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Agent-Based Modelling Analysis of the Market Penetration of Fuel Cell Vehicles in Germany

Master thesis

by
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Abstract

Concerns about climate change and the problem of supply security of fossil fuels brought the German government to set the ambitious goal of covering 80% of the gross electricity consumption with renewables energies within 2050. Due to the fluctuating nature of these energy sources and grid limitations, large amounts of excess energy are likely to be available on the grid if this target is to be met. A promising use for this surplus energy is producing hydrogen to power fuel cell vehicles. Yet the successful introduction of this new technology is likely to present a barrier: car manufacturers will not produce fuel cell vehicles until filling stations start selling hydrogen, whereas the refuelling infrastructure will not develop unless a significant number of fuel cell vehicles on the road is observed. In order to overcome this obstacle, referred to as “chicken and egg problem”, policy is needed. In this master thesis, an agent-based model is implemented to investigate the effect that a tax on internal combustion engine vehicles or a subsidy for fuel cell vehicles, coupled with different refuelling infrastructure development programs, would have on the market penetration of fuel cell vehicles. Analysing this model will help gain deeper insights about how to design a policy to foster the diffusion of this new technology, making sure to minimise negative effects on consumers and on the automotive industry.

Key Words: Agent-based modelling, Fuel cell vehicles, Hydrogen economy, Hydrogen infrastructure, Market penetration

Sommario

La preoccupazione per il cambiamento climatico e il problema della sicurezza dell’approvvigionamento energetico hanno portato il governo tedesco a stabilire l’ambizioso obiettivo di coprire l’80% del consumo elettrico con le energie rinnovabili entro il 2050. A causa dei vincoli della rete elettrica e della variabilità di queste fonti, grandi quantità di energia in eccesso sarebbero presenti sulla rete se questi obiettivi fossero raggiunti. Una promettente soluzione per l’utilizzo di questa energia è la produzione d’idrogeno da usare come combustibile in veicoli fuel cell. La diffusione dei veicoli a idrogeno presenta tuttavia un ostacolo: le case automobilistiche non cominceranno a produrre veicoli fuel cell fino a quando un determinato numero di stazioni di rifornimento non comincerà a vendere idrogeno, mentre l’infrastruttura per l’idrogeno non si svilupperà finché non sarà possibile osservare un numero significativo di veicoli fuel cell sulle strade. Questo ostacolo, cosiddetto dilemma “uovo-gallina”, può essere superato con l’aiuto di politiche incentivanti. In questa tesi un modello basato su agenti è stato implementato al fine di analizzare l’effetto che una tassa sui veicoli con motore a combustione interna o un sussidio per i veicoli fuel cell, abbinati con un piano di sviluppo dell’infrastruttura per il rifornimento d’idrogeno, avrebbe sulla diffusione dei veicoli fuel cell. Analizzare questo modello aiuterà ad acquisire le conoscenze necessarie a sviluppare un’efficace politica incentivante, limitando gli effetti negativi sui consumatori e sull’industria dell’auto.

Parole chiave: Simulazione basata su agenti, Veicoli a idrogeno, Economia dell’idrogeno, Infrastruttura per l’idrogeno, Diffusione sul mercato

Declaration of originality

Hiermit versichere ich, die vorliegende Arbeit selbständig und ohne Hilfe Dritter angefertigt zu haben. Gedanken und Zitate, die ich aus fremden Quellen direkt oder indirekt übernommen habe, sind als solche unter Angabe der Quelle als Entlehnung kenntlich gemacht. Dasselbe gilt sinngemäß für Tabellen, Karten und Abbildungen. Diese Arbeit hat in gleicher oder ähnlicher Form noch keiner Prüfungsbehörde vorgelegen und wurde bisher nicht veröffentlicht.

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1 Introduction

1.1 Motivation

Increase in climate change awareness and limited security of supply of fossil fuels are pushing towards a future in which most of the electric power is bound to be produced from renewable energy sources (RES). This is especially true for Germany, where, due to the ambitious goals set by the government with the Renewable Energy Act (Erneuerbare-Energien-Gesetz*)*, 40% to 45% of the gross domestic power consumption is set to be covered by renewable energy sources by 2025, with this number increasing to 55% to 60% in 2035 and 80% in 2050 (EEG, 2014). If the renewable installed power increases to meet these targets and the number of conventional power plants decreases, large quantities of excess power will be available on the grid due to fluctuations of RES and grid limitations. Fig. 1 shows an estimate of the surplus power distribution in Germany at the county level. These results are based on the assumptions that the installed renewable power will follow (EEG, 2014) and that all the projects for the extension of the grid indicated in the German grid development plan will be realised within 2035. As the figure shows, considerable amounts of surplus energy will be observed as soon as 2025, most of which in the north of Germany, where most of the large offshore windfarms are located. Under each graph, an estimation of the total value of excess power in the whole country is indicated: this value is extremely high for the year 2050, considering that the total electric power consumption in Germany in 2015 was 576.5 TWh (IEA, 2015).

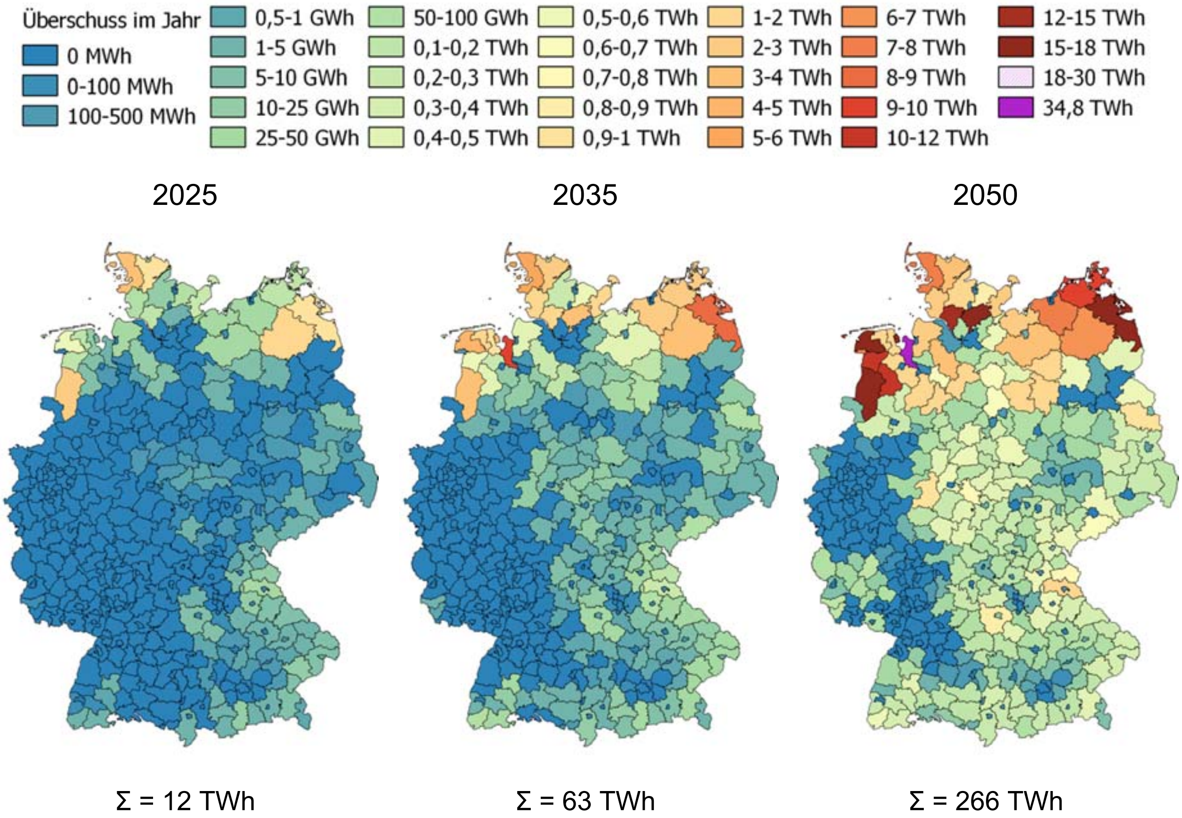

Fig. 1: Estimate of the cumulated surplus power in Germany (Bartels, 2016)

Reaching the above-mentioned targets requires the use of large-scale energy storage, which would allow to balance fluctuations in renewable energy production and store surplus power. The current storage capacity available in Germany, mainly represented by pumped storage hydropower, adds up to only 77 GWh (Kühne, 2012), which is orders of magnitude smaller than the estimates shown above. Storage capacity on the TWh scale can however be achieved storing surplus power in the form of chemical energy and a very promising option in this area is a process called “power to gas”. In this process, power from the grid is fed in large-scale electrolysers that convert it into hydrogen. The hydrogen produced in such a way can have different utilization paths, like producing methane or directly feeding it into the natural gas grid, but the best option from an economical standpoint is to use it in the transportation sector to power fuel cell vehicles (Schiebahn et al., 2015). In this solution hydrogen would become a link between two game-changing technologies, renewable energies and electromobility, coupling the two sectors with the highest total emissions in the country. With respectively 38% and 17% of the total CO_2 emissions in Germany, the electricity and transportation sectors present in fact the highest potential for emissions reduction (Umweltbundesamt, 2014).

Fuel cells generate electricity via an electrochemical reaction in which oxygen and hydrogen are combined to form water. In fuel cell vehicles (FCVs), a fuel cell is used to generate electricity that powers an on-board electric motor: hydrogen from the tank and oxygen from the air are used as an input for the fuel cell. The absence of a combustion process and the use of an electric motor allow FCVs to reach overall efficiencies that are approximately twice as high as those of internal combustion engine vehicles (JRC, 2014). In addition, the use of fuel cell vehicles instead of internal combustion engine ones would allow for lower CO_2 emissions, lower emission of local pollutants and reduced noise level in cities.

Although very promising, such a solution presents several challenges: surplus power is not yet as high as to justify large-scale hydrogen production, large electrolysers like those needed for such a solution do not exist yet, there are only 22 hydrogen filling stations in Germany (CEP, 2016) and the total amount of registered FCVs in Germany is, simply put, negligible. Due to the lack of experience with such a new fuel and the high investments required to make this solution a reality, both car manufacturers and filling station owners are hesitant to enter this newly-born market. Without a refuelling infrastructure in place to support them, the auto industry is reluctant to start producing FCVs. Simultaneously, filling station owners will have no incentive to start selling hydrogen unless there is a significant number of FCVs on the road. The situation that FCVs face is known as chicken and egg problem, and poses the question “What comes first, the vehicle or the fuel?”

A solution to this dilemma can however be found in the use of policy, combined with an infrastructure development program: a tax on conventional vehicles or a subsidy for fuel cell vehicles, coupled with incentives to filling stations that start selling hydrogen, can help the FCVs market move past this barrier. In designing such a policy, it is nonetheless crucial to limit potential negative effects on the car market, especially in the light of its importance for the German economy.

In order to address this problem, an agent-based model is used in this master thesis to analyse the complex system made up of car manufacturers, consumers and filling station owners. This modelling technique follows a bottom-up approach that consists in defining the behaviour of single actors (called agents), like producers and consumers, and then observe the behaviour of the system as a whole when a policy to foster FCVs diffusion is applied. The model will allow gathering insights on the effects that a policy might have on the interested parties, so as to anticipate how they could be affected, where the oppositions might come from and where negative effects can be limited.

1.2 Aim of the thesis

The aim of this master thesis is developing an agent-based model based on (M. Schwoon, 2006) to study the diffusion of fuel cell vehicles in the German car market while demonstrating how such a model is implemented and analysed. The specific objectives are:

- Developing an agent-based model that will serve as a basis for future work;
- Showing how such a model is implemented and analysed and what kind of insights can be gathered from it;
- Comparing a tax on internal combustion engine vehicles and a subsidy on fuel cell vehicles as policy options to foster the diffusion of fuel cell vehicles in Germany
- Comparing the obtained results with those provided by the model on which the present one is based.

1.3 Structure

This master thesis is organised as follows:

Chapter 2	In this chapter, the theoretical foundations needed to understand agent-based modelling (ABM) are laid. After describing the characteristics of the systems that can be analysed with this modelling approach, the anatomy of such a model is described. At the end of the chapter, advantages and limitations of agent-based modelling are explained.
Chapter 3	This chapter describes the model in detail. In the first section, a general overview about the organization of the model is presented. In the rest of the chapter the behaviour of the agents, the underlying assumptions and the structure of their interactions are presented.
Chapter 4	This chapter provides a description of how the conceptual model was converted into software and its correct operation verified. The first section is about the choice of the modelling environment and the structure of the software implementation. The second section describes the verification process in detail.

Chapter 5	In this chapter, the analysed scenarios and the calibration of the model are presented. First, the assumptions behind the scenarios and their structure are presented. Then, the calibration of single agent behaviour is discussed.
Chapter 6	In this chapter results of the model are presented and discussed. In the first two sections, the results for tax and subsidy scenarios are described. In the third section, a brief evaluation of the environmental benefits of the market penetration of fuel cell vehicles is provided. In the fouth part, a sensitivity analysis of the crucial parameters is carried out. The fifth section deals with the differences in implementation and results between the original model and the present one. Finally, in the last section, the limitations of the model are discussed.
Chapter 7	The last chapter summarises the main points and conclusions of this master thesis. After presenting a short summary of its content, indications for future work on the model are provided.

2 Fundamentals of agent-based simulation

The following chapter aims at laying the necessary theoretical foundations needed to understand the complexities of agent-based simulation. First of all, complex adaptive systems, that agent-based modelling attempts to model, are defined and briefly described. After that, agent-based modelling (ABM) is compared to system dynamics as a modelling technique for complex adaptive systems. Lastly, the anatomy of an ABM is described in detail.

2.1 The concept of complex adaptive system

2.1.1 Definition of complex adaptive system

A complex adaptive system is a specific type of system often defined as a "complex macroscopic collection of relatively similar and partially connected micro structures formed in order to adapt to the changing environment and increase its survivability as a macro-structure" (MacLennan, 2007). Although this all-encompassing definition includes all the main features of complex adaptive system, a better understanding can be gained explaining the words that make up this name separately, starting with the definition of system.

