to 61% of its initial value by 2040. For the whole power plant, this corresponds to a cost-reduction of only 85% of the initial value – limiting the overall impact of technological learning. Nevertheless, if no technological learning is assumed at all, i.e. the costs by 2040 are at 100% of the initial value, we do observe a noticeable impact. In total, 12 GW less CCS-enabled capacity comes online by 2040 compared to the Base Case. We can therefore conclude for the CO_2-38 scenario, and as long as learning is assumed in the first place, that the actual level of learning does not significantly alter the diffusion of CCS.

If we focus on the CO_2-25 scenario, we first notice the long delay until CCS-equipped power plants enter the market. Compared to the CO_2-38 scenario, in which deployment starts in the late 2010s, the low CO_2 prices of the CO_2-25 scenario delays the stand-alone profitability of the technology by almost 10 years to the mid-2020s. This confirms the expectation that CO_2 prices are the key driver for CCS success and at these CO_2 prices the widely-anticipated commercial readiness of CCS by 2020, that requires about 21–23 GW of capacity, (McKinsey, 2008), will not be realistic without subsidies and public support.

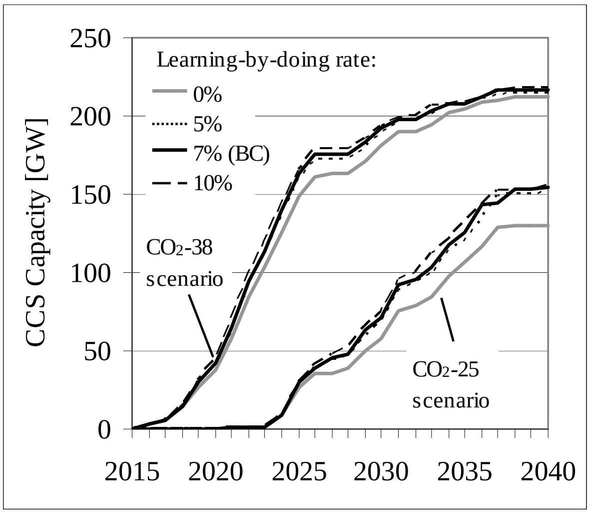
The overall progress rate is very similar compared to the CO_2-38 scenario; the investment costs of CCS plants drop to 88% of their initial level in the Base Case, and to 92% at 5% learning and 84% at 10% learning; these values are 2–3 percentage points higher than in the CO_2-38 scenario. The impact, however, is noticeably stronger: The 10% learning case leads to 12 GW of additional capacity over the Base Case, a plus of 8% (compared to 1% for the CO_2-38 scenario). Especially the simulation without learning leads to a significantly altered diffusion path: CCS capacity is reduced by 31 GW (or 20%) by 2040, with a continuously growing gap over time between the case with and without learning – representing the growing impact of learning with time. The 5% learning rate results are similar: CCS capacity is reduced by 11 GW (or 7%) compared to the Base Case by 2040 (also compared to 1% CCS

[22] Learning rate for supercritical coal-fired power plants from Jamasb (2007).

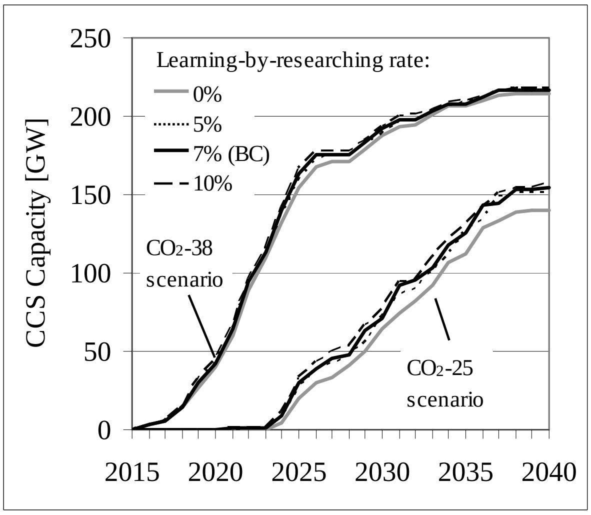
capacity reduction for the CO_2-38 scenario). As the progress rate is more or less comparable, the increased impact of technological learning arises from the different CO_2 price: In the CO_2-38 scenario, CO_2 prices are, especially beyond 2025, at a level where CCS is clearly the preferred investment option for fossil-fuel-based base-load generation and is clearly favorable over conventional combined-cycle gas, hard-coal, or lignite technology. Therefore, slight changes in investment costs do not significantly alter the relative profitability or result in a switching of fuels. This, in turn, leads to a moderate impact in terms of deployment. The lower CO_2 price in the CO_2-25 scenario increases market competition, and even small changes in investment costs can lead to a different technology as the optimal base-load investment option.

