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Learning-by-doing, Learning Spillovers and the Diffusion of Fuel Cell Vehicles

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Abstract

Fuel cell vehicles (FCVs) running on hydrogen do not cause local air pollution. Depending on the energy sources used to produce the hydrogen they may also reduce greenhouse gases in the long-term. Besides problems related to the necessary investments into hydrogen infrastructure, there is a general notion that current fuel cells costs are too high to be competitive with conventional engines, creating an insurmountable barrier to introduction. But given historical evidence from many other technologies it is highly likely that learning by doing (LBD) would lead to substantial cost reductions. In this study we implement potential cost reductions from LBD into an existing agent based model that captures the main dynamics of the introduction of the new technology together with hydrogen infrastructure build up. Assumptions about the learning rate turn out to have a critical impact on the projected diffusion of the FCVs. Moreover, LBD could imply a substantial first mover advantage. We also address the impact of learning spillovers between producers and find that a government might face a policy trade off between fostering diffusion by facilitating learning spillovers and protecting the relative advantage of a national technological leader.

Keywords: Fuel cell vehicles, Hydrogen, Learning by doing, Agent based modeling

JEL classification: O33, D11, D21

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1. Introduction

Current activities of major car producers indicate that fuel cell vehicles (FCVs) running on hydrogen are likely to start displacing fossil fueled internal combustion engine vehicles (ICEVs) in the next decade, or at least capture a substantial niche market. Inherent in the use of fossil fuels are emissions of carbon dioxide (CO_2), with their well-known effect on global warming.[1] Thus, a large-scale introduction of FCVs has the potential to shift to carbon free individual transport, implying also lower geostrategic risks associated with fossil fuel supply. It should be seen as a potential, because the actual reduction of carbon dioxide emissions and fossil fuel demand depends on the mix of energy sources used to generate the required hydrogen. Current scenarios of a shift to a "hydrogen society" indicate that for most countries low cost production of hydrogen requires the reformation of natural gas, which would still imply significant CO_2 emissions as long as no (costly) CO_2 sequestration technology is applied. But due to the fact that hydrogen can be produced from any energy source, a long-term decarbonization of energy generation would directly lead to lower emissions from individual transport (Barreto et al., 2002; Ogden, 2002, 2004; EC-JRC, 2006). Particularly promising seem to be recent scenarios to produce hydrogen from photovoltaics and particularly from (offshore) wind energy, as this would circumvent problems related to fluctuations in energy production implied by sun and wind as energy sources (Altmann et al., 2001; Gonzales et al., 2003; Sorensen et al., 2004).

Further advantages of the FCVs are the low noise generation and the general absence of any local emissions like particulate matter, ozone, sulfur dioxide, and carbon monoxide. Strong emission regulations particularly in the US, Japan and Europe have initiated major technological progress of catalytic converters and the use of cleaner fuels (unleaded and desulfurized gasoline), so that local emissions from ICEVs have substantially been reduced over the last decades. But some of these reductions have been compensated by increased car travel and heavy-duty transports, so that future reductions of total emissions would require even more complex (and expensive) end-of-the-pipe technologies.

Even though the fuel cell technology itself is nowadays well developed and tested in daily life situations there are two major economic barriers to a fast diffusion of FCVs. Firstly, there is the so called chicken-and-egg problem saying that people are not willing to buy FCVs as long

[1] Internal combustion engines also emit other greenhouse gases like methane and nitrous oxide.

as there is no area-wide coverage with hydrogen outlets, and on the other hand, filling station owners (or "the oil industry") would not invest in a hydrogen generation and distribution system unless there is a significant demand for the new fuel. Secondly, fuel cells are at the moment simply too expensive to compete with internal combustion engines. Schwoon (2006) uses an agent based diffusion model to investigate whether different tax systems and infrastructure scenarios in favor of FCVs are able to lead to a successful introduction of the new technology. Calibrated for the German compact car market, his model results suggest that a tax on ICEVs in the range of today's car taxes in most European countries - together with an infrastructure build up comparable to the rather slow development of compressed natural gas (CNG) outlets in Germany - is sufficient to overcome the chicken-and-egg problem. But Schwoon (2006) employs a simple point estimate for the costs of fuel cells if produced on a large scale.

Therefore, the current paper will extend the model by implementing a more realistic approach towards the costs of fuel cell production. There is a general notion that fuel cells costs at the moment are prohibitively high, but on the other hand learning by doing in the technology will lead to substantial cost reductions (Rogner, 1998; Lipman and Sperling, 1999; Tsuchiya and Kobayashi, 2004). If costs follow an experience curve, the assumed learning rate turns out to be critical, so that too low gains from experience might create an insurmountable obstacle. Additionally, if the producers' planning horizons are short, diffusion might also be severely hampered.

The car industry is characterized by technology clusters and common sub-contractors of major parts - two important preconditions for the existence of learning spillovers. Including learning spillovers in the model increases the speed of diffusion. Moreover, spillovers are important when it comes to the question, which producers gain during the diffusion period. In any case, there is a substantial first mover advantage due to learning, but with spillovers this advantage is reduced for the benefit of early followers.

The outline of the paper is as follows. The next section gives a brief overview of the existing model that is extended by LBD. Section 3 starts with a general discussion of the experience curve concept and its implementation in the model. Then calibration issues and simulation scenarios are discussed, before results of FCV diffusion in the presence of LBD are presented. In section 4 we argue why learning spillovers are likely to occur in fuel cell production and show their impact on the speed of diffusion. Furthermore, we address interactions between spillovers and first mover advantages. Section 5 is dedicated to policy implications and section 6 concludes.

2. Dynamics of the model

The model at hand is an extension of an existing agent based diffusion model. A detailed description of the structure and calibration can be found in Schwoon (2006). Figure 1 shows a scheme of the model. An arrow from variable A to variable B indicates the order of computations (within one period) and should be read as "A is a major determinant of B". There are four types of agents: consumers, producers, filling station owners and the government. The government acts as an exogenous driver by implementing a tax on ICEVs and increasing the speed of the built up of hydrogen outlets. Filling station owners simply react to the development of the share of FCVs on the road and can increase the share of stations with an H_2-outlet.

Consumers buy the car that maximizes their utility according to their preferences relative to the price. They are heterogeneous with respect to their preferred car characteristics and are to some degree influenced by their neighbors' buying decisions. The expression "neighbors" is used as a synonym for friends, colleagues or relatives. A high share of neighbors already driving FCVs increases the likelihood of a consumer to also buy one.[2] Consumers are heterogeneous in their driving pattern. Some consumers considering a car will use it mainly locally, e.g. for shopping trips or the daily way to work, whereas others, like e.g. a traveling salesman, will regularly drive in unfamiliar regions. According to Dingemans et al. (1986) the former are likely to be the first ones to buy an alternative fuel vehicle, whereas the latter will wait until there is substantial infrastructure coverage.