A system consists of interacting and interrelated elements that act as a whole, where some pattern or order is to be discerned (Dam, Nikolic, & Lukszo, 2013). All systems (Ryan, 2008)

- are an idealization, meaning that they are an abstraction of a part of the real world;
- have interdependent components that interact with each other forming patterns;
- present emergent properties, that is to say properties that cannot be deduced just looking at the single components, but result from the organization of these components;
- have boundaries;
- are enduring, since they have to last long enough to be observed;
- affect and are affected by the environment, which is simplified in modelling using a small number of relevant variables;
- exhibit feedback, since they contain loops in which A influences B and in turn B influences A;
- have non-trivial behaviour, that is to say they can react to a given input in a totally unexpected way.

A system is considered adaptive when it is capable of improvement over time in response to changes in the environment. In order for a system to be adaptive, it is not enough that its state changes in response to environmental changes, but these changes must also be an improvement in terms of achieving a certain goal or objective.

Finally a system is said to be complex when the whole can be considered more than the sum of its parts. Complexity implies that having a perfect knowledge about the behaviour of a group of single elements does not guarantee that it will be possible to predict what happens when those element are let interact in a system.

2.1.2 The concept of emergence

One of the most important properties of complex adaptive systems, that causes the complexity of their behaviour, is emergence. In system theory emergence is defined as a macro-level phenomenon that results from local-level interactions, and represents the overall system behaviour of a complex adaptive system. A very good example of emergence is given by a traffic jam, defined as a large number of vehicles on the road that are either unable to move or move very slowly. Although such a phenomena can be sometimes caused by an accident, it is, many other times, difficult to justify: the traffic jam emerges from the behaviour of single car drivers when certain conditions are met. The properties of the system that derive from this mechanisms are called emergent properties and are often counterintuitive: as an example, a traffic jam moves in the opposite direction to that of the cars that cause it. An interesting aspect of emergent properties is that they result from agent interaction and in turn constraint agent behaviour: the traffic jam is created by cars, and cars cannot move because of it. This causal relationship of a higher level to a lower level of the system is called downward causation and it is one of the effects of emergence.

2.1.3 Socio-technical systems

A socio-technical system is a complex system made up of two highly interconnected subsystems: a social network of actors and a physical network of technical artefacts (Allenby, 2006). A typical examples of socio-technical system is the electricity infrastructure. The technical subsystem is in this case made up of thousands of technical components, it provides electric power and includes power plants, the transmission and distribution grid, transformers and so on. The social subsystem is made up of all those actors that sell or buy electricity, like power plant owners, industrial consumers and private consumers, and by the legislative and regulatory framework that constraints the behaviour of these actors in the electricity infrastructure. Each actor in the social network makes decisions based on a certain set of rules, that can be studied more or less in depth depending on the focus of the system analysis. In this particular case the regulatory framework is very important, as can be deduced from what happened in the last 20 years in Europe: a change in rules from a vertically integrated system to a liberalised one brought about a lot of changes to which both consumers and producers had to adapt, completely reshaping the existing market. In this system the social network determines the development and operation of the technical system, which in turn affects the actors in the social network.

2.2 Modelling approaches

A model of a complex adaptive system is a formalisation of a modeller's interpretation of reality and developing it the modeller is faced with two opposing needs. On the one hand the model should represent reality as accurately as possible, so that all the dynamics that one can observe in reality are also to be found in the model. On the other hand, the model should be simple enough to allow a better understanding of the modelled system: a model that is as detailed and as complex as what happens in the real world, would give the modeller no more information than studying reality directly.

Following the description given by (Dam et al., 2013) a model of a complex adaptive system should always possess three main characteristics: multi-domain and multi-disciplinary knowledge, generative capacity and adaptivity. One of the defining characteristics of complex adaptive systems is that they cannot be thoroughly explained using a single formalism and this is why different points of view have to be considered in the study of these systems. As a consequence, developing a model for a complex adaptive system requires knowledge to be gathered from experts in different fields and also their active collaboration, since the modeller only has a partial understanding of the model complexity. Secondly, since a complex adaptive system is generated from the bottom up, the model will have to have a generative capacity. This means that the modeller will need to be able to "grow" the macroscopic regularity that can be observed in the real system using autonomous entities that interact with each other. Finally, the model has to be adaptive and be able to evolve over time: the individual entities‘ behaviour and the collective model behaviour should be able to mutate in response to selective pressures.

Due to the difficulties in developing a model that possesses all these characteristics, there is a tendency to solve these problems by reducing complexity and representing these systems using cost/benefit analysis, in which each system component is assigned a monetary equivalent. Yet there are modelling approaches that allow to address the problem on a more complex level. In modelling the market diffusion of innovations in general and the diffusion of alternative fuel vehicles in particular, the most used approaches that allow to retain complexity are system dynamics and agent-based modelling (Gnann & Plötz, 2015).

System dynamics is a modelling paradigm in which processes that happen in the real world are represented using delay structures and interacting feedback loops, that either balance or reinforce each other. From a mathematical point of view this representation corresponds to a system of differential equations and much of the modelling effort is spent on developing a structure that closely resembles the one observed in the real world. In system dynamics the main assumptions about a system's behaviour lie in the global structure of the system and the effect of the global behaviour on the components is studied. In Agent-based modelling, on the other hand, the behaviour of the autonomous entities called agents and their interactions are simulated to study the effect that they have on the system as a whole. In ABM the structure of the model is not a precondition, as happens for system dynamics, but it emerges from actions and interactions of the agents.

The main difference between these two approaches is that agent-based modelling follows a bottom-up approach, in which the behaviour of the model emerges from the interaction of lower-level components of the system, while in system dynamics, that follows a top-down approach, the rules that describe the global behaviour must be chosen beforehand. In modelling complex adaptive systems the use of ABM can be advantageous when the modeller has no complete understanding about how the different parts of the model interact and cannot, as a consequence, set up a model description of unknown or partially-known behaviours.

ABM is particularly suited to model socio-technical systems. Assuming that the behaviour of real actors can actually be captured by the model, agent-based simulations allows the modeller to observe how the social part and the technical part of a complex system co-evolve and what is the system behaviour that can emerge due to this co-evolution. Running ABM simulations the modeller can conduct ex-ante analyses of the possible outcomes of a certain decision or solution to be better informed about what could happen if this solution is applied to the real system. It should be remembered though that ABM is no “crystal ball” that can predict the future: its goal is helping in the decision-making process, more often than not pointing at “what could go wrong” if a certain solution to a problem is deployed.

Further explanations about when to use ABM, its advantages and limitations are given in section 2.3.3.

2.3 Agent-based Modelling

Even though the concept of agent-based modelling (ABM) was first introduced in the late 40s, it can still be considered a relatively new approach to system modelling, since, due to its computational-intensive requirements, it only started being used in the 90s.

As anticipated above ABM is a modelling approach meant to examine the global effects caused by interactions of low-level entities in a complex adaptive system. These global effects emerge from the combined actions of all the agents, which are determined by a set of behaviour rules, and bring to results that can be surprising or difficult to predict otherwise. Agent-based modelling should not be confused with multi-agent system: even though these two modelling techniques can look similar, their goal is different. While in ABM agents are set up with the characteristics of real world equivalents and then emergent phenomena are observed, in multi-agent systems agents characteristics are set so that a certain emergence is obtained as a result.

ABM can be used to try and replicate complex phenomena that can be witnessed in reality and for which it is difficult to determine how things evolved in that specific way. Making assumptions about the behaviour of the single agents and causing the system to evolve similarly to reality can bring an understanding of how the system got there in the first place. Studying an agent-based model can be compared to being a new employee in a company: it takes a while to understand who relates to whom and how, because the pattern of relationships is not yet perceivable. After becoming familiar with the new environment, however, the pattern becomes clear. As it is usually said in the field of generative science, “If you did not grow it, you did not explain it” (Epstein, 1999). Another promising possibility is using ABM to infer what it takes to make something happen, and this is exactly the type of question that this master thesis tries to answer for the successful difussion of fuel cell vehicles.

2.3.1 The agent

Following the definition given by (Jennings, 2000) an agent is an encapsulated computer system that is situated in some environment and that is capable of flexible, autonomous action in that environment in order to meet its design objectives. Agents

- are encapsulated, that is to say they have well-defined boundaries and interfaces;
- are situated in a particular environment, meaning that they receive inputs about the state of their environment through sensors and act on the environment through effectors;
- have design objectives, that means they have a specific goal to achieve;
- are autonomous, that is to say they have control over their internal state and their own behaviour;
- are capable of flexible problem solving behaviour, meaning that they can respond to changes in the environment and act in anticipation of future goals.

The agent is the smallest part of an agent-based model and its structure can be divided into states and rules.

A state is a collection of parameters that defines an agent at a given moment (Wooldridge & Jennings, 1995). States can be divided into internal state (only pertaining to one agent), local state (includes the internal state and the public variables of the agents that interact with the current one) and global states (all the relevant states in the observable environment). Imagining an application of ABM to the example of the electricity infrastructure, industrial consumers are agents whose internal states are represented by parameters like the amount of power they buy each year, the voltage level at which they take power from the grid and so on. The local state includes, besides the internal variables, also those of the neighbouring consumers that can be directly observed, like which electric company they buy electricity from. The state that contains all the variables accessible to one agent in the model is called global state. In this example the global state also contains variables like the price of electricity or the amount of taxes on electricity purchase.

Rules (or behaviours), on the other hand, define how an agent acts based on its internal, local or global state. This rules can have different characteristics and structures: the agent might act in some specific way if a parameter has a specific value and act in a completely different way if the parameter has another value (if-else statements). In some other cases the agent might choose how to act from a list of different possibilities based on the value of a utility function. An industrial consumer, for example, can decide to change the electric company from which it buys electricity if it observes that most of its neighbours are buying electricity from another provider and that they are paying a lower price for it.

All the agents in the ABM are contained in the environment: the environment contains all the information that the agents need to make decisions, that are not part of the internal state. The environment variables can be divided into two subgroups: model parameters and emergent properties. A model parameter is chosen by the modeller and can be both static or dynamic: the collection of all model parameters represents a scenario. Emergent properties, on the other hand, result from actions and interactions of the agents and cannot be known beforehand by the modeller: the wholesale price of electricity, for example, can emerge from the match between supply and demand in a regulated market and is a consequence of the decision of all the actors involved. In Fig. 2 a simple representation of an ABM is given: the agent in the middle receives inputs from other agents and from the environment, acts on itself to change its own state and finally acts on other agents and the environment.

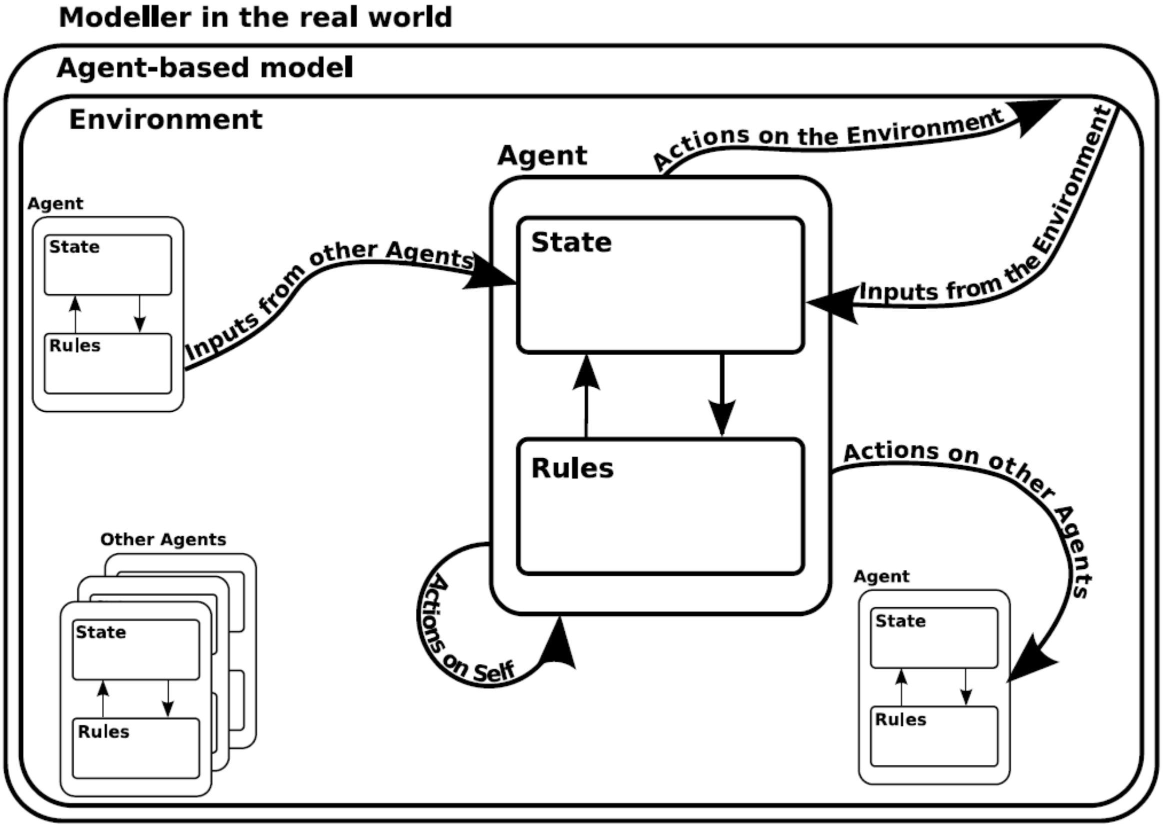

Fig. 2: Structure of an agent-based model (Dam et al., 2013)

The environment in which agents interact is also usually characterised by a specific structure that determines a subset of neighbours that each agent can interact with: this can be a so called soup (in which each agent is equally likely to interact with all other agents), space (in which each agent has a specific location and a distance between two agents can be defined) or networks that more closely resemble human ones (e.g. small-world networks, scale-free networks, etc.).