Figure 5: CCS capacity development across all model regions over time

(a) Variation of learning-by-doing rate



(b) Variation of learning-by-researching rate



In a next step, we individually change the learning-by-doing rate (Figure 5a) and learning-by-researching rate (Figure 5b), with all other assumptions as in the Base Case. For the learning-by-doing sensitivity in the CO_2-38 scenario, the development is almost unaffected by the learning rate; the Base Case reaches a CCS deployment of 217 GW by 2040, the 5% learning-by-doing sensitivity 214 GW, and the 10% sensitivity 218 GW. For the sensitivity without any learning-by-doing effects, we obtain 212 GW by 2040, i.e. a value only 2% below that of the Base Case. The impact of learning-by-doing for the CO_2-25 scenario is similar, as the Base Case has 154 GW of CCS by 2040, and the 5% and 10% sensitivities 150 GW and 156 GW, respectively. The simulation without learning-by-doing reaches 129 GW, 24 GW or 16% less compared to the Base Case. We can therefore conclude that, while the overall impact of learning-by-doing on CCS diffusion is rather limited, there are stronger effects in the low CO_2 price scenario, confirming the findings of the combined learning-by-doing and learning-by-researching sensitivity highlighted in Figure 4.

The sensitivity for learning-by-researching also leads to the similar finding that the impact is almost negligible in the high CO_2 price scenario and noticeable, but still relatively little, in the low CO_2 price scenario: The overall variation is below 3 GW or 2% with CO_2-38 and below 10 GW or 8% with CO_2-25, again measured as the range observed between the Base Case and the different sensitivities for CCS capacity by 2040.

This confirms the hypothesis outlined in the regression analysis to obtain the 2FLC for FGD in Section 3, that both learning factors – diffusion and research – have a relatively similar impact, unlike most other technologies for which 2FLC are available. However, whereas the diffusion effect was marginally stronger than the researching effect, the simulation results show the opposite effect, yet again with marginal differences. In the CO_2-38 scenario, the range of observed values for CCS capacity by 2040 for both the learning-by-doing and learning-by-researching sensitivities was within 2% of the Base Case. In the CO_2-25 scenario, this was 7% for learning-by-doing and 8% for learning-by-researching. Obviously, given the general uncertainties of long-term forecasting, it is difficult to derive any insights from these marginal differences.