The utility maximization of the consumer does not take environmental friendliness of the car into account. The reason is that first of all high efficiency and environmental benefits are usually considered to have only a minor impact on buying decisions (Steinberger-Wilckens, 2003). Moreover, in a stated preference analysis Bunch et al. (1993) revealed that fuel availability is a much more important determinant of vehicle choice and people are only willing to pay a premium on low emission vehicles if emissions are drastically reduced compared to conventional vehicles. But in the model conventional ICEVs are assumed to be

[2] Consumer behavior mainly follows "deliberating consumats" as in Janssen and Jager (2002).

already low emitting using for example hybrid technologies. Recent studies show that overall environmental benefits of FCVs will significantly exceed those of low emitting advanced (hybrid) ICEVs only if hydrogen is generated by renewable energy sources (Ogden, 2004; EC-JRC, 2006; Demirdöven and Deutch, 2004). As this is not likely to be possible on a large scale in the near future, early adopters of FCVs cannot claim extraordinary environmental awareness. However, if consumers considered FCVs as more ecological and were willing to pay a premium for that, in the model this would simply require a lower tax on ICEVs to promote diffusion of FCVs.

Producers offer cars that are heterogeneous but close substitutes.[3] Thus, the producers act as price setters with limited market power depending on their market share. In each period they maximize a weighted average of expected revenue and market share.[4] The maximization is subject to capital/investment constraints, where credit availability is higher for larger producers than for small ones (as indicated by the backward loop from producers' capital in Figure 1). Each producer can either produce ICEVs or switch to the production of FCVs, which is assumed to be more capital intensive.

The switch is made as soon as FCVs imply a higher expected value of the objective function. Producers are more likely to switch, the higher the tax on ICEVs, the higher the share of filling stations with an H_2-outlet and the higher the expected cost reductions from LBD. The latter impact, which significantly adds to the original model, is described in the next section. Producers are also doing R&D so as to change the car characteristics according to the consumers' preferences.

Supply and demand is matched as follows. Producers set prices first and adjust their production capacity, but only produce as many cars as consumers order. So there is no excess supply and inventories are omitted. This implies that producers, which overestimated the demand for their products, are penalized by their overinvestment in capacity but not by high variable costs. In the case of excess demand, not all consumers can be satisfied, because a period is not long enough for capacity extensions or price increases. If a consumer cannot get

3 The supply side of the model is based on Kwasnicki's (1996) behavioral model of producers.

4 The objective function is constructed such that small producers try to increase their market share (survival strategy), whereas large producers focus on profits. Kwasnicki and Kwasnicka (1992) show that such a behavior in the long run outperforms a pure profit maximizing strategy, given the uncertainties about the behavior of competitors, R&D success and so on, which prohibit intertemporal profit maximization.

his favorite product, because it is sold out, he will choose a less preferred product and he can actually end up with nothing and has to wait for the next period.

3. Learning by doing

3.1. The experience curve concept

LBD is an appealing view of technological progress as it models an intuitively comprehensible relationship between experience and process or product optimization. Empirical studies go back as far as 1936 when Wright described the cost development in the aircraft industry. While studies addressing macroeconomic implications of learning trace back to Arrow (1962), managerial decision-making on the basis of so-called experience curves became popular particularly due to the influence of Boston Consulting Group (1970). The experience curve concept attracted a lot of attention recently for determining future potentials of renewable energy technologies (Neij, 1997; Mackay and Probert, 1998; Wene, 2000; Neij et al. 2003; Junginger et al., 2005) and has become a crucial tool in energy system modeling (Messner, 1997; Grübler and Messner, 1998; Rasmussen, 2001; Manne and Richels, 2004; Manne and Barreto, 2004).

Throughout the paper we will use the expressions learning-by-doing and experience curve interchangeably for a rather wide notion of experience.[5] Following Abell and Hammond (1979) sources of experience - besides the directly improved labor efficiency due to learning - are work specialization and enhanced methods, new production processes, better performance from production equipment, changes in the resource mix, i.e. employment of less expensive resources, product standardization and product redesign. All of these sources are likely to be exploited during mass production of fuel cells, hydrogen tanks and other drive train related components. We restrict cost reductions from learning to these components and assume that they are learning at the same rate.[6] Other car components of the FCV are learning at the same rate as the ICEV. Actually, we assume that the cumulative production of other car components (and also of the internal combustion engine) is already so high that cost reductions due to learning are negligible.

[5] Some studies also use the terms learning curve and progress curve to describe the same phenomenon (Argote and Epple, 1990).

[6] Neij et al. (2003) point out the difficulties to derive aggregate learning rates for several subsystems, but the fuel cell itself is by far the most expensive component in the drive train so that its learning rate dominates the overall learning rate of the system.

We follow the standard approach of modeling LBD by using cumulative output as a proxy for experience and apply the following experience curve for the fuel cell drive train:

(1) $$c(unit_T) = c(unit_1)\left(\sum_{s=1}^{s=T} unit_s\right)^{-E},$$

i.e. the costs to produce the T^{th} fuel cell unit equals the costs for the initial unit $c(unit_1)$ times cumulative output of all units up to unit T raised to the negative of the experience parameter E.[7] A high experience parameter indicates rapid cost decreases. A more intuitive indication of the learning potential of a certain technology is the learning rate (*LR*), which is the reduction of costs due to a doubling of cumulative output. Using equation (1) it can be easily confirmed that

(2) $$LR = 1 - \frac{c(unit_1)\left(2\sum_{s=1}^{s=T} unit_s\right)^{-E}}{c(unit_1)\left(\sum_{s=1}^{s=T} unit_t\right)^{-E}} = 1 - 2^{-E}$$

holds, so that e.g. an experience parameter of 0.23 implies a learning rate of 0.15, i.e. unit costs fall by 15% each time cumulative output doubles, independent of the initial costs or the level of cumulative output.

3.2. Limitations of the approach

One drawback of the experience curve concept is that production costs can fall infinitively if production volumes increase. Thus, we use the costs for a conventional internal combustion engine ($\overline{c}$) as a lower bound for cost reductions ($c(unit_T) \geq \overline{c}$). Lipman and Sperling (1999) identify two justifications why reduction limits are indicated. Firstly, cost reductions cannot go further than material costs. The current requirements of noble metals for fuel cells would imply a particularly high lower bound. Even though it is also reasonable to expect that material substitution options will be identified, material requirements will nevertheless prevent infinite cost reductions.[8] Secondly, Lipman and Sperling state that institutions like the Partnership for a New Generation of Vehicles established cost targets for fuel cell drive trains.

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7 The presentation of the experience curve follows mainly Wene (2000), but can similarly be found e.g. in Abell and Hammond (1979), Dutton and Thomas (1984), Argote and Epple (1990) or Lipman and Sperling (1999) in the context of FCVs. The specific notation is chosen so as to make clear that costs are a function of output quantities and not of time. However, if $q_t \geq 1$ for $t \leq T$, i.e. if at least one unit is produced in every period, we observe monotonously decreasing costs, leading to a common misinterpretation of the experience curve that costs are decreasing over time.

8 See also Spence (1981) and Ghemawat and Spence (1985).

Once these targets are met, companies' efforts to further reduce costs are limited. This argumentation should be taken with care as it implies a pure satisficing behavior and companies would forego potential competitive advantages. However, it seems reasonable to believe that ones the fuel cell drive train costs approached those of an internal combustion engines, their costs would leave the center of attention for the benefit of quality improvements or cost reducing potentials of other vehicle components.