Another important aspect of ABM is time. Since agent-based models are run on computers, time will inevitably be discrete, while most of them try to model real world systems with continuous time. The discrete time unit used in an ABM is called tick and the choice of its length depends on the speed of the dynamics that are to be analysed with the model: a tick could represent a second if the model analyses the movement of birds in a flock or years if the phenomenon under investigation is the development of the electricity infrastructure. As a consequence of discrete time, actions of agents that happen in parallel in reality have to be executed one after the other in the model, yet avoiding that some agents have an advantage just because they act before other agents. One solution to avoid this problem is using a random order of action: in this way every agent has the same probability to go first and the effect of the advantage is evened out over a large number of actions. Another way to do it is to separate the decision about the action and the action itself: first all the agents make a decision about how to act and only afterwards the actions are performed. Failing to implement this process correctly can cause some agents to have a "glimpse into the future" just because they sees the already-updated state of other agents.

2.3.2 Example of an agent-based model

One of the simplest examples of agent-based model is Conway's Game of Life, a two-dimensional cellular automaton invented by the mathematician John Horton Conway in 1970. A cellular automaton is a computational machine that performs actions based on certain rules. The "world" of Game of Life is a grid in which each square contains a cell that can have two states, alive or dead. The state of a cell in the next time step depends on its current state and the states of its neighbours, that is to say the 8 cells around it.

The rules of the game are quite simple and are applied to each one of the cells at each time step:

- If the cell is alive and has less than two neighbours it dies (Lonely)
- If the cell is alive and more than three neighbours are alive it dies (Crowded)
- If the cell is alive and has either two or three neighbours it lives on to the next generation (OK)
- If the cell is dead and exactly three neighbours are alive it also comes alive (Born)

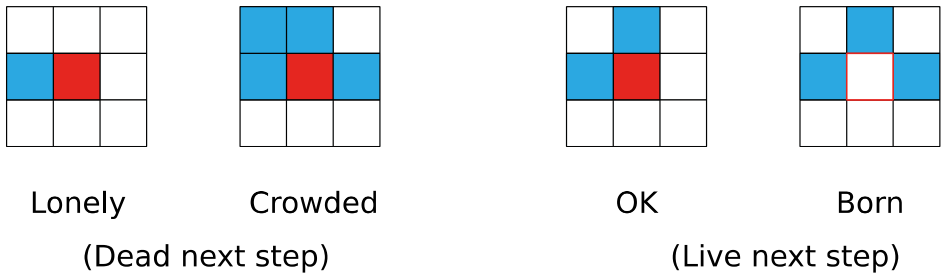

Fig. 3: Rules of Conway's Game of Life (Bindel, 2014)

Game of Life can be initialised with any initial distribution, one possibility being a definition of the density of live cells, and it will evolve based on the above-mentioned rules. After the model starts running, the population of cells will constantly be changing and many different patterns will start to emerge, some of which will survive and increase in complexity and some others will die out. Fig. 4, for example, shows a pattern called pulsar that is rather common in Game of Life and oscillates between three different states in a cyclical fashion: this pattern emerges from the selective pressures generated by the rule of the game.

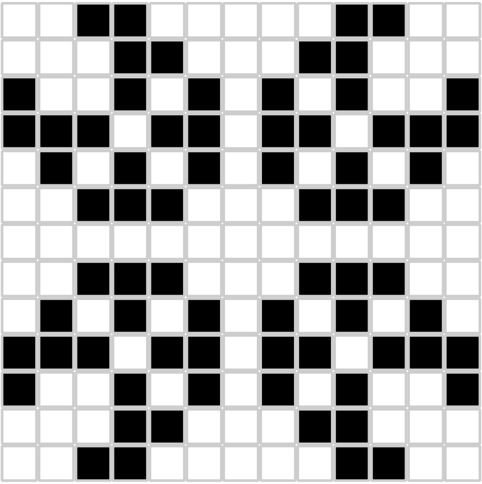

Fig. 4: Pulsar (Wikimedia, 2007)

What is striking about this simple model is that from such simple rules hundreds of thousands of different patterns can emerge, patterns that would be impossible to predict from the rules that govern the survival of one cell. This concept continues to be valid when more complex models are considered.

2.3.3 When to use agent-based modelling

As stated in section 2.2 ABM presents several advantages over other modelling techniques like system dynamics. These advantages make ABM particularly suitable for the study of complex adaptive systems. Just like any other modelling technique, however, ABM presents both advantages and limitations and these will be briefly discussed in this section.

The main advantages are: ability to capture emergence, natural description of the system and the possibility to add heterogeneity to the model. The ability to capture emergence is intrinsic to the concept of ABM phenomena, since its concept is based on interacting entities: this makes it the best choice when the modelled system involves individual behaviour, which is ill suited to be modelled with differential equations. Individual behaviour is in fact non linear and often characterised by thresholds. Moreover emergent phenomena can be highly counterintuitive and system dynamics allows studying a phenomenon only if this is explicitly described in the differential equations: as a consequence radically new system behaviours can only be captured by agent-based modelling. Another advantage of ABM is that it provides a natural description of the system, since in real complex systems the structure is generated from the bottom up and not vice versa. This natural approach provides an easier way of implementing the model rather than trying to describe the global behaviour directly. This characteristic allows for heterogeneity in the model that cannot be included when differential equations are used. This allows for example grouping agents based on specific parameters and studying what is the difference between innovators and early adopters when a new technology enters the market. This feature of ABM will be used in the model developed in this master thesis to group producers based on their market share and see how their decision to switch to FCVs depends on this variable.

Of course ABM presents also some disadvantages that limit its possible uses: among these are the impossibility of having a general-purpose model, the difficulty of modelling human behaviour and its computational requirement. First of all, just like any other modelling technique, an agent-based model has to answer a specific question and no ABM can exist that captures all the complexities of a given system. The model should be build with the right level of complexity to serve its purpose. Another issue regards ABMs that simulate human behaviour: since human behaviour can hardly be converted in numbers and formulas it follows that most of the times the results of ABMs can only be interpreted on a qualitative level. However, this mainly depends on the degree of accuracy of the used input data and on the expertise of the modeller, which in some cases could allow a quantitative interpretation as well. Lastly, it should be noted that ABM can be extremely computational intensive, especially if the analysed system is large and the number of agents is high. Due to the randonm initialization of agent variables and the randomness of their interactions the model needs to be run a large number of times in order to obtain statistically significant results. As a consequence, ABM often requires the use of a computer cluster to run simulations in a reasonable amount of time.

3 Model description

This chapter describes the agent-based model used in the master thesis project. After giving a general description of how the model is organised, the anatomy of the agents and the structure of their interactions are described in detail.

3.1 General structure of the model

The model implemented in this master thesis is based on (M. Schwoon, 2006). It tries to capture the main dynamics of the system made up of consumers, car manufacturers (here indicated as producers), filling stations operators and the government. This system can be interpreted as a socio-technical system: the technical subsystem includes the refuelling infrastructure and the cars, whereas the social subsystem includes all the actors indicated above.

In this model the government makes use of a policy to promote the diffusion of fuel cell vehicles: this policy is either a tax on the purchase of internal combustion engine vehicles (ICEVs) or a an equivalent subsidy for fuel cell vehicles (FCVs). Provided that this incentive to buy FCVs is high enough, consumer will start buying them and filling stations will in turn start selling hydrogen. The tick, that is the time unit in the model, represents one quarter. Every single tick the following series of events happens in the model:

- Producers choose the drivetrain technology and price for their cars that maximise a weighted average of expected income and expected sales, taking limited capital availability into account
- Total demand for cars is calculated using a simple function in which demand is inversely proportional to the average car price set by producers
- A number of consumers corresponding to the total demand is randomly drawn from the population of consumers, asked to evaluate all the cars on the market and buy the one that they consider the best choice and is still available
- Producers engage in research and development to improve their product and make it more appealing for customers
- If FCVs have been sold in this tick the hydrogen refuelling infrastructure develops and the share of filling stations that offer hydrogen increases

In order to allow comparability between products this model only focuses on the compact car segment, which makes up roughly 25% of the German car market. The choice fell on this segment because, being it the largest in the German car market, it is the most likely to generate a high enough hydrogen demand to stimulate the growth of the refuelling infrastructure. The results of the model are mainly interpreted in terms of the share of FCVs in the quarterly car sales (unless otherwise stated the share refers to the compact car segment only).

3.2 Consumers

Consumers in the model symbolise German compact car owners: each one of them owns a car and will buy a new one when randomly selected to do so. Each car is characterised by different features, represented by an array of 4 values between 0 and 1 (z_j) and a boolean variable that indicates the technology of the drivetrain (FCV). A car is thus represented as

$$c = c(FCV, z_j) \tag{1}$$

where FCV is 1 for fuel cell vehicles and 0 for internal combustion engine vehicles.

At the beginning the simulation all the cars in the model are ICEVs and the features array of each car is initialised with random values from a uniform distribution between 0 and 1. Although such an array cannot represent real car characteristics, it allows to create heterogeneity in consumers preferences and to model producers' efforts to improve car features.

Each consumer is assigned a location in a simple grid, similar to that of Game of Life, in which it is surrounded by 8 neighbours. Fig. 5 shows a subset of the consumers' grid in which a consumer, represented in blue, and its neighbours, in red, are found: the entirety of the coloured cells is called neighbourhood. This is a representation of the social network of the consumer in which neighbours represent people whose buying decisions have an effect on the consumer's own decision, like friends, colleagues, relatives, etc. In order for all consumers to have the same number of neighbours and to avoid edge effects the grid cells are connected as to form a toroidal surface like the one shown in Fig. 6, which is common practice in spatial agent-based models.

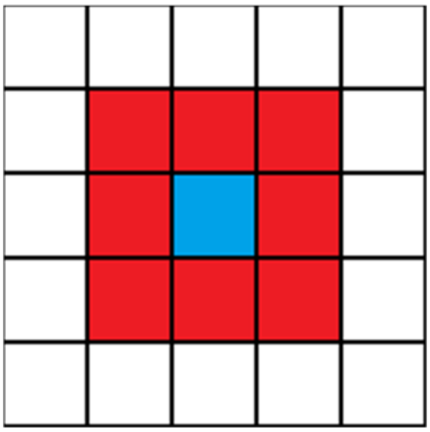

Fig. 5: Representation of a consumer's neighbourhood (Wikimedia, 2013)

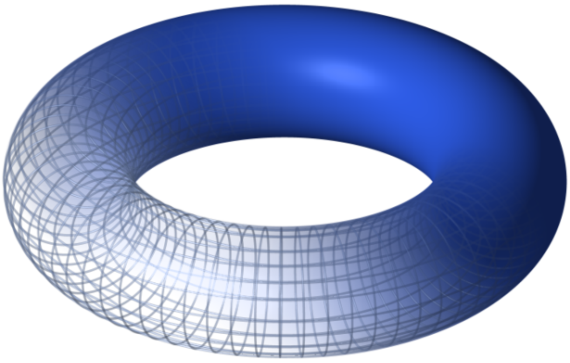

Fig. 6: Toroidal surface (Wikimedia, 2015)

3.2.1 The consumat approach

The way consumers make buying decisions in the model follows the consumat approach (Jager, 2000), a model of consumer behaviour meant to be applied to artificial consumers (the consumats). In this approach each consumat makes a buying decision based on expected utility associated to the product and the experienced uncertainty in the decision. The expected utility is in turn divided into two parts, namely a social need and a personal need. The personal need represents the personal preference for certain product features and its satisfaction depends on the difference between these preferences and the real product characteristics. The social need is related to social identity and can be formalised as having a preference for consuming the same products as the neighbours: the more neighbours consume the same product, the higher the satisfaction of the social need. The expected utility (U_j) of a certain product j is given by

$$U_j = \frac{\beta_j PN_j + (1 - \beta_j) SN_j}{p_j^{\kappa}} \tag{2}$$

where PN_j represents the personal need, SN_j the social need, β_j the relative importance of the personal need, p_j the price of the product and κ is a scaling parameter, which states the relative weight of price. When the expected utility of a product is above a given threshold, the consumat is said to be satisfied with this product. The second part of the decision is determined by the experienced uncertainty (I_i), defined as:

$$I_i = \sqrt{\left|U_{i,t} - U_{i,t-1}\right|} \tag{3}$$

where $U_{i,t}$ is the current value of expected utility and $U_{i,t-1}$ is the value of the utility in previous period. The experienced uncertainty is high when there is a large variation in expected utility between two subsequent ticks. If this value is lower than a given threshold, the consumat is said to be uncertain.

In deciding what product to consume the consumat can employ different cognitive processes, based on its level of expected utility and experienced uncertainty :

- Repetition (satisfied and certain), the consumat consumes the same product as before
- Deliberation (dissatisfied and certain), the consumat evaluates the expected utility of product and chooses the one that maximises it
- Imitation (satisfied and uncertain), the consumat consumes the product with the largest share in the neighbourhood
- Social comparison (dissatisfied and uncertain), the consumat evaluates the product it was previously consuming and the one with the largest share in the neighbourhood: the one with the largest expected utility is consumed

It is assumed that in the process of buying a new car the need satisfaction is rather low, and for this reason the processes of repetition and imitation are not considered. It is usually agreed upon that social comparison plays an important role in the choice of a car and becomes particularly important if the consumer experiences uncertainty due to a new product like a FCV. Yet, including this cognitive process would be rather difficult in this model: this problem will be further discussed in section 6.5.1. It is important to point out however that considering social comparison would give a lower market penetration at the beginning since the consumers that do follow this cognitive process will not even consider the purchase of a FCV. Having removed the possibility for social comparison consumers will only deliberate.

3.2.2 Choice of the car

Starting from formula (2), adding the refuelling effect ($RFE_{k,t}(c_{i,t})$) and using the price elasticity (ε_{own}) as a scaling parameter the total expected utility for a car is obtained. The value of total expected utility of the i-th car model for the k-th consumer is defined as follows:

$$U_{k,t}^{tot} = \frac{[\beta_k U_{k,t}(c_{i,t}) + (1 - \beta_k) SN_{k,t}(c_{i,t})] RFE_{k,t}(c_{i,t})}{\{p(c_{i,t})[1 + taxOrSubsidy(t, FCV)]\}^{|\varepsilon_{own}|}} \tag{4}$$

In order to choose which car buy it evaluates the total expected utility that it would get from buying each one of them and then buys the one with the highest total expected utility that is still available.