6. The impact of R&D and investment subsidies on CCS diffusion

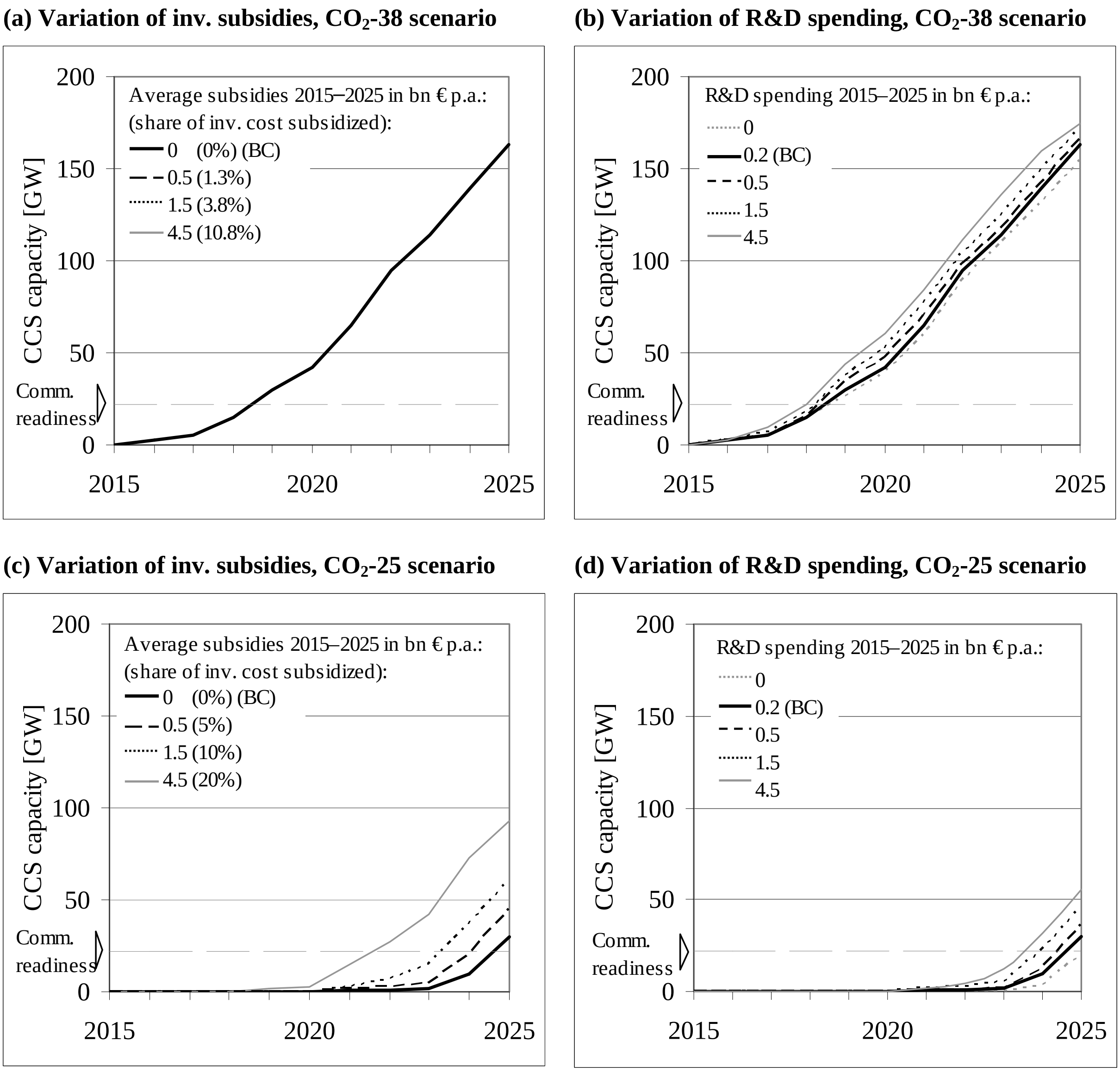
We now analyze the effectiveness of policies that address the two learning effects. First, we deploy an investment subsidy policy, which covers a certain percentage of initial investment costs of CCS plants, thereby reducing the cost, promoting diffusion, and addressing learning-by-doing. Second, we deploy an R&D spending policy, which varies the annual R&D expenses and therefore contributes to learning-by-researching. We assume that the policy applies to all 19 European countries covered by the model in the same way and we do not distinguish between the geographical sources of R&D grants. Instead, capacity and R&D progress applies to the same, European-wide learning development. Furthermore, not all costs need to come from a governmental body: We only analyze based on the overall budget and whether it is privately or publicly funded is irrelevant. If a utility company decides, for example, to deduct x% of the investment costs for its NPV calculation and hence its investment decision for a new CCS-equipped power plant, this has the same effect on the model as a governmental policy that subsidizes x% of the investment cost. The same is true for R&D, as the learning-by-researching progress does not distinguish between governmental or private funding. Therefore, any policy budgets mentioned are always total numbers, and the portion needed to be addressed by the government may be lower.

In the upcoming analysis, we use the Base Case in its two scenarios – CO_2-25 and CO_2-38 – as the starting point, which assumes a prolongation of current CCS R&D expenses without any investment cost subsidies as the basis[23]. We then deploy a sensitivity analysis separately for the two policy options and show the results in Figure 6 (plots a,b for the CO_2-38 scenario and plots c,d for the CO_2-25 scenario).