A more severe limitation of the experience curve concept refers two difficulties in parameterization. Estimated learning rates ex post usually have a high statistical goodness of fit, which is not surprising for non-stationary variables. McDonald and Schrattenholzer (2001) collect learning rate estimates from 26 data sets of different studies for energy related technologies and find the majority of estimates in the range of 5-25%. For 21 learning rates, the R^2 as a measurement for the goodness of fit between the data and the experience curve is reported. 17 have an R^2 higher than 0.75 and of those 11 even exceed 0.9. However, ex ante parameterizations for new technologies are extremely difficult. Due to the exponential impact of the learning rate on production costs only small changes in the rate might determine the success of a new technology. Low expected learning rates might lead to prohibitively high production requirements for the new technology to become competitive. On the other hand, high expected learning rates might involve too optimistic cost reductions. Moreover, exact cost measurements of the very first units produced would be necessary for a reliable cost prediction. But actual costs of prototypes and initial limited-lots for testing are not only difficult to evaluate within a firm, but are also kept secret, as they would provide competitors with important information on potential market introduction.

Finally, there are some objections against the general validity of the concept of experience curves. Hall and Howell (1985) criticize that industries starting from scratch usually have substantial financing costs, which decline over time if being successful. Therefore, the long run correlation between cumulative output and costs might be spurious and real gains from learning are likely to be exhausted after a relatively short period of time at least at the plant level. Furthermore, they find that regressing price (which is usually taken because of the difficulties of getting cost data) on cumulative output has no additional explanatory power than just using current output, so that LBD cannot be separated from scale effects. But these criticisms do not apply for our model. Our main focus is indeed on the early cost reductions due to learning and mass production, without differentiating between. These reductions are crucial for the decision of a producer to switch to the production of FCVs. Financing costs play only a minor role, because car producers, who are introducing FCVs, are not starting a completely new industry but rather make a major advancement within an established one. Moreover, they are big enough to get loans without a noteworthy risk premium for applying a new technology.

3.3. Implementing LBD in the existing model

Learning by doing enters the model by changing producers' expectations about future income due to changes in variable costs. The expected income of the producer is computed as

$$(3) \qquad INC^{exp} = \sum_{s=t}^{s=t+\tau} \left(q_t^{exp} \, p_t(\mathbf{car_{t,FCV}}) - \sum_{T=q_{s-1}}^{T=q_s^{\exp}} c(unit_T) \right) e^{-(s-t)r} ,$$

where τ represents the length of the producers' decision horizon, $\mathbf{car_{t,FCV}}$ is a vector of characteristics of a car produced by a specific producer, with $FCV = 1$ if the car has a fuel cell drive train (otherwise $FCV = 0$) and $p_t(\mathbf{car_{t,FCV}})$ is the price of the car. The expected number of cars sold q_t^{exp} is a function of the price ($q_t^{exp} = q_t^{exp}(p_t(\mathbf{car_{t,FCV}}))$, where the demand is determined by certain market conditions (like competitors prices and market shares). Moreover, the expected number of cars sold cannot exceed production capacities. The right hand side of equation (1) reduces to the term in large brackets, if the producers' forward looking horizon does not go beyond the current period ($\tau = 0$). Then income is simply expected revenue minus expected variable costs. But in contrast to the earlier model, variable costs $c(unit_T)$ now follow an experience curve as in equation (1), if the car in question is a FCV. Then variable costs depend on the number of FCVs already constructed in previous periods and each unit produced reduces the costs of the next one. Thus, if the producer expects to sell, e.g., 50,000 units ($q_t^{exp} = 50,000$) and has already produced a cumulative number of FCVs of 100,000 units until the last period, then the total variable costs expected for the current period are the sum of the individual costs of car number 100,001 ($c(unit_{100,001})$) to car number 150,000 ($c(unit_{150,000})$). In the case of an ICEV learning potentials are already exhausted. Thus, costs are independent of cumulated productions, so that the second term in the large brackets of equation (3) equals $q_t^{exp}\bar{c}$.

As a further deviation from the original model a producer now bases her optimization on a longer time horizon ($\tau > 0$), so according to equation (3) INC^{exp} becomes the sum of the discounted expected incomes. This extension is a concession to the problem that otherwise the likelihood to switch to the production of FCVs would depend on the length of the time step of the model. In the original model the producer sets the price that maximizes her objective function, which is determined by expected income (normalized relative to total income in the whole industry) and expected (relative) market share, where expectations are limited to one period, representing a quarter of a year. As long as the producer has not switched to the production of FCVs, she computes optimal prices for the car being either a FCV $(\mathbf{car}_{t,1})$ or an ICEV $(\mathbf{car}_{t,0})$. With learning by doing, this switching decision now also includes the notion that aggressive low pricing might pay off via increased quantities, which lead to lower costs. The rather short decision horizon of a quarter ignores the fact that switching now implies cost reductions in future periods due to learning. Moreover, as the switch requires additional capital, it is even more unrealistic that such a major decision focuses only on the next three months. Thus, we assume that producers evaluating the production of FCVs focus on their income over the next periods. Based on the duration of a lifecycle of a car, we set the decision horizon to three years in our central case. In reality, producers might consider a strategy of switching to the production of FCVs and not only setting low prices initially to sell high quantities, but also later on increase prices (Dasgupta and Stiglitz, 1988). However, implementing such a strategy would require intertemporal optimization, which is ruled out in the modeling framework due to substantial uncertainties about the behavior of competitors, the development of H_2-infrastructure, the acceptance of the technology by consumers and changing taxes.

3.4. Parameterization of the experience curve

McDonald and Schrattenholzer (2001) compile learning rates for energy technologies in general, which occur to be in the range from 5% to 25%.[9] Table 1 lists several studies, which explicitly use learning rates to predict future costs of fuel cell technologies. The data show that researchers calculate with learning rates, which are within a wide range and rather high. The comparability of the underlying experience curves is limited due to the different assumptions regarding initial fuel cell costs and the initial cumulative production. Further differences arise from the different units of measurement. Some studies focus on the overall wattage produced, where also an increase in the number of stationary fuel cells has a cost decreasing impact on fuel cells in mobile applications. Others fix the power of a fuel cell at 50

[9] Learning rates in energy technologies turn out to be in the same range as observed e.g. by Dutton and Thomas (1984) for a variety of industries. For the case of wind power see also the overview or learning rate estimates in Junginger et al. (2005).

or 70kW and derive learning rates for the number of units produced. In general, the model specifications deviate from the theoretical setup of the experience curve, because initial costs do not refer to the very first unit produced but rather are cost estimates for a certain initial "mass production".

In our model we use a rather low learning rate of 15% for the central case and vary it from 10 to 20%. This can be justified by the assumption that several parts of a FC drive train system (electric motors, batteries or super-capacitors and generators for recovery of breaking energy etc.) would also be implemented in an advanced (hybrid) ICEV and would therefore not represent FCV specific learning. Roughly in line with current cost projections of Arthur D. Little (2000) and the detailed cost estimates by Tsuchiya and Kobayashi (2004), we expect (for an initial production size of 10,000 units at 50kW) initial costs of 13,000€, which are five times the drive train costs of an ICEV.[10] Initial costs are of course also uncertain and additional model runs with different initial costs have been conducted. Beside the straightforward result that lower initial costs lead to earlier diffusion, the linear impact is dominated by the exponential impact of the learning rate, so we refrain from presenting those results and focus on different learning rates.