The total expected utility takes four aspects into account:

- The direct utility ($U_{k,t}(c_{i,t})$) the consumer would derive from buying a certain car. This quantity depends on its preference about car features, described by an array of values between 0 and 1 ($pref_{k,j,t}$), in which each element corresponds to the preference about a specific car feature

  $$U_{k,t}(c_{i,t}) = 1 - \frac{1}{n_j} \sum_{j=1}^{n_j} |z_{i,j,t} - pref_{k,j,t}| \tag{5}$$

  The value of direct utility is as close to one as the car features are close the preferences of the consumer.

- The social need ($SN_{k,t}(c_{i,t})$) reproduces the effect that neighbours' decisions have on the decision of the consumer. This is represented by the share of cars with a certain drivetrain technology that neighbourhood would have if the deciding consumer bought a car with the same drivetrain technology.

  $$\begin{gathered} SN_{k,t}(c_{i,FCV=0,t}) = \frac{1 + numOfICEVNeighbors}{numOfNeighbors} \\ SN_{k,t}(c_{i,FCV=1,t}) = \frac{1 + numOfFCVNeighbors}{numOfNeighbors} \end{gathered} \tag{6}$$

The higher the share of consumers that already have a car with the considered drivetrain technology, the higher the satisfaction of the social need.

The relative importance of direct utility and social need is different for each consumer to discern people that give a high importance to own opinion from the ones that tend to give more importance to the opinion of other consumers. This heterogeneity is represented in the total expected utility via the parameter β_k: for the extreme case of $\beta_k = 1$ the consumer is not in any way influenced by its neighbours, while for $\beta_k = 0$ it completely neglects its own opinion. Since the last case is rather unlikely, a lower threshold of 0.4 is chosen for β_k. The value of this parameter is thus randomly drawn from a uniform distribution between 0.4 and 1.

- The refuelling effect $RFE_{k,t}(c_{i,t})$ takes into account the disadvantage that FCVs would have compared to ICEVs due to a lower number of filling stations that sell hydrogen compared to conventional fuels. This is defined as

$$RFE_{k,t}(c_{i,FCV,t}) = 1 - FCV\ DP_k \exp(\gamma s_{H_2,t}) \tag{7}$$

where DP_k is the driving pattern of the consumer, $s_{H_2,t}$ is the share of hydrogen filling stations and γ is the fuel availability factor. The refuelling effect is always equal to 1 for conventional vehicles and is determined by car usage and the share of filling stations that sell hydrogen for FCVs. The driving pattern describes consumer car usage that is close to 0 for few short trips or closer to 1 for many long distant trips. The assumption here is that the importance of having a high share of hydrogen filling stations (HFSs) is higher if the consumer in reality drives often and to distant places. Fig. 7 shows how the refuelling effect varies with the share of HFSs for consumers with different driving patterns: it is clear form the chart that consumers with a high value of DP_k will have a very low refuelling effect for low shares of HFSs and are thus not likely to buy a FCV when the technology is first introduced. On the other hand, the refuelling effect has a very low impact on consumers with a low driving pattern so that they are the most likely to become early adopters of FCVs. As the share of FCVs sold in one tick increases, the amount of HFSs increases accordingly, so that consumers with high driving pattern are more and more likely to consider the purchase of a FCV.

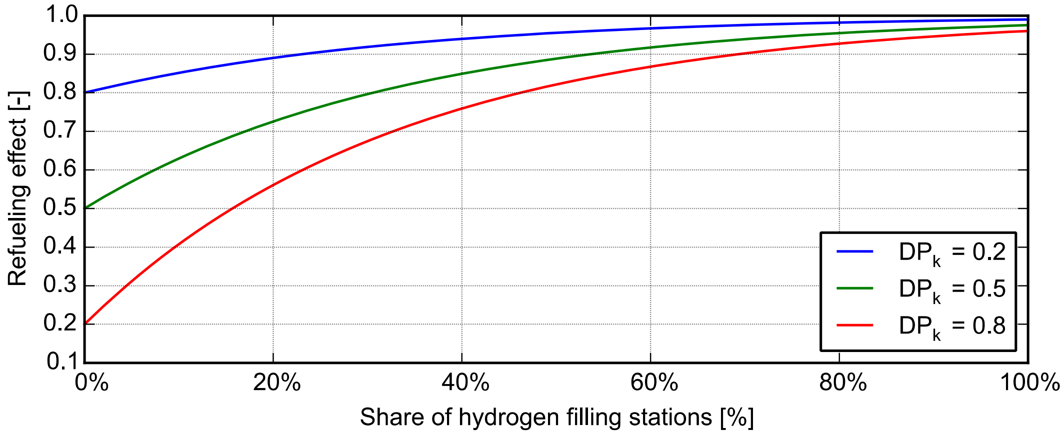

Fig. 7: Refuelling effect with varying share of hydrogen filling stations

The importance of the share of filling stations that sell hydrogen in the refuelling effect is directly influenced by the fuel availability factor, set to be – 3 in the central case, and indirectly by the own price elasticity of the consumer

- The consumer price, at the denominator of the total expected utility function, plays an important role in the consumer decision and its importance is determined by the own price elasticity (ε_{own}), that replaces the scaling factor used in the consumat approach. Own price elasticity is a measure used in economics to show the responsiveness of demand to a change in price of a certain product and is defined as

$$\varepsilon_{own} = \frac{\left(\frac{dQ}{Q}\right)}{\left(\frac{dP}{P}\right)} \tag{8}$$

where Q is the demanded quantity and P is the price. To be more precise, it represents the percentage change in quantity demanded in response to a one percent change in price.

3.2.3 Change in consumer preferences

Consumer preferences are not constant, but change as the products consumers are exposed to change with time, due to the mere-exposure effect. This phenomenon, extensively studied and used in marketing, causes consumers to prefer products they are most familiar with rather than others they have never encountered before (Zajonc, 2001). This effect is taken into account in the model with a shift of preferences of all the consumers towards the characteristics of the “average car” sold in one quarter, where each feature is represented by an average across all car models sold weighted by market share. This mechanism gives an advantage to large producers, because they have a higher impact on the determination of the average car and can thus influence future consumer decisions. The preferences of each consumer are updated at the end of each tick using the following formula:

$$pref_{k,j,t+1} = \zeta\left(pref_{k,j,t}\right) + (1-\zeta)\sum_{i=1}^{n_i} z_{i,j,t} \cdot s(c_{i,t}) \tag{9}$$

where $pref_{k,j,t}$ is the preference for the specific feature k in the current quarter, $pref_{k,j,t+1}$ is the one for the next quarter, the summation represents the feature k of the average car and ζ indicates the speed at which prefereces vary. The value of ζ is set to be 0.99, as to have a small but noticeable change during one model run.

3.3 Producers

Since producers are the main focus of this model, particular attention was given to a realistic representation of their behaviour. Each one of the producers has to make a decision at the beginning of the quarter about the price to set and the corresponding quantity of cars it expects to sell. A quarter is considered too short of a time to adjust the production capacity if the demand is higher than expected, thus the expected quantity also represents the maximum amount of cars a producer can sell in one quarter.

3.3.1 Production decision

In order to determine the optimal price for its car in one quarter every producer performs an objective function maximization, in which not only income is considered but also the expected market share. The objective function is defined as:

$$\begin{gathered}\max Obj_t = \left(1 - W_{i,t}\right)\frac{INC_{i,t}^{e}}{\sum_{i=1}^{n_i} INC_{i,t-1}} + W_{i,t}\frac{q^e(c_{i,t})}{\sum_{i=1}^{n_i} q(c_{i,t-1})} \\ \text{with } W_{i,t} = \exp\left(-\eta\frac{q^e(c_{i,t})}{\sum_{i=1}^{n_i} q(c_{i,t-1})}\right)\end{gathered} \tag{10}$$

where $INC_{i,t}^{e}$ is the expected income, $q^e(c_{i,t})$ is the expected sales, $\sum_{i=1}^{n_i} INC_{i,t-1}$ and $\sum_{i=1}^{n_i} q(c_{i,t-1})$ are, respectively, the total income and the total sales of all producers in the previous period.

The expected income is defined as

$$INC_{i,t}^{e} = q^e(c_{i,t})p(c_{i,t}) - q^e(c_{i,t})v_i\left(q^e(c_{i,t})\right) \tag{11}$$

where $p(c_{i,t})$ is the price and $v_i(q^e(c_{i,t}))$ is the variable cost per unit, which is considered constant across producers and 10% higher for FCVs compared to ICEVs. The main assumption behind this number is that all the cost reduction due to learning curves will have already been realised by the year in which the tax or subsidy is introduced. Even though this is a very strong assumption, it is necessary to keep the number of model dynamics low. Considering learning curves to take cost reductions into account is one of the possible ideas for future work.

(Kwasnicki & Kwasnicka, 1992) shows that producers using this function maximization in the price setting process perform better than the ones simply maximizing income. The weight function is conceived as to focus more on market share when the current producer had a low market share in the previous period and more on income in case of previously high market share. It is relatively straightforward that the two components of the objective function push the price in different directions: choosing a low price will decrease income and increase expected quantity, thus increasing the expected market share, while a high price will do exactly the opposite. In case the producer had a negative income in the previous quarter only expected income is maximised ($W_{i,t} = 0$).

Each producer, that hasn't switched to fuel cells yet, performs an optimization of the objective function at each tick for both ICEVs and FCVs, and decides to switch to FCVs as soon as the maximum value of the objective function is higher for FCVs. Since switching the whole production to FCVs is expensive and the production line needs to be adapted to the new drivetrain technology, producers that make the switch cannot go back to producing ICEVs.

3.3.2 Expected quantity estimation for a given price

The estimation of the expected quantity $q^e\left(c_{i,t}\right)$ corresponding to a specific price $p\left(c_{i,t}\right)$ is done by the producers in four steps.

First of all each producer evaluates how competitive its car is compared to the average car on the market in the previous period (at the end of the previous tick the car of the current producer has been improved with R&D): to do so it tries to replicate the way consumers evaluate the total expected utility of cars using known variables available from its customers and publicly available data (e.g. car features, market shares).

The variable is called competitiveness ($\vartheta^e\left(c_{i,t}\right)$) and is defined as follows:

$$\vartheta^e\left(c_{i,t}\right) = \frac{\left\{\bar{\beta}_{t-1}(1-\Delta c) + \left(1-\bar{\beta}_{t-1}\right)E\left[SN_t\left(c_{i,FCV,t-1}\right)\right]\right\}E\left[RFE_t\left(c_{i,t}\right)\right]}{\left\{p\left(c_{i,t}\right)\left[1+taxOrSubsidy(t,FCV)\right]\right\}^{|\varepsilon_{own}|}} \tag{12}$$

$$\text{with } \Delta c = \frac{1}{n_j}\sum_{j=1}^{n_j}\left|z_{i,j,t} - \sum_{i=1}^{n_i} z_{i,j,t-1} \cdot s\left(c_{i,FCV,t-1}\right)\right|$$

where Δc is the sum of the differences between the features of the producer's car model and the weighted average features on the market. The social need and the refuelling effect are estimated using the accessible information. Producers know the driving patterns of their customers from maintenance records and use its average value to estimate the refuelling effect. As regards the social need, this is estimated using the total number of existing FCVs and the total number of vehicles owned by the consumers, thus obtaining an "average density" of FCVs in the neighbourhood of every consumer. This approach is a little bit different from the one used in (M. Schwoon, 2006), where the estimation is made assuming that the share of FCVs sold in the previous period can also be found in the individual customer's neighbourhood. This approach is somewhat unrealistic since, on average, a new car is bought in a specific neighbour only once every 10 quarters and thus the share of FCVs in the specific neighbourhood will always be lagging the share of FCVs in the newly registered cars. The result would be that producers always overestimate the share of FCVs in the average neighbourhood and might erroneously decide to switch when this is not yet convenient for them.

Knowing the competitiveness of its own product, the producer can use it to determine how its market share will change in the current tick compared to the last one. To do this it has to compare this value with the average competitiveness of all producers, to determine whether it is below or above average.

The average competitiveness is referred to the cars sold in the previous tick and is computed as follows

$$\bar{\vartheta}_{i,t} = \sum_{i=1}^{n_i} \vartheta(c_{i,t}) s\left(c_{i,t}\right) \tag{13}$$

Since the current producer has no access to the driving pattern of the other producers' customers, the estimation of the refuelling effect is done using the average driving pattern of own customers. This means that the estimated average competitiveness will be different for each one of the producers.

Assuming that the change in average competitiveness of this period will be equivalent to the one observed in the last tick we have

$$\frac{\bar{\vartheta}_{i,t}}{\bar{\vartheta}_{i,t-1}} = \frac{\bar{\vartheta}_{i,t-1}}{\bar{\vartheta}_{i,t-2}} \xrightarrow{yields} \bar{\vartheta}_{i,t} = \frac{\bar{\vartheta}_{i,t-1}^{2}}{\vartheta_{i,t-2}} \tag{14}$$

The estimated average competitiveness depends on the decision of the current producer and is computed as

$$\bar{\vartheta}_{i,t}^{e}(c_{i,t}) = \frac{\bar{\vartheta}_{i,t-1}^{2}}{\vartheta_{i,t-2}} \left[1 - s\left(c_{i,t-1}\right)\right] + \vartheta^{e}\left(c_{i,t}\right) s\left(c_{i,t-1}\right) \tag{15}$$

Finally the new market share can be estimated comparing own competitiveness with the average competitiveness.

$$s^{e}\left(c_{i,t}\right) = s(c_{i,t-1}) \frac{\vartheta^{e}\left(c_{i,t}\right)}{\bar{\vartheta}_{i,t}^{e}(c_{i,t})} \tag{16}$$

In order to obtain the expected quantity from the expected market share the total demand needs to be estimated. This is done assuming that the size of the market is constant (no market growth with time) and that the total demand decreases when the weighted after tax average price of cars increases, and extent to which this happens is taken into account by the elasticity of demand of the whole market segment (ε_{seg}).