If we analyze the CO_2-38 scenario, we notice a strong deployment even if no stimulation policies are applied at all. The average difference between the Base Case and a CCS stimulation policy budget of an additional €1.5 billion is only 6 GW (or 10%) for investment cost subsidies and 7 GW (or 11%) for R&D grants. The overall impact of additional CCS stimulation policies is therefore rather limited, and we also cannot observe any early-mover advantages in the long run: By 2025, the relative difference has gone down to 4% (investment subsidies) or 5% (R&D grants), even at €1.5 billion spending per year. In any case, more than 21–23 GW of CCS capacity is installed by 2020, which is regarded as a requirement for the technology to achieve sufficient learning for a large-scale commercial deployment (McKinsey, 2008). If no further R&D efforts are undertaken at all, i.e. the current level of €0.2 billion p.a. is reduced to €0 and no cost reductions through learning-by-researching take place, CCS diffusion is still at a high level. By 2025, we observe 155 GW of CCS capacity, compared to 163 GW in the Base Case with €0.2 billion annual R&D expenses. This means, with €0.2 billion annual R&D expenses, CCS capacity grows by 8 GW until 2025. In contrast, an increase from €0.2 to €0.5 billion p.a. only leads to 3 GW additional capacity and a further increase from €0.5 to €1.5 billion p.a. to only 5 additional GW. We can thus see the diminishing returns typical for the exponential shape of the learning curve.

[23] To obtain the total budget within an investment subsidy sensitivity, the €0.2 billion for R&D therefore have to be added.

Figure 6: CCS capacity development across all model regions over time in CO_2-38 scenario



To additionally test for robustness of the results, we also evaluate an annual spending level of €4.5 billion. Whereas the impact on CCS diffusion is rather limited if the funds are directed towards R&D grants, the subsidies' policy type does lead to a noticeably stronger diffusion of on average 22 GW (or 36%). At this level, the model subtracts about 11% of the power plant's investment costs for NPV-based investment decisions. At the initial cost of 2000 €/kW, this corresponds to subsidies of €110 million for a 500 MW plant. For comparison purposes, the EU's current CCS subsidy program EEPR provides €100-180 million to each of its six subsidized CCS pilot plants (EU Commission, 2009b).

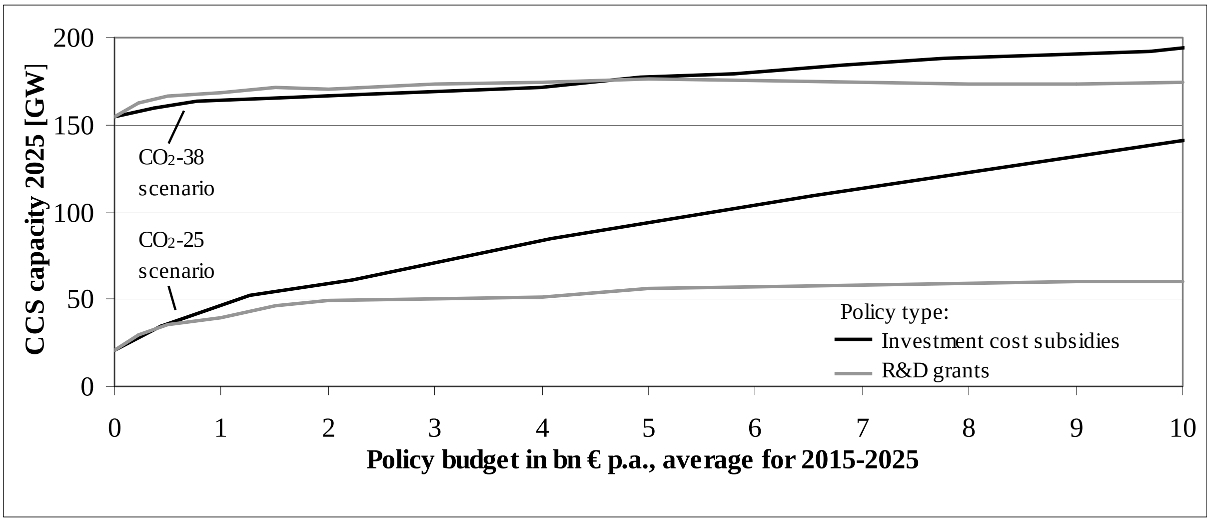
Looking at the CO_2-25 scenario, the picture shifts significantly, as overall profitability of CCS capacity is reduced considerably. In the Base Case, CCS demonstration capacity is becoming profitable and therefore comes online in 2024, almost a full decade later than in the CO_2-38 scenario. Therefore, sufficiently effective policies will need to be in place promoting the technology. Analyzing the investment cost subsidies policy first, we notice that it is a viable method for promoting CCS diffusion. At average annual subsidies of €0.5 billion, it is possible to subsidize 5% of each plant's construction costs, which leads to an increased CCS diffusion to in total 44 GW in 2025, compared to only 30 GW in the Base Case – equivalent to almost 50% more. For a comparison, in the CO_2-38 scenario the same subsidy budget of €0.5 billion p.a. did not lead to any additional CCS capacity at all, as CCS was profitable anyhow. If we further increase the policy budget, we are able to noticeably further promote diffusion. At €1.5 billion p.a., CCS capacity grows to 60 GW by 2025, over twice the amount without any stimulation policies. At €4.5 billion p.a., 93 GW are constructed, three times as much as in the Base Case.