3.5. Main calibration and scenario assumptions

All other parameters unrelated to LBD have not been altered from Schwoon (2006). The model is calibrated so as to mimic some of the main features of the German compact car segment. There are 12 important producers in the segment of compact cars in Germany with market shares exceeding 2%. However, one producer (*Volkswagen*) dominates the market with a market share of about 1/3. To mimic the fact that the market is unequally partitioned, we draw initial market shares randomly from a normal distribution with mean 100/12% and a standard deviation of 10%.[11] Restricted by computation time, we allow for 6400 different consumers. In the control run without any policy about 125 consumers buy each period, i.e. if we assume that each consumer represents about 2,000 similarly behaving ones, we end up at 1mio sales per year, which corresponds to the size of the segment we are modeling. Initially, there are about 400 fuel stations with an H_2-outlet. Like in the "exogenous H_2" scenarios of Schwoon (2006), we assume a public infrastructure program that provides 80 filling stations with a hydrogen outlet each year. Moreover, the tax scheme implemented by the government

[10] In Schwoon (2006), unit costs of 13,000€ for an average compact car are used. As a rule of thumb, drive trains of ICEVs account for about 1/5 of total costs, i.e. 2,600€. Thus, with fuel cell drive train costs of 13,000€, initial FCV costs add up to 23,400€.

[11] The minimum market share is 2% and the sum of all market shares is scaled to sum up to 100%.

lies in-between the "gradual tax" and the "shock tax" scenarios, by assuming, that the government shocks the market with a 5% tax by the year 2010 and increases it by additional 5% in the consecutive years until a tax level of 40% is reached. The tax represents not only purchase taxes, but also the net present value of total lifecycle taxes (on ownership, insurance, fuel etc.). Therefore, a 40% level can be considered as rather low, compared to current taxes in Europe (Burnham, 2001).

A major problem with calibration in the context of LBD is that learning would occur globally, i.e. producers selling FCVs e.g. in Japan or the US would achieve cost reductions, providing them with different starting positions for the German market. On the other hand, concerted governmental action in these countries is unlikely. Thus, the results should be seen as relevant for a situation, in which a government decides to push in a solo attempt the introduction of the new technology in a market of comparable size to the German market. Looking at the history of pollution regulation of cars, this seems to be not unrealistic. The independent introduction of unleaded fuels and the support of 3-way catalytic converters in Japan, the US and later on in Germany, which preceded most other Western Europe countries as described in Westheide (1987) can be seen as examples for successful policies on a national level. Moreover, the substantial impact of the zero emission vehicle regulations of the State of California on the R&D activities of car producers world wide (Hekkert and van den Hoed, 2004) show how influential policies for a single (but significant) market can be.

The model is implemented in the Laboratory for Simulation Development (LSD) and is available from the author upon request. The LSD environment includes a user-friendly graphical interface that allows testing e.g. parameter changes without a detailed knowledge of the underlying program.[12]

3.6. Diffusion curves in the presence of LBD

Figure 2 shows how predictions of the penetration of the German compact car market with FCVs depend on the actual learning rate in fuel cell drive train technology. The diffusion curves are averages of 100 simulation runs with different random seeds. The time horizon producers employ to evaluate the switching option is set to three years. The figure clearly demonstrates that even rather small variations in the assumed learning rate determine the diffusion process. For a low learning rate of 10% fuel cell costs do not sufficiently decline

[12] For a description of LSD see Valente and Andersen (2002).

within the decision horizon, so that hardly any producer switches production and FCVs do not gain a noticeable market share over the computed time horizon. With higher learning rates, producers successfully introduce FCVs; and the higher the learning rates the earlier and faster FCVs take off. Note that for a learning rate of 15 to 20% the share of newly registered FCVs increases at an increasing rate for the first three years after initial introduction and then continues increasing on a rather steady rate. The reason is that hydrogen infrastructure does not reach full coverage within the first few years of fast FCV diffusion and small producers can establish a temporary (relative) successful niche serving those consumers with high infrastructure demand.[13]

Figure 3 shows that the longer the producers' decision horizon the earlier and faster the diffusion or conversely, a very short perspective can severely hamper diffusion.[14] Thus, in the presence of LBD a limited time horizon creates a major barrier against the introduction of the new technology. Even though this result is not surprising, given the discussion of the model setup in section 3.3 it has an interesting policy implication. The government could foster diffusion by supporting long-term investment decision-making by appropriate depreciation allowances or options to carry forward losses associated with the production switch.

4. Learning spillovers

4.1. Channels of learning spillovers

So far, learning effects have been treated as being only dependent on the producers' own experience. This is usually referred to as proprietary learning in opposite to spillover learning, where producers can also gain from their competitors' experience. There are various channels for such spillovers, e.g. reverse engineering, inter-firm mobility of workers, proximity (industry clusters), or learning on sub-contractor level. All these channels can be expected to apply for fuel cell technologies. Once the first FCVs are sold at the market, producers lagging behind technologically are likely to dismantle FCVs of their competitors.[15] According to Franco and Filson (2000) inter-firm mobility of workers and the active poaching of high skilled experienced workers is particularly observable in high-tech industries. The existence of car technology clusters like Detroit/US or Stuttgart/Germany facilitates such learning

[13] The niche is only temporary, because the model setup implies that as soon as every filling station offers hydrogen all producers switch production, so as to avoid the (high) taxation of the ICEV.

[14] Note that the main influence of the decision horizon is on the date when first producers switch. After about ten years of diffusion, there is no significant difference in the share of newly registered cars anymore, as long as the decision horizon is at least two years long.

[15] Reverse engineering has previously played a major role in car production (see Lee, 2000).

spillovers. In the Canadian fuel cell producer Ballard Power Systems, several major car producers have a common sub-contractor, so that producers would gain from experience accumulated there.[16]

A rarely addressed channel for spillovers is weak patent rights. A government might force producers to license environmental friendly technology to competitors. Thornton and Thompson (2001) analyze wartime ship building in the US as an extreme case. At that time the government actively transferred knowledge from one firm to the other. They find a small but significant spillover effect: 15 ships produced within the industry increased productivity of the individual firm by the same amount as one ship produced by its own. Empirical evidence of spillovers in general is rather inconclusive. Spillover effects are existent but low also in the case of nuclear power plants (Zimmerman, 1982; Lester and McCabe, 1993) and semiconductors (Irwin and Klenow, 1994; Gruber, 1995). But for agricultural production on the one hand (Foster and Rosenzweig, 1995) and samples of the manufacturing sectors in the US (Jarmin, 1996) and Spain (Barrios and Strobl, 2004) on the other, there is evidence for extremely high learning spillovers, with industry experience being even more important than own experience. Barrios and Strobel (2004) suppose that this rather counterintuitive result is due to the general diffusion of (other) new technologies. This effect is difficult to separate from pure learning effects. However, given that all the studies agree that learning spillovers exist, they should not be ignored from the analysis. The empirical evidence also suggests that learning spillovers are industry depend and therefore hardly transferable to new industries. Thus, their magnitude in fuel cell technologies is subject to substantial error. But recalling the above discussion of potential spillover channels there, a sensitivity analysis should also include simulations with high spillover potentials.