The average price of cars is weighted by market share and is estimated assuming a constant change in the last two ticks, just like the case of average competitiveness.

$$\bar{p}_{i,t}^{e} = \frac{\bar{p}_{t-1}^{2}}{\bar{p}_{t-2}}\left[1 - s\left(c_{i,t-1}\right)\right] + p\left(c_{i,t}\right)\left[1 + taxOrSubsidy(FCV, t)\right]s\left(c_{i,t-1}\right) \tag{17}$$

and then the total demand is estimated

$$Q_{i,t}^{e} = \frac{M_0}{\bar{p}_{i,t}^{e}{}^{|\varepsilon_{seg}|}} \tag{18}$$

where M_0 is the size of the market in monetary terms. Now that the total demand and the estimated market share are available, the expected quantity can be easily computed as

$$q^{e}\left(c_{i,t}\right) = s^{e}\left(c_{i,t}\right)Q_{i,t}^{e} \tag{19}$$

It should be noted that producers with a higher market share can better predict the number of sales in the certain period due to their higher impact on the average price and average competitiveness.

In last step of the production decision process the producer verifies whether it has enough capital to produce an amount of cars equal to the expected quantity. The required amount of capital is given by

$$K_{i,t}^{r} = \frac{q^{e}(c_{i,t})}{A} \tag{20}$$

where A is the productivity of capital, that is to say the number of products that is possible to produce with a unit of physical capital. When a producer switches to FCVs the productivity of capital decreases by 25%, so that the number of cars that is possible to producer after the switch without a capital expansion also decreases by 25%. If the required capital is higher than the available capital the producer can access the capital market and expand the production capacity through investments, which are limited to 30% of the currently available capital. If the capital is still not enough after the investment the expected quantity will be limited to the maximum amount of cars that it is possible to produce with the current capital plus investment, thus

$$q^{e}\left(c_{i,t}\right) = A \cdot K_{i,t} \tag{21}$$

For a more detailed description of the adjustment of capital stock refer to (M. Schwoon, 2006).

A visual representation of the objective function is given in Fig. 8 for producers with different market shares in the previous quarter. In the left part of the plot the value of the objective function increases with increasing price due to increasing expected income, while in the right part it decreases as a result of decreasing expected quantity. With the optimization process the producer chooses the price to which the maximum value of the function is associated, that is higher for producers with a higher market share, since income has for them a higher weight in the objective function. The value of the function is also higher for higher market share because the expected quantity is higher in this case.

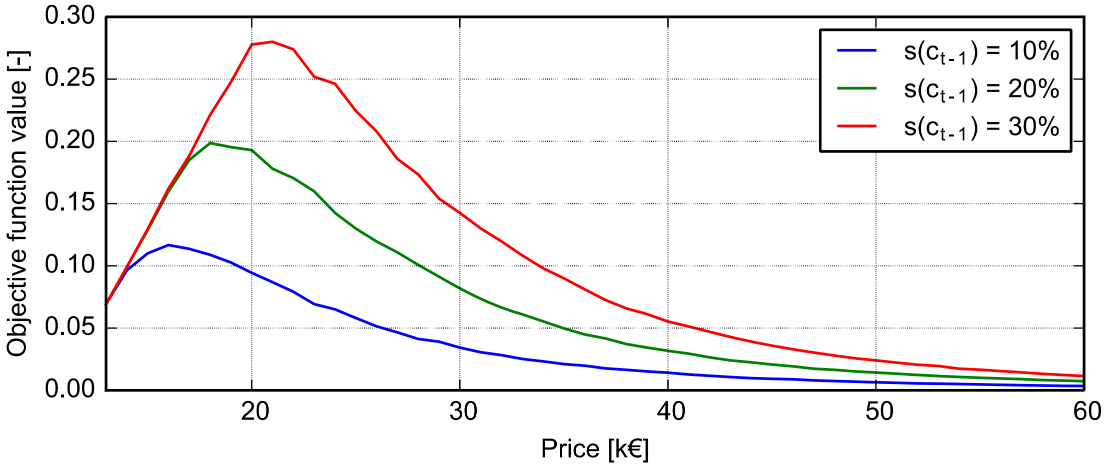

Fig. 8: Objective function value with varying price

3.3.3 Research and Development

After the selected consumers have bought a car the producers try to improve their product so that its features will be more appealing to potential customers in the next quarter. They cannot observe consumer preferences directly, but the characteristics of the cars sold in this quarter are readily available and with these the features of the “average car”. Because producers are aware of the mere exposure effect, with which preferences shift towards the average car, they will try to change the features of their car models so that they get closer to those of the average car. Since not all the features can be improved at once, producers focus on the farthest and closest to the average car respectively, as to both maintain its advantages and reduce its major shortcomings.

It is rather difficult to determine the success of the research and development process, but it stands to reason that the probability of improving the design of the product should increases if the producer invests more money in these activities. The R&D expenditures of one producers at time t are a fixed fraction of the capital

$$R_{i,t} = \varphi K_{i,t} \tag{22}$$

where φ is set to 0,12%. The improvement of the two features on which research and development focus is computed as

$$z_{i,t+1} = \left[1 - G\left(R_{i,t}\right)\right] z_{i,t} + G\left(R_{i,t}\right) \sum_{i=1}^{n_i} z_{i,j,t} \cdot s\left(c_{i,t}\right)$$

$$\text{with } G\left(R_{i,t}\right) = 1 - \frac{1}{\left(1+\sigma_1 Z \cdot R_{i,t}\right)^{\sigma_2}} \tag{23}$$

where σ_1 and σ_2 are non-negative parameters and Z is a random value drawn from a uniform distribution between 0 and 1. As it can be seen from the formula, the likelihood of improving a specific feature increases when the R&D expenditures increase.

3.4 Match of supply and demand

After all the producers have made their decision about price and production quantity total demand is estimated with the formulas

$$Q = \frac{M_0}{\bar{p}_t^{\,|\varepsilon_{seg}|}}$$

$$\text{with } \bar{p}_t = \sum_{i=1}^{n_i} p\left(c_{i,t}\right) \left[1 + taxOrSubsidy(FCV, t)\right] s\left(c_{i,t-1}\right) \tag{24}$$

where $\bar{p}_t$ is an average of the after tax price across all producers weighted by market share in the previous tick. It is assumed that the total demand varies based on the average price and Q represents the number of consumer willing to buy a car at this price level. A number of consumers corresponding to Q is randomly drawn from the population and each one of them pre-orders a car based on total expected utility and availability. The production of cars happens only after the consumer order, so that producers that overestimate sales will not lose variable costs but have the only disadvantage of a production capacity that is higher than needed. On the other hand they cannot increase the production capacity if the demand is higher than expected, thus implying an opportunity cost. In case the car with the highest total expected utility for a given consumer is not available anymore, it tries to buy the second-best car, and may end up buying the least preferred car if this is the only one left. This behaviour is rather unrealistic, but the alternative would be a stock of unsold cars for every producer that needs to be sold in the next tick: these cars would have features that are almost identical to the ones of the new car and would have to be sold at a different price. This simple approach is chosen to avoid a substantial increase in the complexity of the model.

3.5 Hydrogen refuelling infrastructure

Three different infrastructure scenarios are considered in the model: no exogenous infrastructure, exogenous infrastructure and high exogenous infrastructure. In the case of no exogenous infrastructure, there is no planned growth and the share of hydrogen filling stations (HFSs) increases only in response to an increase in the share of FCVs in the quarterly sales in the whole car market. In the case of exogenous growth, a fixed amount of HFSs is added every quarter, with a fixed 0.15% and 0.3% growth of the share for the cases of exogenous growth and high exogenous growth respectively.

In order to limit the complexity of the model filling stations are not represent as agents, but a general behaviour of the whole infrastructure is assumed. Although no differential equations are used, this is a top-down approach conceptually similar to system dynamics. For all three scenarios, the feedback of the hydrogen infrastructure can be described as follows:

- if the share of FCVs in the cars sold in one period is higher than the share HFSs, the infrastructure grows by the highest amount technologically feasible ($g_{H_2}^{max}$), equal to 1.5%
- if the share of FCVs in the total market is higher than 20%, the infrastructure grows as fast as possible until full coverage is reached
- otherwise the new share of HFSs is given by the formula

$$s_{H_2,t+1} = s_{H_2,t} + \min\left[g_{H_2}^{max}, \nu\left(s_{FCV,t}^{max} - s_{FCV,t-1}^{max}\right) + g_{H_2}^{exog}\right] \qquad (25)$$

where $s_{FCV,t}^{max}$ is the maximum share of FCVs in the car sold up to tick t, $s_{FCV,t-1}^{max}$ the one up to the tick before, ν represents the impact of the growth of the share of FCVs on the infrastructure and $g_{H_2}^{exog}$ the extent of exogenous growth. This means that the growth of the infrastructure will accelerate if the FCV share reaches a new maximum. ν is set to be 1.5 in the central case, as to give an increase in the share of HFSs 50% higher than the increase in the share of FCVs that causes it. It should be noted that the share of FCVs considered for the development of the hydrogen infrastructure is the one in the whole car market: since the considered market segment represent roughly 25% of it, the share used here is obtained by multiplying the share of sold FCVs in the segment by 0.25.

4 Implementation of the model

In this chapter a description is given about how the model described in chapter 3 was converted into the software that will be used for the parametric studies discussed in chapter 5. This chapter is divided into two parts: in the first part the choice of the modelling environment and the structure of the software implementation will be presented; in the second part the model verification process will be described in detail. The approach used for model verification loosely follows the one suggested in (Dam et al., 2013).

4.1 Software implementation

4.1.1 Choice of the modelling environment

The modelling environment is a suite that contains several tools that can help the modeller during the development process and also during data analysis. As regards ABM, several options are available and most of them are reviewed in (Nikolai & Madey, 2009). In the choice of the environment for the model focus has been laid on the three options that are briefly described below.

NetLogo. NetLogo is an open source agent-based modelling platform that first appeared in 1999, whose ease of use made it one of the most popular tool in teaching this modelling approach. It is mainly designed for models with agents that move in space and interact with other agents on a local level and its language is based on Logo, a very simple programming language specifically designed as a tool for learning. An active online community combined with a large number of available example models make it the best tool to approach the topic of ABM for the first time. However, due to the simplicity of NetLogo's language, it would be quite difficult to develop such a complex model as the one presented in this paper on this platform.

MESA. Mesa is an open source framework for ABM created in 2014 to overcome the absence of such a tool in the Python programming language. It allows users to quickly create agent-based models using built-in core components, visualise them using a browser-based interface and analyse their results using Python's data analysis tools (Masad & Kazil, 2015). Although this tool would allow to run the model and analyse the output data in the same program, which is not possible in other modelling environments, its use is, at the time of writing, is still challenging due to absence of proper documentation and example models, especially for people who are not yet familiar with ABM.

Repast Simphony. Repast (Recursive Porous Agent Simulation Toolkit) is a family of open source tools for ABM that has been under development for over 15 years and Repast Simphony is a Java-based modelling system and part of this family. This tool is rich in documentation, user guides and example models, making it very easy for beginners to approach ABM. On top of that, Repast Simphony includes a simplified version called ReLogo, meant to be a starting point for modellers new to Repast. At the same time Repast Simphony offers all the tools needed to develop highly customised and complex models that can easily be adapted to be run on small computer clusters. Another C++-based version for large clusters and supercomputers is also available.

Due to its wide range of uses from very simple models to highly complex and customised ones Repast Simphony has been chosen as a modelling environment for this project. Since output data cannot be analysed inside Repast, an iPython notebook is used in the data analysis part.

4.1.2 Structure of the software implementation

A class-based object-oriented programming approach has been used to implement the model and the code is therefore divided into classes. An object in the model is meant to represent a corresponding object in reality and is described by certain variables (that represent states) and functions (that represent behaviours). A class is a prototype for one type of object: an object created from a class will have all the variables and behaviours defined in that class and is called an instance of that class. For example, a class called Cat contains all the variables needed to represent a real cat (age, colour) and its behaviours (playing, running). From the class Cat a specific object, Fluffy, can be created and this will contain a specific value of each one of the variables (e.g. age: 5 years, colour: black) and will be able to perform all the behaviours described in the Cat class.

The model is divided into 9 different classes of objects, for each of which a brief description is given below.

Car model. This class represents the model of the cars a producer sells during one tick. It can be thought of as a list of all the features with which cars are built and also contains information that result from the production decision process, like price and maximum number of cars of this model that a producer can manufacture and sell in one tick.

Car. A car object represents a real car owned by a consumer, which has been manufactured and sold by a producer. Each car is produced based on the car model a producer manufactures during one specific tick.

Consumer. A Consumer represents a car owner that owns an object of the Car type and has a defined position on the grid that represents the social network. Each consumer has specific preferences about the features a car should have and a specific value for the driving pattern and the importance of own preferences compared to the effect of neighbours' decision. Due to the mere exposure effect preferences slowly vary from one tick to the next. When selected to do so the consumer buys a new car that replaces the old one it already owns.

Producer. A Producer represents a car manufacturer and owns a car model that it improves at the end of each tick. Every time the producer makes its production decision a new car model with updated features is created to replace the old one. Since producers improve their car models doing research and development, the cars sold by the same producers in two different ticks are always slightly different. Each producer has a list of customers, that are consumers that bought a car from them in the previous tick.

Infrastructure. Only one infrastructure object is created from this class and this represents the system of hydrogen filling stations (HFSs). This object contains the share of hydrogen refuelling stations and the method that updates it at every tick.

Government. Only one government object is created and this contains the method that calculates the tax or subsidy for a given tick.

ModelContext. The model context contains the whole model run and is divided into two main function: setup and step. The setup function contains the initialization of the model, that is to say everything that happens before the model starts running. The step function defines all the events that happen during a tick.

MyContextBuilder. Due to the way data collection works in Repast Simphony, in order to collect data from the agents they have to be added to a collection of objects called context, and this can only be done inside the class MyContextBuilder. For this reason producers and consumers are created here and then passed to the ModelContext. In this class a grid is also created, to which all consumers are added. It is also in this class that all the parameters that define a specific scenario that is being analysed are retrieved.

To make the access to a specific agent or object as easy as possible these are grouped in lists: each agent has a specific id that corresponds to its position in the list of all the agents of the same type, so that it can be unequivocally identified. For example, when consumers have to choose a new car they get a list of all of the car models available on the market and for each one of them calculate the total expected utility. Each car model includes the id of the corresponding producer, so that consumers can search it on the producer list, check whether cars with this model are still available and eventually buy one.