The underlying rationale for the stronger impact of policies in the CO_2-25 scenario compared to the CO_2-38 scenario is similar to the conclusions of the previous chapter. The NPV of the technology is not as undoubtedly positive as in the CO_2-38 scenario, so even small changes in investment costs through subsidies can make a difference. Also, the specific plant economics of CCS, which are characterized by low variable costs paired with high fixed components and depreciation (Lohwasser and Madlener, 2009b), limit the situations in which a CCS-equipped plant is preferred over traditional coal and gas capacity to situations in which it can run at maximum utilization. This, however, is only the case when it is in the beginning of the merit order curve, i.e. if there is limited nuclear or renewables capacity in the market. This is different in the high CO_2 price scenario, as its relative advantage over conventional coal and gas technology ensures that it is still profitable even if not at full utilization, allowing it for example to shut down at night and at certain points of the weekend. This broadens its applicability to countries which do have a significant renewables or nuclear portfolio, further explaining the large discrepancy in CCS diffusion between the two scenarios.

Looking into the R&D policy scenario, we observe at €0.5 billion R&D expenses p.a. a CCS capacity of 36 GW by 2025, compared to 30 GW in the Base Case. Increasing the R&D spending level to €1.5 billion p.a. leads to 46 GW and to €4.5 billion p.a. to 55 GW by 2025, which is still a stronger increase compared to the application of this same policy in the CO_2-38 scenario.

In a next step, we directly compare the two policy options and now run a sensitivity sweep for annual policy expenses between zero and €10 billion p.a. individually for both policy options. As we test the individual effectiveness, we set the budget for the R&D policy to zero in the sensitivity of the investment costs policy. The displayed policy budget is therefore allocated exclusively towards the analyzed policy. The results are plotted in Figure 7.