4.2. Spillovers facilitate diffusion

Figure 4 illustrates how different assumptions regarding learning spillovers change the predicted diffusion of FCVs. The proprietary learning graph is identical to the central cases in Figure 2 and Figure 3. The 5% case implements the assumption that 20 FCVs produced by competitors lead to cost reductions equivalent to one own produced FCV. Correspondingly, with 100% learning spillovers cost reductions only depend on cumulative production of all producers. A possible situation, in which this assumption holds is if e.g. Ballard Power

[16] Ballard Power Systems is actually partly owned by DaimlerChrysler and Ford and holds supply contracts with Volkswagen, Mazda and Nissan. Similar cooperations exist between Hyundai, BMW and International Fuel Cells or Renault, PSA and Nuvera Fuel Cells, while GM and Toyota directly collaborate in fuel cell R&D.

Systems was the only supplier of fuel cells and would pass on all its cost reductions to the car producers (because they jointly own the company). Figure 4 indicates that already rather small spillovers encourage much faster diffusion. High spillovers increase the speed of diffusion at the very beginning, but at the end of the simulated period the difference in penetration between e.g. 10% spillovers and 100% spillovers is rather small. The graphs using averages of 100 simulation runs slightly understate the impact of learning spillovers, because some of the individual runs show no diffusion at all. In opposite to the learning rate and the forward-looking horizon of the producers, spillovers do not affect the switching decision of the very first producer. Therefore, the number of simulation runs without diffusion is independent of the assumed learning spillovers and all graphs would be shifted by the same factor, leaving qualitative insights unchanged and implying a (small) linear scaling of magnitudes. Figure 5 compares the impact of small changes in the learning rate with changes in the magnitude of spillovers. Not only the starting point of diffusion, but also the main development is determined by the learning rate. However, once diffusion starts learning spillovers enforce diffusion noticeably. Thus, policies that facilitate learning spillovers are indicated if fast penetration of the environmental friendly technology is intended.

4.3. First mover advantage

In a stylized theoretical model, Dasgupta and Stiglitz (1988) show that in the presence of LBD there is a tendency for a dominant producer to emerge. The reason is that an initial advantage in scale can be extended over time as LBD implies dynamic increasing returns in production. The consequence is a substantial first mover advantage of the first producer starting to accumulate experience. There is some empirical evidence for first mover advantages due to LBD (Gruber, 1998; Madsen et al., 2003, Hansen et al., 2003). According to Ghemawat and Spence (1985) learning spillovers generally increase market performance by reducing the relative advantage of the biggest producer.[17] While a first mover advantage is noticeable in the present model the implications of spillovers are not clear cut. To get an impression of how the first mover performs, we identify from each random simulation the producer who switches to the production of FCVs first. Then we compute for each period the average relative change in profits compared to the profit level before the introduction of tax. We compare these averages with the performance of the producers switching as second, third and so on. Figure 6 shows the results, where we pool the 7th to 12th producers for the matter

[17] Fudenberg and Tirole (1983) show that market performance may decrease if producers behave strategically, recognizing their spillovers to competitors. Such behavior requires intertemporal optimization and can therefore not be implemented in the current model.

of clarity of the overall picture. Actually, they usually do not switch at all during the simulated period (otherwise we would have complete diffusion until 2030, which is not the case according to the figures above). In general the notation 1st to 12th should only indicate the relative behavior of switching, with a major focus on the first mover and early followers. The figure shows that the first mover (like all other producers) suffers losses due to the tax. The average switching period is around 2016, when (relative) profits of the first mover starts rising substantially, exceeding pre-tax levels within few years and further increase until a level of about 160% is reached. The reason for this substantial increase is that costs of FCVs decline rather quickly implying higher profit margins (given that there are still highly taxed ICEVs in the market). Moreover, the tax driven technology switch forces some smaller producers to exit the market, so that market power and hence profits increase. Switching later (as a second mover, third mover and so on) also pays off, but the gains are not as big as for the first one. Note that this first mover advantage is observed on average. In some of the simulations the gains for the second or third mover exceed those of the first, so that we can not conclude that producers should generally aim for being the first.

Figure 7 shows how the net present values of profits change, if spillovers exist using the same interest rate of 10% per year that is also applied for investment decisions during simulations. Surprisingly, the first mover is hardly affected by spillovers. The reason is that there are two balancing impacts. On the one hand the first mover loses some of his cost advantage due to learning to his early followers. But on the other hand he gains from the generally faster penetration of the new technology, which implies a faster infrastructure build up and adoption externalities as consumers depend on their neighbors decisions. It can be seen from Figure 7 that it depends on the spillover magnitudes which effect dominates. For rather small learning spillovers similar balancing effects hold for the second mover, but he can also gain from the cost reductions of his predecessor. But the real winner of small spillovers is the third producer with increases of 14 to 17% of his NPV for spillovers less or equal to 25%. The higher the spillovers the more favorable they are for the second mover. The relative benefit of the second and third mover compared to the first can be seen as weak support for Ghemawat and Spence (1985) result that learning spillovers should increase market performance. But note that the increased speed of diffusion is only clearly beneficial for the first three switchers. Depending on the actual magnitude of spillovers some of the later followers are actually worse off so that the benefit of early followers comes at the expense of later ones.[18]

[18] If we look at the Herfindahl index as a standardized measure of market performance in this model, spillovers seem to have no noticeable impact.

5. Policy implications

The previous sections showed that high learning rates, long planning horizons of the producers and high learning spillovers have a positive impact on the diffusion of FCVs. The government can hardly affect learning rates, but we stated earlier that governmental regulations have some impact on the length of planning horizons. Furthermore, according to Fudenberg and Tirole (1983) the government can influence learning spillovers, e.g. via patent and cartel laws. But especially a mandatory licensing of patents is problematic, as it reduces R&D incentives. Following the channels of spillovers discussed above, another option would be to relax regulations of headhunters to facilitate mobility of high-skilled workers. But this would require accepting a severe intervention into the mutual trust between employer and employees. Less problematic policies seem to be the support of technology clusters, whose importance is widely accepted (see e.g. Krugman (1991) and Porter (1998), Hansen et al. (2003)), or public R&D for the benefit of common sub-contractors.

While promoting learning spillovers as a diffusion policy has rarely been addressed, learning gains and first mover advantages have repeatedly been used as arguments for substantial support of environmentally friendly technologies. If the government expects national producers to be most likely to adopt such technologies, they could "ride down the experience curve" (Neij et al., 2003) and gain a cost advantage over their competitors. This would strengthen their international market position, once global demand increases.[19] As a result, the support of "green" technologies would have an environmental and economic benefit. The simulation results suggest that a similar argumentation in favor of support of FCVs first of all requires some knowledge about the actual learning rate of fuel cell technologies, because learning potentials might be too small for a successful introduction. Moreover, if the government is interested in maximizing the relative advantage of a national first mover then it should prevent learning spillovers. Conversely, if for environmental reasons the government wants diffusion of FCVs to be as fast as possible, it should facilitate spillovers. Thus, the simulations imply that fast diffusion due to spillovers and high first mover advantages might be conflicting targets.[20] Actually, the optimal policy depends on the market structure. If

[19] This infant industry argument is made in the context of the Danish wind power industry, where the national market was totally dominated by home producers (Hansen et al., 2003).