The structure of the model is actually more complex and more realistic than it would be needed for the current version. The motivation for this is that it was developed with future additions in mind, that would be significantly easier to apply with the current structure. As an example, it would be possible to allow producers to manufacture both FCVs and ICEVs at the same time, thus selling two different car models. Thanks to the current structure these car models would simply be added to the corresponding list and bought by consumers without the need of any other changes.

4.2 Model verification

Once the implementation phase is complete a verification is needed of whether the model has been implemented correctly, that is to say whether the conceptual model has been properly translated into the model code. This process, called verification, can be very onerous for agent-based models: having some 2500 lines of code, a large number of agents and an even larger number of possible interactions between them it is not obvious to spot errors in the code or to imagine what effects these errors could have. This is particularly important considering that the main results of the model consist in emergent behaviour and observing it the modeller wants to be sure it originates from real system characteristics rather than from programming artefacts.

Model verification has been performed using the following four methods:

- Tracking agent behaviour with a debugger
- Single-agent testing
- Analysis of production decision
- Lowering the number of dynamics

These methods will be described in detail in the following subsections.

4.2.1 Tracking agent behaviour with a debugger

In order to verify agent behaviour relevant variables can be directly analysed: these variables could be the ones that also represent the agent's input and outputs, but also internal states that are not directly visible in the model outcome. This could be done by recording these variables and analysing them separately or inside the developing environment with the help of a debugger: the latter option was chosen for the purpose. A debugger allows to set break points in the code at which the simulation stops, allowing the modeller to analyse all the agent variables. In this way, it can be made sure that states are modified correctly and that results the modeller expects from simple decisions actually correspond with the observed ones. This verification process is particularly suitable for agents who do not possess a very complex structure or methods and has thus been extensively used to verify the behaviour of consumers. As an example, this technique made it possible to find out that the social need in the evaluation of the total expected utility was not calculated correctly due to the way Java handles the division of integers and it was always either 0 or 1. Finding this error was only possible using the debugger and would have been very difficult otherwise.

4.2.2 Single-agent testing

Single-agent testing allows the modeller to check whether a specific agent behaviour is observed when a particular input is given and to do this in a repeatable manner. This is usually done using a technique called unit testing, that consists in reconstructing the environment in which the agent makes a certain decision and set the input variables so that, in case of a correct construction of the agent, it will behave in the desired way. At the end of the test the actual decision result is compared with the expected one and a positive or negative output of the test is given accordingly. A negative result would mean that either the behaviour prediction is wrong or a part of the agent behaviour is wrong. One advantage of using unit testing is that, once implemented, a test can be run again after changes are made to the code, to verify that agents still pass the test: this works as long as the changes in the code are not too radical (e.g. changes in the type or number of input parameters), in which case the test itself has to be modified. This type of test was implemented to make sure that producers would switch to FCVs when this was by far the best decision. This was done by applying a 40% tax on ICEVs and at the same time removing all the disadvantages that FCVs have in the model compared to ICEVs, like higher variable costs, lower capital productivity and so on. In this case, if the implementation of the agent is correct, the producer will always decide to switch to FCVs, since the only difference between the two technologies is the tax. A positive result of this test made sure that the switching behaviour was functioning properly.

4.2.3 Analysis of production decision

Since unit tests can easily be run with multiple parameter combinations, they can also be used to study the way the output changes when the input varies. This was extensively used in studying the producers' production decision process and found to be a very effective way to both spot anomalies in the code and to get a deeper understanding on how the price decision changes based on the input. The analysis of the test output data was performed using an iPython notebook, because it allows to show explanatory text, code used in data analysis and plots on the same page. In the following, three tests on production decisions are shown in order to illustrate the testing approach as well as to show how the dynamics of the model work.

In all three tests the production decision of one producer is tested, while 2 other producers with equal market share exist in the environment. Just like in the model initialization consumers are assigned to the 3 producers based on the initial market share. All the other variables are set as to reproduce a realistic environment that could be found in the model if the testing assumptions are met. All the results are averaged across 100 runs.

Test 1. How does the production decision output change based on the available capital of a producer?

This question is first answered for a producer that is producing ICEVs and has to set a price for its car in the current quarter and calculate the expected quantity of cars it will sell for that price. Because there is no tax or subsidy in this scenario, the producer always sticks with the current drivetrain technology. The aim of this test is to learn how available capital affects the results of the optimization process and to check whether the output is in line with what the modeller expects. In this test and the following ones the term "expected demand" refers to the amount of cars that a producers could theoretically sell based on its market share in the previous quarter and the competitiveness of its car model, whereas the term "expected quantity" indicates the fraction of expected demand that the producer can actually produce and sell considering capital limitations.

In Fig. 9 it is possible to notice that the expected quantity increases with available capital: this shows that, in the left part of the chart, the tested producer could potentially sell more cars but it does not have enough capital to produce them. The amount of cars that it is possible to produce increases with available capital until expected quantity reaches a plateau at about 650,000 €: this happens because the needed capital to cover the expected demand is either entirely available or obtainable through investments. When the plateau is reached, the producer could, in terms of capital, produce more cars, but it would not be able to sell all of them: the expected quantity is here limited by expected demand. Al the graphs relative to varying available capital are characterised by a stepwise variation, since the expected quantity can only have an integer value.

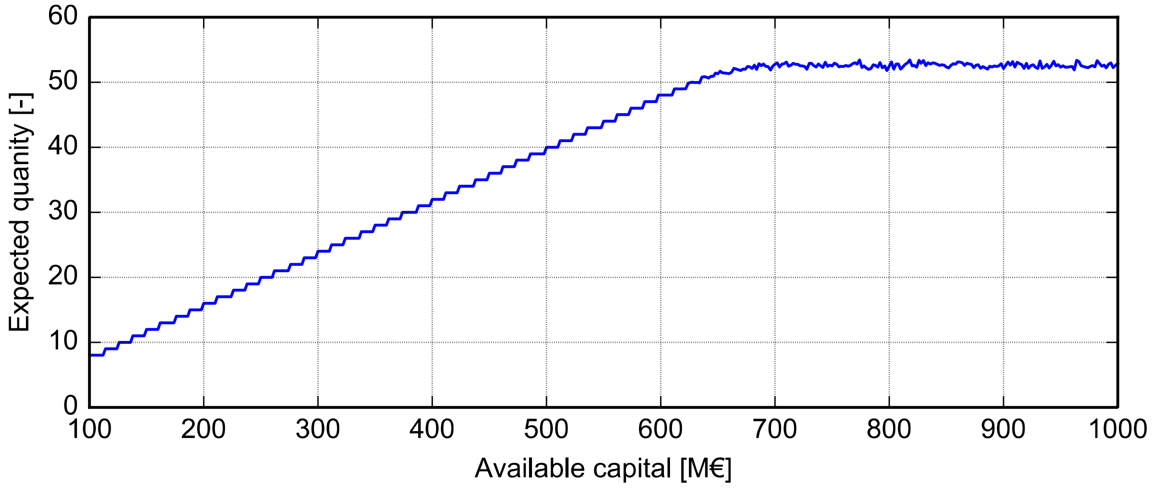

Fig. 9: Expected quantity for varying available capital

One way the tested producer has to increase the expected demand is to lower the price, since there is an inverse proportionality between the two quantities. Fig. 10 shows that the producer chooses a high price when the capital is limited, since expected quantity cannot increase anyway due to capital limitations.

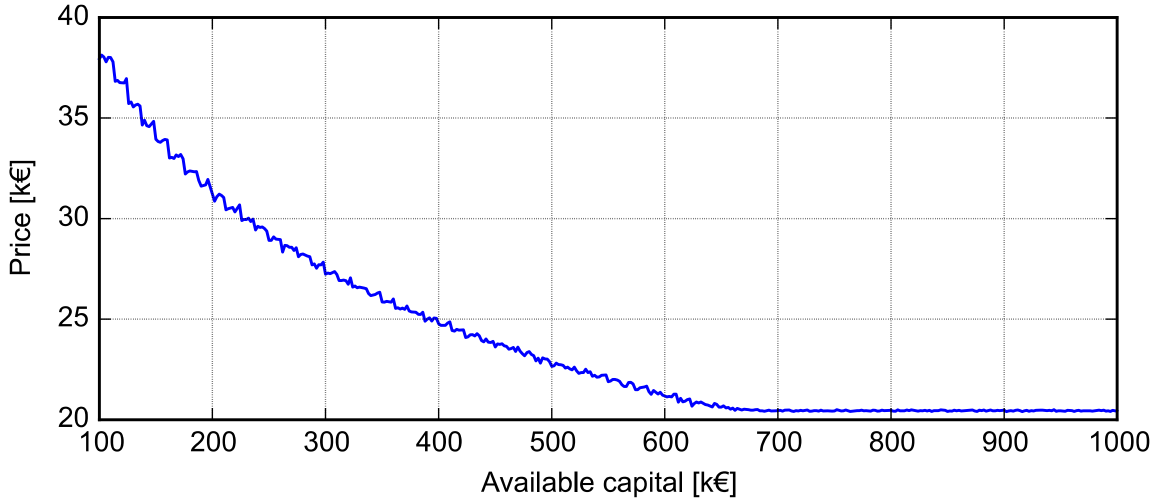

Fig. 10: Chosen price for varying available capital

As the expected quantity grows due to growing available capital the price is lowered to increase expected demand. In Fig. 11 it is possible to see how the combined effects of increasing expected quantity and decreasing price bring to an overall increase of the expected income. It is also interesting to notice that the plateau is here reached for a lower available capital compared to the previous two graphs: this can be explained considering that the objective function value increases not only based on expected income but also based on market share. When the maximum value of expected income has been reached the value of the objective function can still be increased by increasing the expected market share and this is done by lowering the price even further, but in such a way as not to affect expected income.

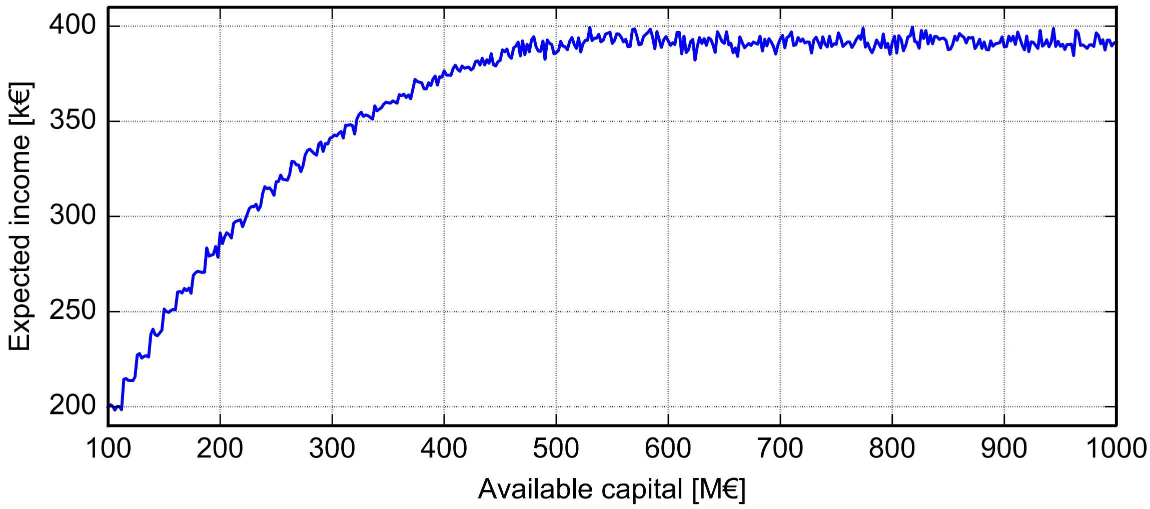

Fig. 11: Expected income for varying available capital

Fig. 12 shows how the investment increases as a consequence of the increased expected quantity and of the higher accessibility to the capital market made possible by higher available capital: up to 6,5 M€ and besides minor oscillations the producer always borrows as much money as possible from the bank to adjust the capital stock, so that it can produce as many cars as possible.

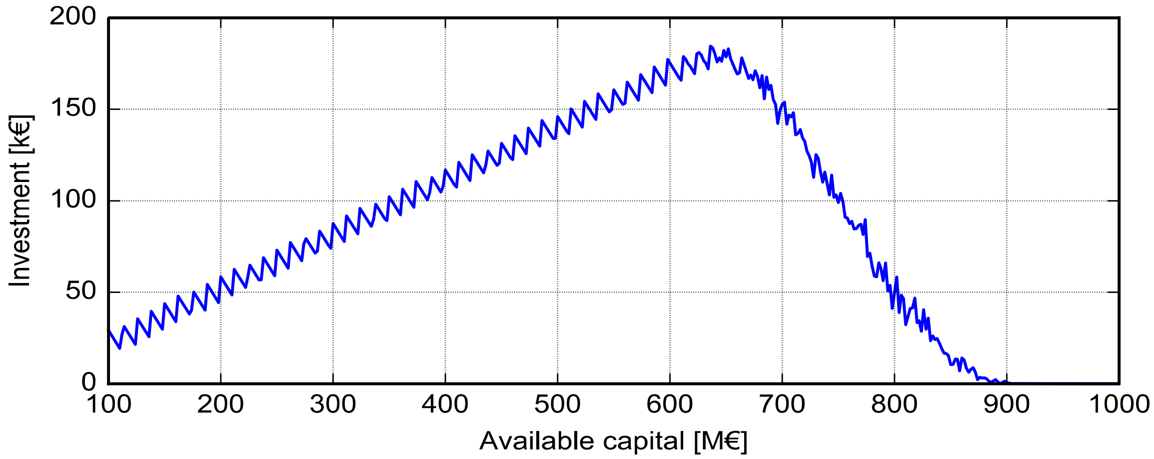

Fig. 12: Needed investment for varying available capital

When the maximum demand is reached, the investment starts decreasing, because the gap between needed capital and available capital shrinks.

After having analysed the case without tax, the question of test 1 is answered for two scenarios with a tax on ICEVs of 35% and 45% of the producer price respectively. Studying these scenarios is meant to illustrate how the decision to switch to FCVs is affected by the tax and by available capital.