Figure 7: CCS capacity by 2025 for two different policy options



In a direct comparison between both policy options, we see that neither R&D grants nor subsidies for investment costs are the dominant policy. In the CO_2-38 scenario, R&D grants are slightly more effective at below €4-5 billion p.a., but the difference is hardly measurable. Beyond that, investment cost subsidies are preferable. Given the fact that CCS subsidies or R&D grants beyond €5 billion annually are rather unrealistic, it is probably safe to say that both policies are very similar in terms of their ability to promote CCS diffusion by 2025 in this scenario, with a slight advantage for R&D-based policies. In addition to this slight advantage, R&D grant-based policies should be recommended, as they permanently reduce investment costs through both learning-by-researching and learning-by-doing, instead of a temporary improvement while investment cost subsidy policies are effective. At an R&D budget of €5 billion p.a., the learning-by-researching progress rate is at 68% by 2025, compared to 89% in the Base Case. At the same time, diffusion is almost identical with the investment cost policy, leading to the same learning-by-doing progress rate of 74%. Jointly with this effect, it leads to an overall power-plant progress rate of 81% or 1620 €/kW by 2025. Comparing this to the investment cost policy, the learning-by-doing progress is comparable, but there has been no learning-by-researching progress, leading to an overall power plant progress rate of 90% or 1800 €/kW by 2025. Paired with the subsidies for investment costs, which are at about 12% in this scenario, the overall investment costs drop down to 1584 €/kW by 2025, a value that is in the same range as in the R&D grants case. Therefore, the effective cost for the investor is very similar, explaining the comparable diffusion of the technology. However, once subsidies for investment costs stop, the overall cost level goes back to 1800 €/kW. Based on this effect, we can conclude that while overall costs and diffusion are relatively similar for both policy options by 2025, the technology will advance further if R&D grants are deployed. In a direct comparison, an R&D grant policy therefore has a slight advantage and should be recommended over investment cost subsidies at this CO_2 price. The overall validity of this insight is, however, limited, since at this high CO_2 price of the CO_2-38 scenario, CCS promotion policies are not required to enable success of the technology in the first place.

This picture changes for the CO_2-25 scenario, as we notice a clear difference in the effectiveness of both policy options beyond a policy budget of €0.5 billion annually. The first billion Euros annually in R&D grants leads to an increase in CCS diffusion by 2025 of 8 GW, the second billion leads to 3 GW, the third billion to 2 GW, and so on. This is the result of the declining marginal returns for research represented in the learning equation, which reduces costs for every doubling of capacity/R&D, i.e. a logarithmic relationship. The policy promoting diffusion through subsidies for investment costs, however, does not have this effect, mainly for two reasons. The first is the obvious learning-by-doing progress through additional diffusion, indirectly reducing the investment costs and therefore improving the economic attractiveness. Just as with the R&D grant policy, we observe declining marginal returns due to logarithmic consideration of capacity/R&D in the learning equation. The second effect, however, is a direct (and not logarithmic) improvement of power plant economics through the subsidizing of investment costs. This is a linear relationship between additional policy expenses and economic attractiveness of a power plant as a driver for capacity investments, unlike the logarithmic effect through technological learning. As both the learning-by-doing rate and the learning-by-researching rate are at 7%, the cost reductions driven by advancements in R&D are not strong enough to compensate for the investment subsidies. This is only the case for R&D policy budgets below €0.5 billion p.a., i.e. early in the learning progress.

We can therefore conclude that, while both policy options are comparably effective up to an annual budget of about €0.5 billion, subsidies for investment costs lead to a noticeably stronger CCS diffusion compared to R&D grants. The relative advantage of the subsidies for investment costs policy hereby increases with the policy budget, as CCS capacity more or less linearly grows with the policy budget, due to the direct and linear relationship between investment cost subsidies and the plant's economic profitability. For the R&D grant policy, CCS capacity growth flattens off beyond an R&D policy budget of €1–2 billion p.a. due to the logarithmic impact of R&D efforts in the underlying learning-by-researching curve concept.

7. Summary and concluding remarks

CCS is a technology with a very large GHG abatement potential, yet it is still far from reaching technological maturity and commercial readiness. To date, significant public and private funding is already dedicated to the technology. However, we know little about how different subsidy schemes relate to the success of the technology in the market, especially with regard to the impact of R&D. A method to relate R&D efforts to the economics of a technology is the concept of two-factor learning, which describes the relationship between the costs of a technology with its cumulative deployment through a learning-by-doing rate, and with cumulative R&D efforts through a learning-by-researching rate. It extends the well-known and intensively-researched notion of technological learning, which just relates cumulative deployment with R&D efforts.

To estimate the learning rate for CCS, we estimate the values for FGD based on its empirical R&D, capacity and cost development between 1970 and 2000. FGD uses SO_2 scrubbers, which are technologically similar to the CO_2 scrubbers deployed in post-combustion CCS, so that this analogy was also already applied to CCS for (one-factor) learning in related work.