[20] In any case, producers face substantial losses during the introduction of the tax, and there is a significant increase in market power later on. This seems to be unavoidable downsides of the tax-induced diffusion process.

national producers are expected to be early followers, then promoting spillovers not only accelerates diffusion but also supports national industry. Governments of Germany, France, Japan or the US with dominant national producers would face the above trade off. On the other hand, for China, which currently builds up an own car industry, it might actually be beneficial to force foreign producers to switch and let national producers gain as early followers, ending up with a fast diffusion of FCVs.

6. Conclusions

This paper extends an existing agent-based model to simulate potential diffusion paths of FCVs in a large but confined market like the German compact car segment with LBD in fuel cell technologies. While the original model uses fixed unit costs of mass-produced fuel cell drive trains, in this paper unit costs follow an experience curve and producers' decisions to switch to the production of FCVs include cost projections. Diffusion is driven by a tax on ICEVs that is phased in at the beginning of 2010. The results suggest that diffusion strongly depends on the underlying assumption regarding the learning rate, so that low learning can even prohibit diffusion. Moreover, the tax can only successfully induce diffusion, if the planning horizon of the producers is long enough, such that they can incorporate long term cost reductions.

We also allow for learning spillovers and find, unsurprisingly, that higher spillovers lead to faster diffusion. There seem to be substantial first mover advantages, as the producer, who switches first, starts accumulating experience first. Learning spillovers can decrease this first mover advantage. Since regulation has at least some influence on learning spillovers, the model results suggest that if the government is not only interested in fast diffusion of the new technology, but also cares about national champions, the government faces a trade off when setting the regulatory environment. But there is no trade off if national producers are early followers, because they appear to be the main beneficiaries of high spillovers.

The current model has the advantage of being detailed enough to represent the main dynamics that drive the complex diffusion process of a new power train technology without concealing the major cause and effect relationships. The setup can be easily adjusted to comparable market segments in other countries or e.g. in the EU as a total. Updated estimates of cost developments or prospects of the timing and character of taxes (or subsidies) are implemented right away.

As discussed in Schwoon (2006), there are several limitations of the model, which are inherent in the setup itself. These include the restriction to a certain segment of the car market, so that consumers can not evade to a cheaper segment; the assumption, that producers make a radical switch to fuel cell technology instead of introducing it smoothly in parts of the product line; and the simplistic representation of hydrogen infrastructure. Now, the current representation of LBD adds other potential shortcomings. The empirical base of the parameters of the experience curve is weak. The same is true for the learning spillover potentials. We addressed these uncertainties with sensitivity analysis. A more realistic behavioral model of the producers would involve different expectations of own learning rates (and spillovers), which could follow probability distributions and perhaps a risk averse understatement of learning potentials. But such improved realism is likely to obscure the general model behavior without changing qualitative insights. Another limitation is the simple price setting and technology switching behavior of the producers that ignores their own spillovers to others via LBD and the externality via an increased share of filling stations with H_2-outlet. Moreover, a more realistic model would also allow producers to support filling station owners to provide more H_2-outlets, because they could then sell their FCVs at higher prices, since consumers need less compensation for limited fuel availability.

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Table 1: Learning rates, initial FC costs and initial number of units

Reference	Learning rates used for simulation (in %)	Base fuel cell costs in US$/kW	Base cumulative production
Rogner (1998)	10; 20; 30; 40	2,500; 4,500; 10,000	2MW
Lipman and Sperling (1999)	15; 20; 25	1,800; 2,000; 2,200	5MW
Gritsevskyi and Nakicenovic (2000)	20	n.a.	10MW
Lovins (2003)	20-30	100-300 by year 2010	
Schlecht (2003)	20; 30; 40	129-516	10,000 units
Sørensen et al. (2004)	10; 20	392(€/kW)	50,000 units
Tsuchiya and Kobayashi (2004)	26	167	50,000 units