Fig. 13 shows with which probability the tested producer decides to switch to FCVs in the two tax scenarios. First of all it is evident that the producer switches only if it has enough capital and the minimum amount of capital required for the switch depends on the tax: a higher tax implies a lower threshold, since it makes the choice of sticking to ICEVs less convenient. The graph also shows a high variability of the output in the neighbourhood of the lower threshold, indicating a high sensitivity of the drivetrain choice with respect to available capital around this value.

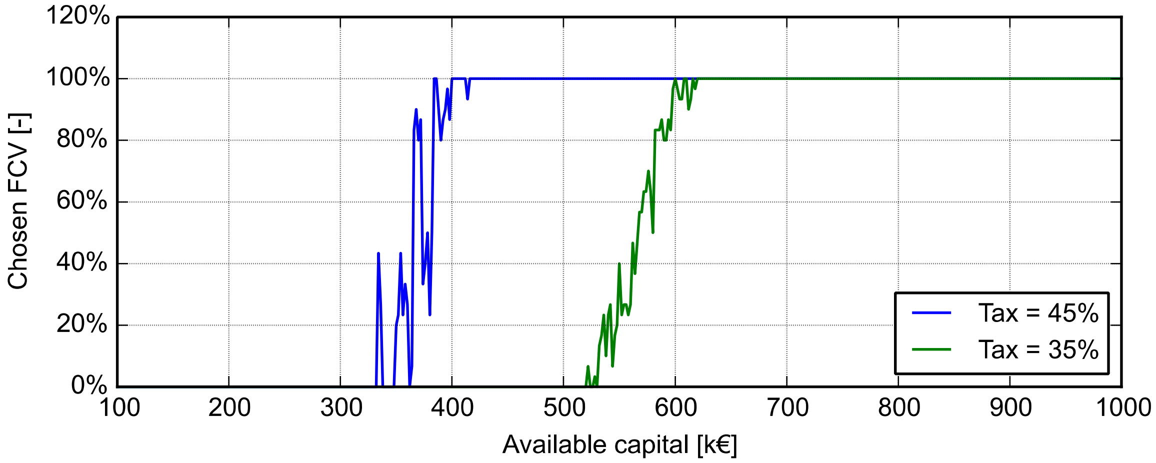

Fig. 13: Chose drivetrain with varying available capital and tax on ICEVs

As it is possible to see in Fig. 14 the price chosen by the producer increases when it decides to switch, since a FCV without a tax is more competitive than a taxed ICEV and

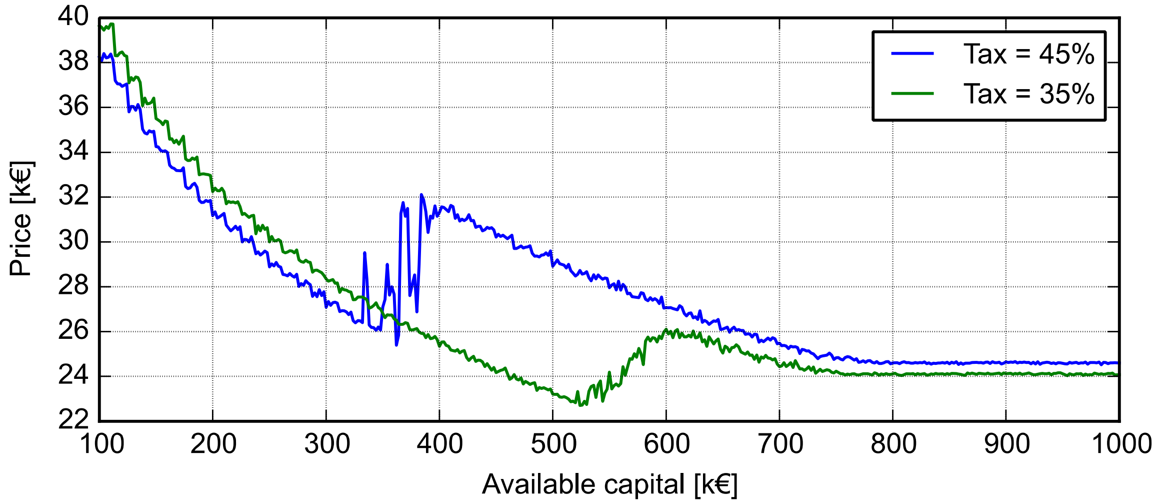

Fig. 14: Chosen price for varying available capital with tax

how it is possible to see in Fig. 15 switching causes a drop in the expected quantity. This can be explained considering that switching to FCVs comes with a 25% reduction in capital productivity that corresponds to an equal reduction in expected quantity since the producers is already borrowing as much money as possible from the bank.

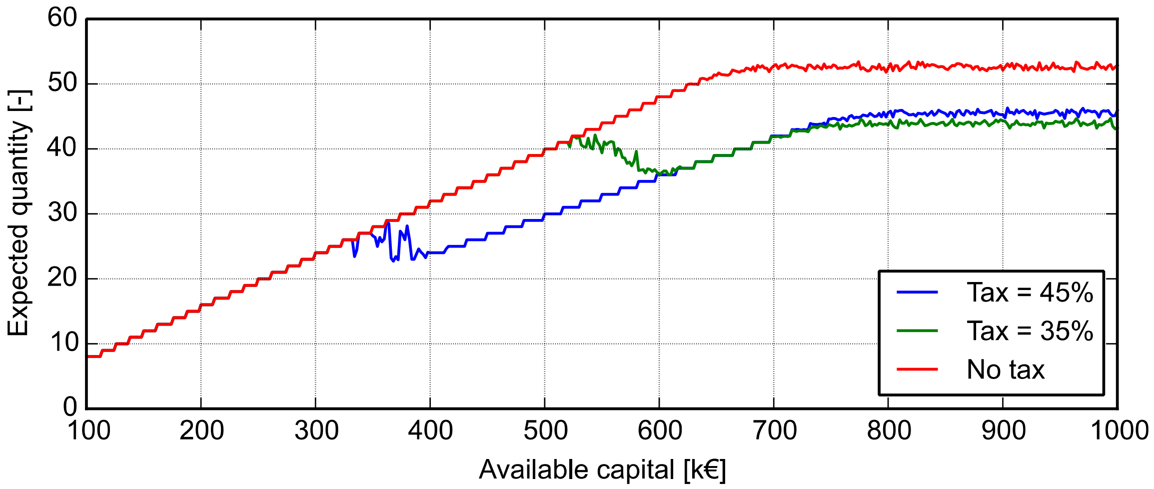

Fig. 15: Expected quantity for varying available capital with tax

Test 2. How does the tax and the share of hydrogen filling stations (HFSs) affect the product decision of a ICEV producer?

To answer this question a setting is used in which the 2 other producers are already selling FCVs while the current producer has not switched yet. Since the other producers have the advantage of selling tax-free vehicles, their price from the previous quarter is set to be higher than that of the tested producer. To simultaneously analyse the effect of the tax and the share of HFSs the tax is let vary between 0% and 100%, while the share of HFSs is set to 3% and 30% HFS respectively.

Fig. 16 shows how the producer decides to switch to FCVs only if the tax value is above a certain threshold and that this threshold is higher in the case in which only 3% of the filling stations sell hydrogen. A higher amount of HFSs gives a refuelling effect that is closer to 1, thus reducing the disadvantages of FCVs and making producers switch for a lower tax.

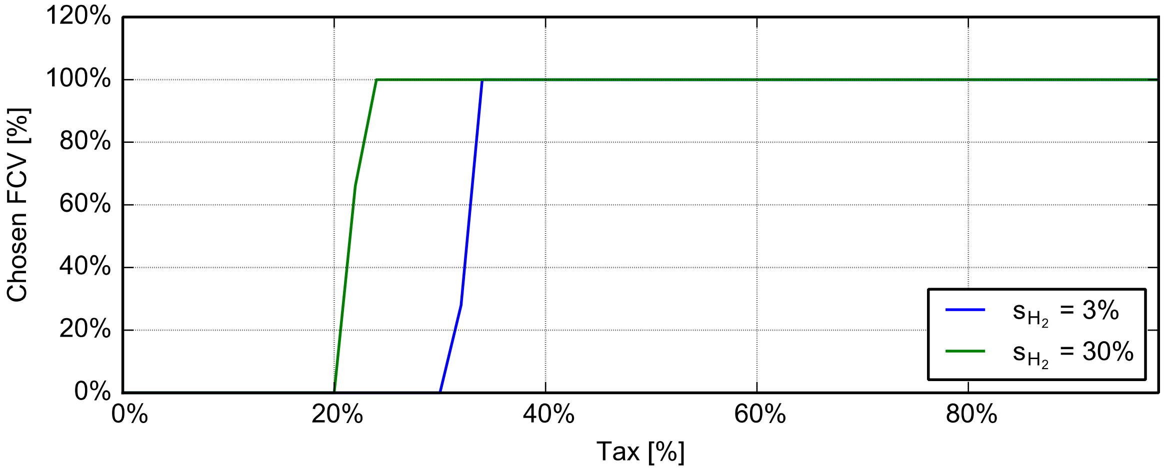

Fig. 16: Chosen drivetrain technology for varying tax on ICEVs

In the price chart in Fig. 17 two different zones can be observed: one before the switch and one after. Before the switch ICEVs are being produced and the chosen price decreases with increasing tax to compensate the raise in after-tax price: here the chosen value is lower in the case of HFS 30% due to a higher refuelling effect of the competing producers. After the switch the situation is inverted and the price increases with the tax because the tested producer starts selling FCVs and what used to be a disadvantage becomes an advantage.

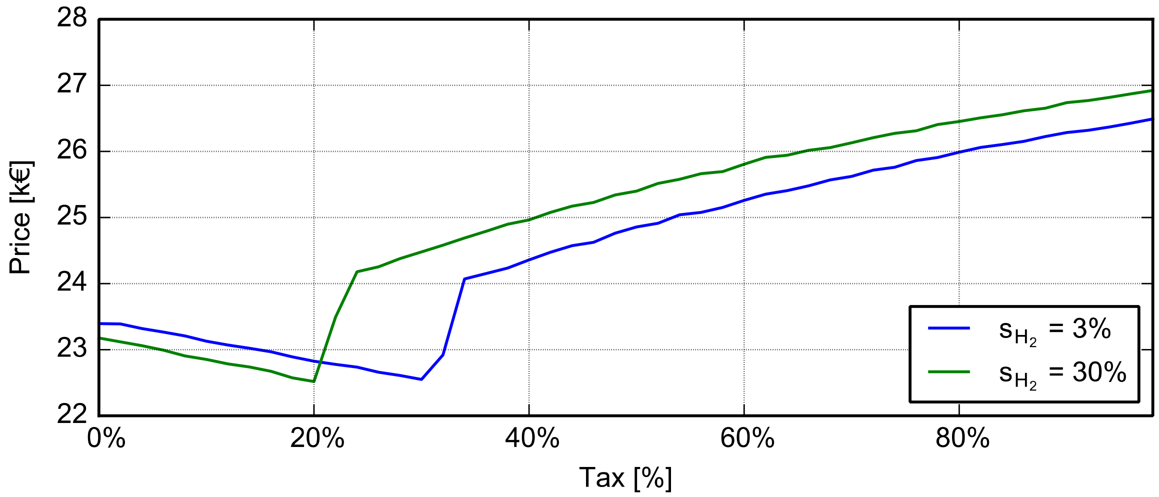

Fig. 17: Chosen price for varying tax on ICEVs

A similar inversion can be observed for the expected quantity in Fig. 18. From this two graphs it can be inferred that a tax that is not high enough has a particularly bad effect on producers that are not able to switch: they are forced to lower the price of their car model and will sell less car than they would in the case without a tax, causing a significant drop in expected income.

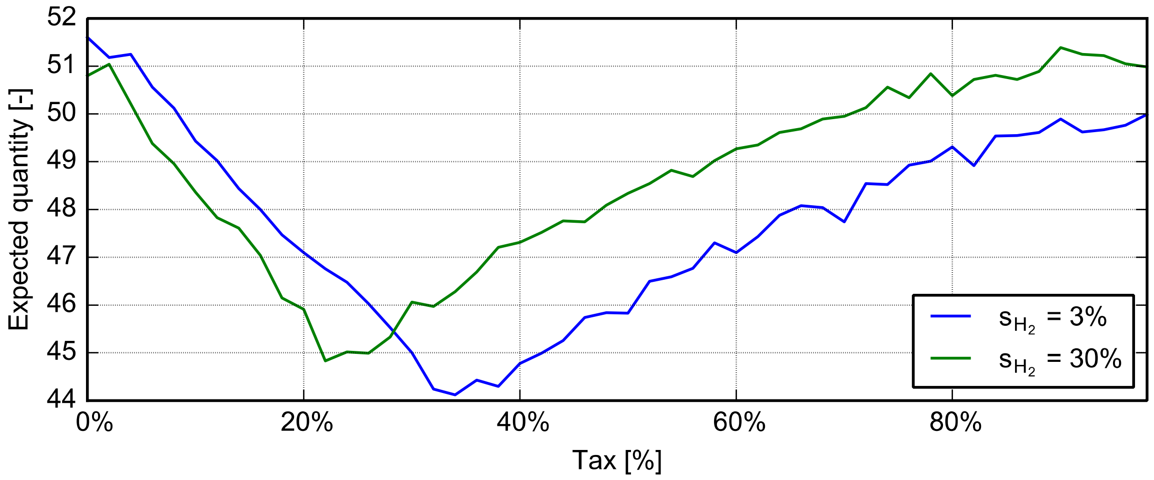

Fig. 18: Expected quantity for varying tax on ICEVs

Test 3. How does the production decision result change based on the existing share of FCVs among consumers?

As indicated by formula (6) the share of existing FCVs is used by producers to estimate the share of FCVs in the individual customer neighbourhood and therefore to evaluate the social need of a FCV for consumers. A higher social need of a FCV corresponds to a higher total expected utility for this drivetrain technology and thus a higher probability of purchase. The environment settings for this test are the same as test 2, with the difference that here two tax scenarios with 20% and 30% tax on ICEVs respectively are considered. Fig. 19 shows that the choice of drivetrain technology is as expected more likely the higher is the share of existing FCVs and the higher is the tax on ICEVs.