We find that the learning-by-doing rate is 7.1% and the learning-by-researching rate 6.6%. This effectively means that the cost reduction caused by a doubling of installed capacity is roughly the same as for a doubling of R&D efforts. Other technologies that are currently promoted through subsidies and other funding types, such as solar power and wind power, have learning-by-researching rates that are 2–5 times higher than their learning-by-doing rate, indicating advantages for R&D-driven policies over capacity-addition-driven policies. This conclusion cannot be drawn for CCS, however, as the observed learning rates are very similar, a fact that should be considered when comparing or even applying wind and solar promotion policies to potential CCS promotion policies. The observed values are also in line with expectations drawn from existing publications in the literature.

To understand the relevance of technological learning for commercial success, we simulated CCS deployment across 19 European countries with different learning rates with the bottom-up, hourly electricity market model HECTOR. As a simulation result, we observe only a relatively limited impact of technological learning, with CCS capacity variations of only 2–3 GW by 2040, depending on the learning rate in the high CO_2 price scenario CO_2-38. This is marginal, considering an overall capacity of 217 GW. Even without learning, CCS capacity is only reduced by 12 GW. The impact of learning is stronger in the low CO_2 price scenario CO_2-25, but still quite low. Total CCS capacity is, however, almost halved, due to the less favorable market conditions, at only 154 GW by 2040 at the standard 7% learning rate. This effectively means that the learning rate is not the real driver for the market success of CCS. Instead, other factors such as CO_2 prices or national plant portfolios, play a far more important role in terms of plant profitability, the driver for investment in our model. A key reason for the relatively low importance of learning is that it only applies to the CCS equipment; the attached coal-fired power plant makes up the majority of the cost, but hardly experiences any learning at all.

In an individual sensitivity measurement for each learning rate, a variation of the learning-by-doing rate has a slightly larger impact than the learning-by-researching rate, leading to the conclusion that technological advancement through capacity additions plays a slightly more important role than through R&D.

To link specific CCS promotion policies to technological learning, we analyze two policies. One provides R&D funding, addressing learning-by-researching progress. The other provides a subsidy for new CCS plants, reducing the investment costs investors have to pay by a certain percentage. This demand-side policy promotes diffusion and addresses learning-by-doing. At high CO_2 prices, both policies only slightly improve the diffusion of CCS technology, and the policy type – i.e. R&D or investment subsidies – plays only a secondary role as their effectiveness is relatively similar, with slight advantages for an R&D-based policy. At lower CO_2 prices, the impact of the investigated policies rises and they provide a suitable method for improving CCS diffusion. However, even a massive policy budget cannot compensate for CO_2 prices as a key driver for CCS success. Even if €5 billion is spent annually after 2015 on CCS, the technology will not reach the capacity needed to reach commercial readiness of 21–22 GW by 2020, regardless of policy type. In a direct comparison between both policies, their effectiveness is similar at a budget below €0.5 billion p.a., but beyond that, investment subsidies are the more effective policy type. This is due to the logarithmic impact of R&D effort on investment costs, which cannot compensate for the linear reduction of investment costs of the investment cost subsidy.

The overall situation is difficult for policy-makers: If CO_2 prices are sufficiently high, no diffusion stimulation policies are needed in the first place. If not, opportunities for specific CCS promotion policies exist and do improve the situation, but their impact will never outweigh the unfavorably low CO_2 prices, unless extraordinarily high budgets are allocated for CCS. Aggressive GHG reduction policies with high CO_2 prices are therefore of prime relevance for CCS. If CCS policies are deployed at relatively low CO_2 prices (such as 25 €/t), the impact of R&D and investment subsidy policies on CCS diffusion is about equally effective below €0.5 billion p.a.; beyond that, R&D policy effectiveness stagnates, compared to a continued linear growth for investment subsidies. In summary, we can therefore conclude that both effects on technological learning – R&D and capacity diffusion – are very similar for CCS, suggesting a simultaneous and balanced two-way policy, an insight consistent with the findings in Sections 3 and 5. Given the already high policy budget of over one billion Euros annually across Europe, however, the R&D stimulating portion should be lowered.

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