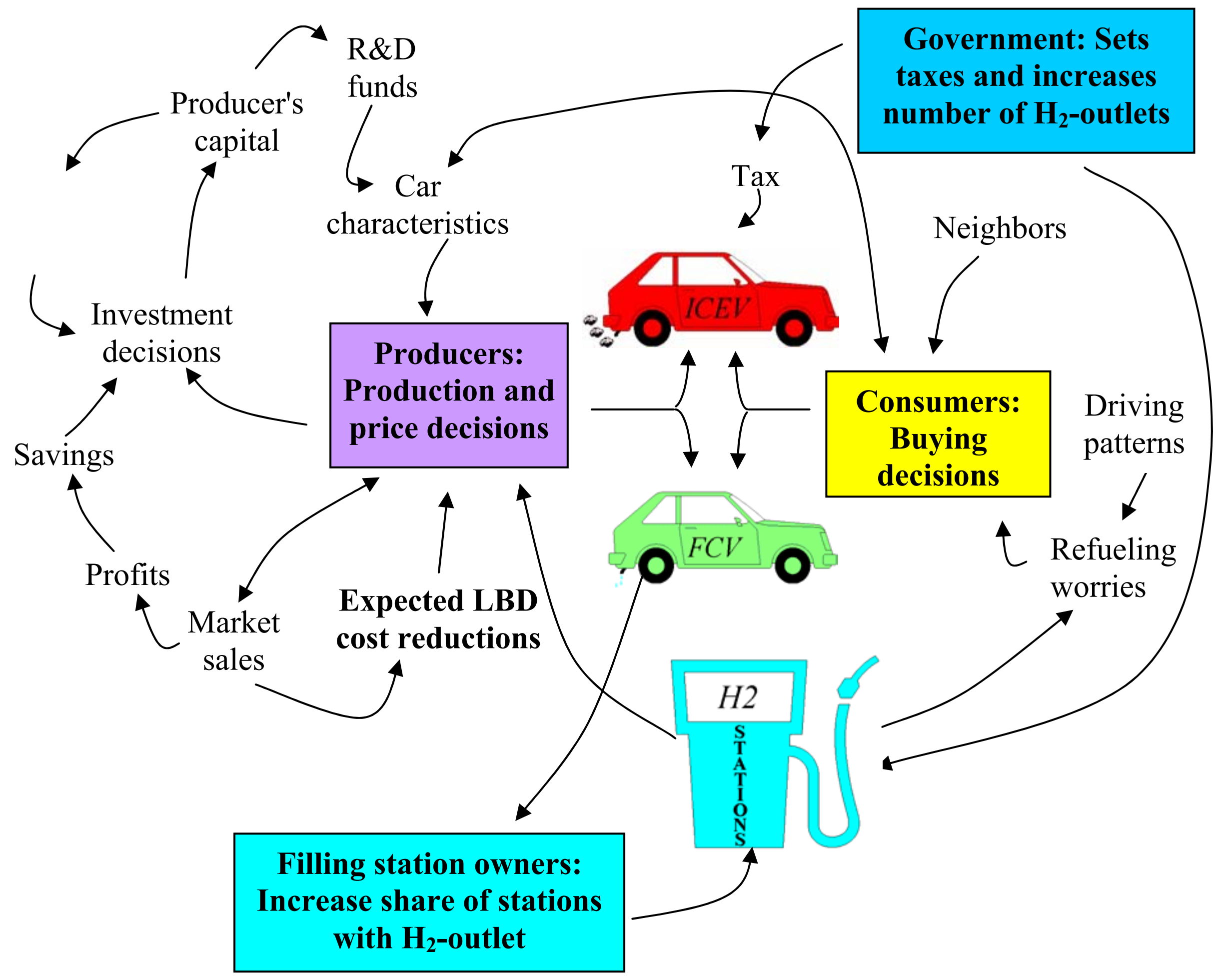

Figure 1 Model scheme

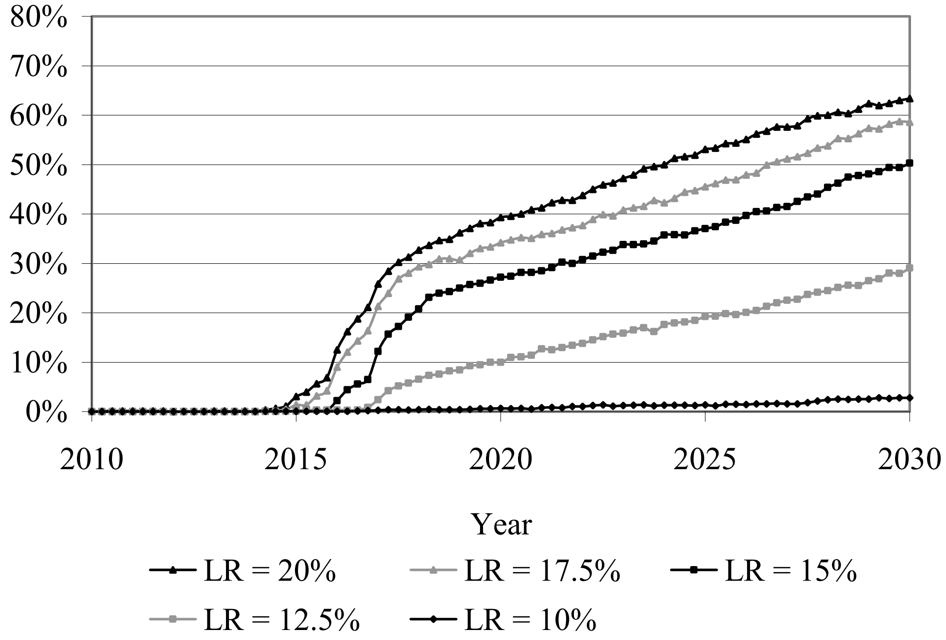

Figure 2 Percentage share of FCVs within newly registered cars in the German compact car segment: Different learning rates in fuel cell technologies

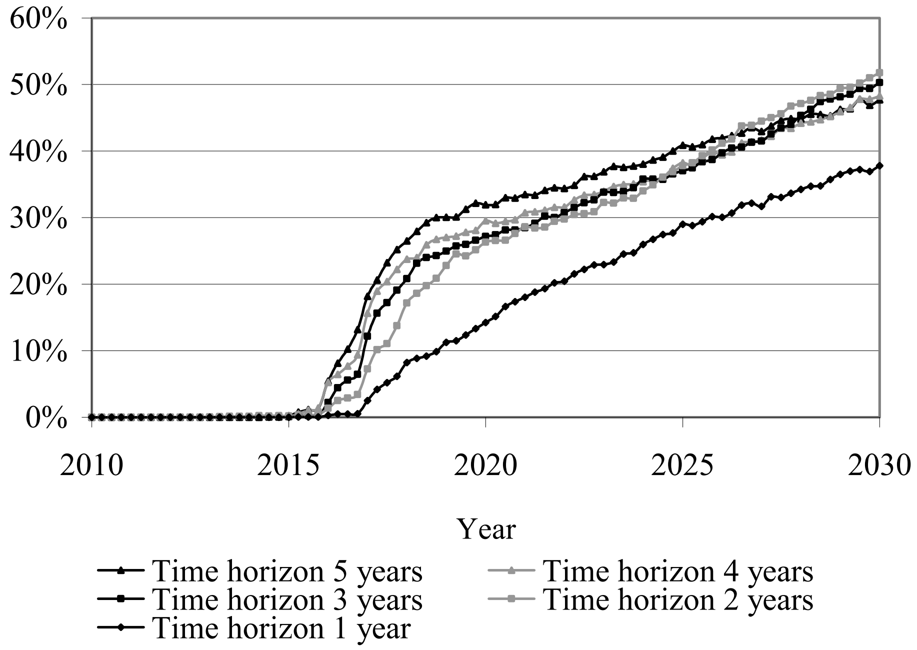

Figure 3 Percentage share of FCVs within newly registered cars: Different lengths of the producers' decision horizons

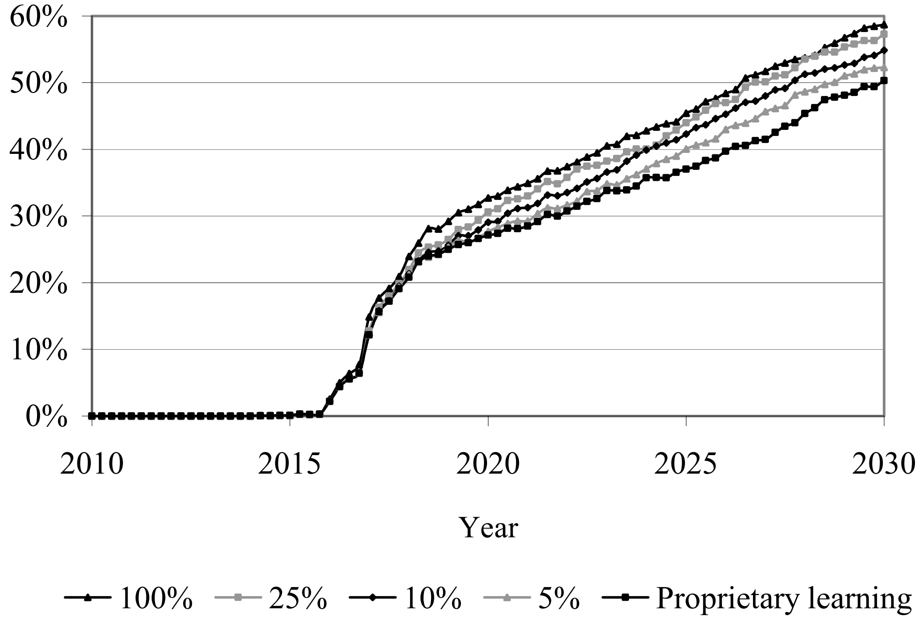

Figure 4 Percentage share of FCVs within newly registered cars: Different rates of learning spillovers

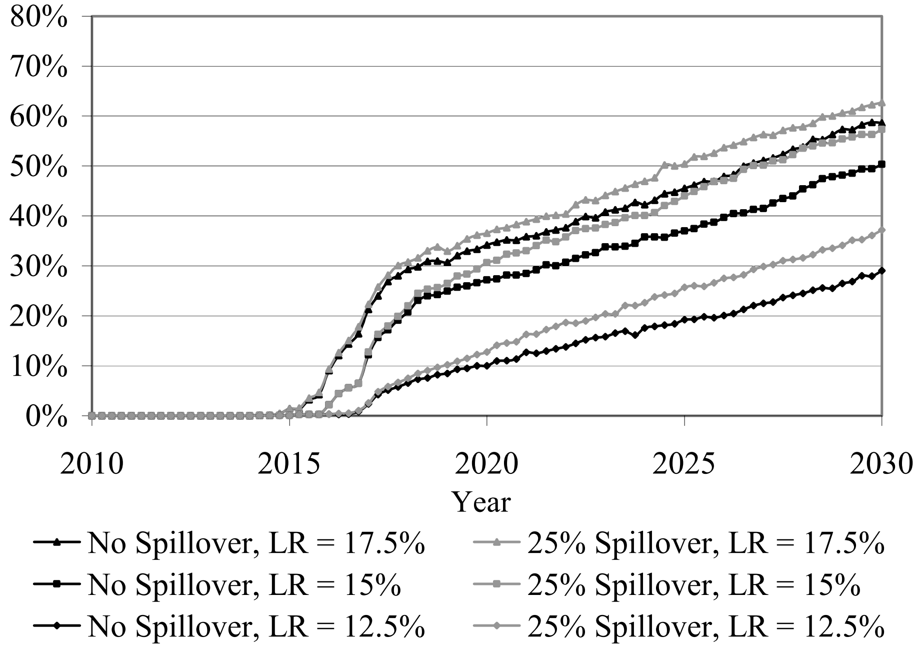

Figure 5 Percentage share of FCVs within newly registered cars: Impact of learning rates vs. impact of learning spillovers

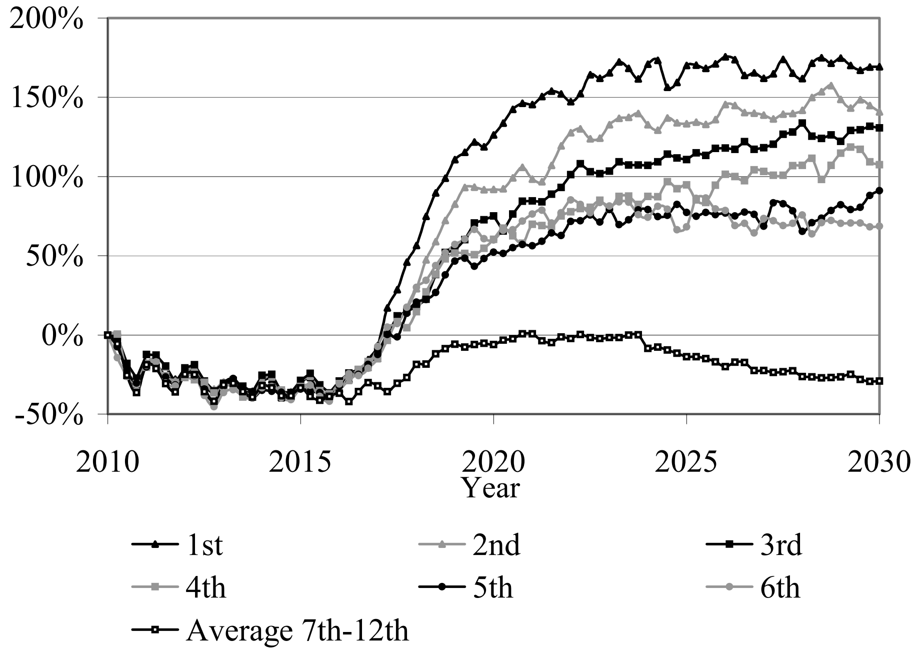

Figure 6 Change in producers' profits relative to pre-tax level, dependent on their order of switching to the production of FCVs

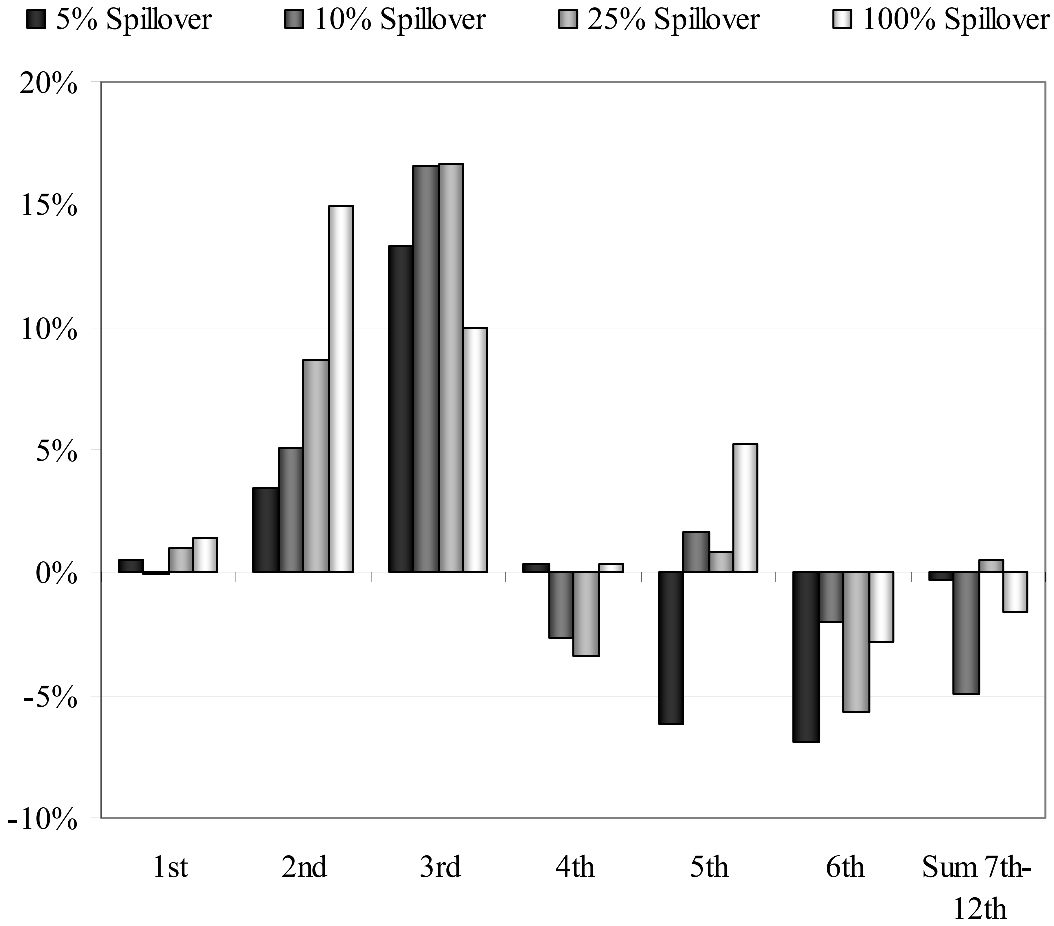

Figure 7 Change of producers' profits with spillovers relative to no spillover case

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