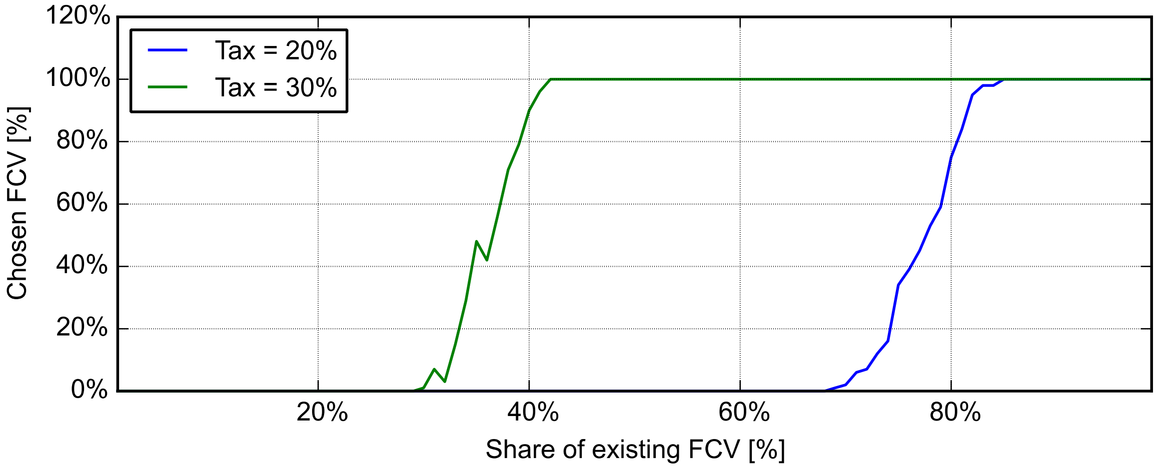

Fig. 19: Chose drivetrain with varying share of existing FCVs

As in the other tests Fig. 20 shows an increase in price when the producer switches to FCVs and yet the difference between the price before and after the switch is a lot larger in magnitude compared to the cases presented before.

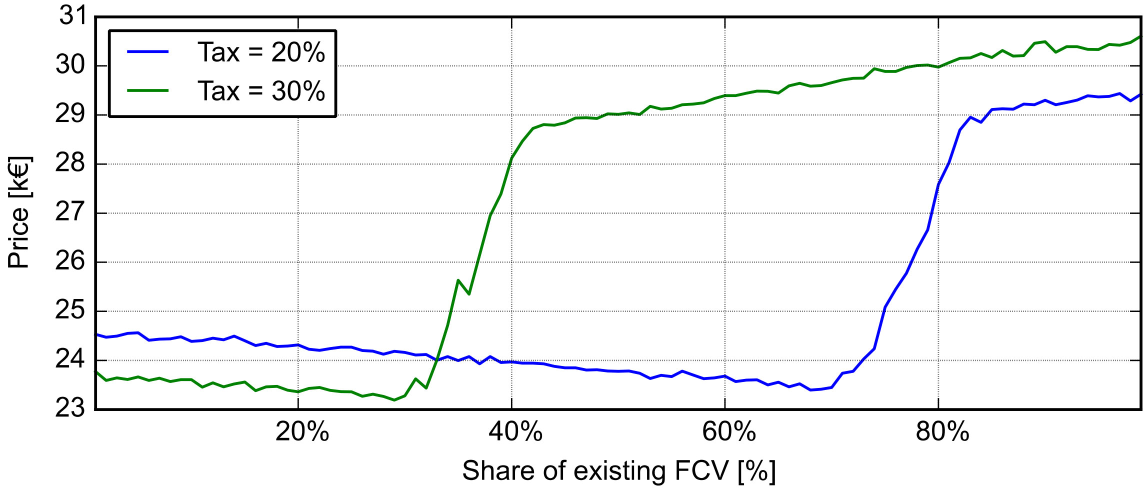

Fig. 20: Chose price with varying share of existing FCVs

This large difference is due to the fact that while the share of existing FCVs increases the social need of FCVs it also decreases the social need of ICEVs, thus giving a large advantage to producers that switch. This effect of decreasing social need for ICEVs is very clear before the switch in the case of 20% tax, where the chose price noticeably drops for growing share of FCVs. However, as will be shown in the next chapter, the effect of decreasing social need for ICEVs only plays a minor role in the final results, because the share of FCVs in the existing cars never exceeds 40%.

4.2.4 Reducing the number of dynamics

Another method that was extensively used during the verification process is reducing the number of dynamics in the model in order to make problem identification easier. While the above-mentioned techniques only apply to the agent level, the current one has been employed for verification of the model as a whole. This approach consists in initially reducing the amount of “moving parts” in the model to the bare minimum, that is to say enough so that the model can run, and then, once at a time, reactivate all the dynamics while checking the model output for anomalies.

In the specific case of this model all the mechanisms that create a difference between a producer choosing FCVs over ICEVs are intended as dynamics, and they are:

- Lower infrastructure coverage for FCVs
- Lower social need for FCVs
- Higher variables costs for FCVs
- Productivity reduction when switching to FCVs
- A tax on ICEVs or a subsidy for FCVs

If all of these differences are removed all the producers are expected to switch to FCVs for a tax on ICEVs as low as 1%, because switching means avoiding the tax and all the rest stays the same: if this does not happen there might a problem in the code. As an example, when this was first done in the model, it would happen that some of the producers were not switching to FCVs when the tax was introduced. Using the debugger it was then discovered that these producers were assigned such a low market share at the beginning of the simulation that their expected quantity would be zero and their market share would therefore stay zero for the rest of the simulation. A lower limitation of 2% for the initial market share assignment was added to solve the issue. Deactivating all the dynamics helped in identifying where the error was, since it allowed to exclude all the other possible causes. Once this set-up of the model works seamlessly it is possible to add, one at a time, the dynamics that were previously removed and verify each time that the model output is the correct one. Repeating this process until all the dynamics were back and all the errors were corrected has been of great help in implementing the model.

5 Scenario assumptions and input data

In this chapter, the input data and the calibration of the model are described: this part relies on the assumptions made in (M. Schwoon, 2006) and integrates them with more recent data.

5.1.1 Policy scenarios

The model is run for 100 ticks and each one of them is meant to represent one quarter: the chosen policy is introduced at tick number 20, which is assumed to correspond to the first quarter of 2020. Given this assumption, the model covers a period of 25 years, from 2015 to 2040. The first 5 years are there to allow the model to reach a pre-policy equilibrium, that minimises the effect of randomness in the final result. Although a parallel is drawn between time in the model and time in reality, it should be noted that the goal of the model is getting a better understanding of how the dynamics in reality work rather than making predictions. This is why the focus of the model analysis will be comparing different scenarios rather than looking at the numerical results.

Four different types of policy are considered: a tax on ICEVs or a subsidy for FCVs, and both can either be shock or gradual. In the shock case the maximum amount of the tax or subsidy is directly applied in the first quarter of 2020 and stays constant until the end of the simulation. In the gradual case the tax or subsidy starts from the same year and increases by 1% each quarter, until it reaches the maximum value and stays constant until the end. This policy, in addition to a tax or subsidy on the purchase price of the car, is also to be interpreted as the net present value of the differences in the annual car taxes and fuel costs, assuming that hydrogen will be cheaper than gasoline or diesel after taxes. The maximum value is 40% in the tax case and 30% in the subsidy case. Although taxes on car use and car ownership cannot be precisely measured, (Burnham, 2001) shows that they are generally a lot higher than the chosen values in European countries.

5.1.2 Infrastructure scenarios

The four policy scenarios are combined with three different infrastructure scenarios: in the first scenario there is no exogenous growth and the infrastructure develops only in response to an increase in FCVs sales, as indicated by formula (25). At the time of writing there are 22 hydrogen filling stations in Germany that are open to the public (CEP, 2016) out of 14,500 filling stations overall. However H_2 MOBILITY, a joint venture of 6 companies from the car, gas and petroleum industry set the target of increasing the number of hydrogen filling stations to 50 by the end of 2016 and to 400 by the end of 2023, that would correspond to 2,7% of hydrogen coverage with respect to the current number of filling stations. Considering that the number of filling stations in Germany has been falling for the last 45 years (MWV, 2016), the value of 3% has been chosen as the initial value for the simulation. Due to the lack of experience with a big change such as the one needed to add hydrogen to many filling stations a parallel can be drawn with the addition of compressed natural gas (Stromberger, 2003). Germany has seen an average growth of CGN filling stations of 0,10% per quarter in the last 13 years, with 15 new filling stations being added every quarter, even though the market penetration of CNG vehicles was not a success. Other countries where diffusion of CGN vehicles was a success, of which Italy is an example, experience mich average growth rate in the number of CGN filling stations. In light of this, 0,15% is chosen for the the exogenous scenario and this value is doubled for the high exogenous one. In all three scenarios, however, the growth of the refuelling infrastructure is limited to 1,5% per quarter, so that not more than 215 filling stations can be converted in each quarter: this value is meant to represent a technical limit for infrastructure expansion.

5.1.3 Producer parameters

The number of producers in the model is based on the data from the German Federal Motor Transport Authority relative to the year 2014 (Kraftfahrt-Bundesamt, 2014). Each one of the 12 car manufacturers in the German compact car segment with a market share higher than 2% is represented by a producer in the model. As can be seen from Fig. 21 market shares in this segment are not equally distributed and Volkswagen alone covers about 1/3 of the total market.

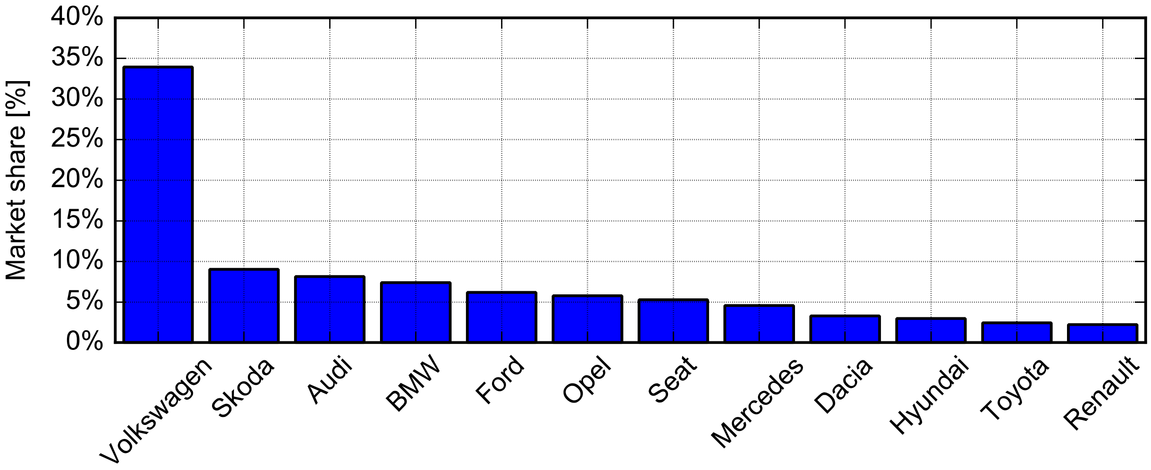

Fig. 21: Market share distribution in the German compact car segment

In order to take the uneven distribution into account, market shares are initially assigned from a normal distribution with mean 100/12 and standard deviation 10%, with a lower bound of 2%. The productivity of capital (A) is set to be 0.0000625, so that the production of 1,000 ICEVs requires a capital of 16 million euros. After market share assignment each producer is given enough capital to cover the initial sales in the market. Variable costs for FCVs are assumed to be 10% higher than those of ICEVs, which are set to 13,000 € per unit. The strong assumption here is that by the year 2020 the FCV variable cost reductions due to learning and scale effects have already been realised so that there is a constant difference between those of ICEVs and FCVs. Although variables cost reduction plays an important role in the diffusion process, this assumption is meant to keep the number of dynamics low in this first version of the model and will be relaxed in future versions. The effect of this parameter will however be analysed in the sensitivity analysis. The rest of the variables that are used by producers follow the calibration of (M. Schwoon, 2006) and are summarised in Table 1.

5.1.4 Consumer parameters

Every consumer represents a German compact car owner: in 2014 the number of registered compact car in Germany was about 11,7 millions (Kraftfahrt-Bundesamt, 2014). Choosing the number of consumer agents in the model two opposites needs should be taken into account: on the one hand the higher the number of consumers the higher the computational power and time required to run the model, on the other hand, having a small number of agents causes problems when representing producers with very low market share, since they might end up with 0 or only 1 customer, making the decision process unrealistic. The trade-off was found at 90,000 consumers, meaning that each consumer agent represents 130 German compact car owners. It should be noted that running a model with such an high number of agents was only made possible by the use of a computer cluster.

One of the most delicate part in calibrating consumer parameters is determining the relative importance of price and refuelling effect, that is affected by own price elasticity (ε_{own}): for high price elasticities the decision would be independent from refuelling infrastructure coverage while for very low values it would be dominated by the refuelling effect. Several studies exist that try to estimate the value of own price elasticities in different car segments for different countries:

- (Grigolon & Verboven, 2014) calculates price elasticities for the compact car segment in Germany between -1.09 and -3.66
- (Schiraldi, 2011) estimates ε_{own} for mid-sized cars to be between – 9.31 and -2.87 in Italy
- (Bordley, 1993) measures values between -2.1 and -4.9 for the US

As it is possible to gather from this estimates confidence intervals for own price elasticity estimation tend to be rather wide, thus implying a high uncertainty. However, the more recent values from the above-mentioned studies are not too dissimilar from those considered for the calibration of the original model: therefore the value -3, also used in the (M. Schwoon, 2006), is chosen for ε_{own}. Two other consumer parameters are needed in order to calculate the refuelling effect: the fuel availability factor (γ) and the driving pattern (DP_k). Using the same method as the original model the distribution of the amount of kilometres German people drive their car in one year is used as a benchmark for their refuelling needs. It is assumed that a consumer that drives its car more than average would have higher refuelling needs than one with a lower driving distance. A survey with a sample of 25,000 household carried out in Germany in 2008 (INFAS, 2009) resulted in a distribution of yearly driving distance shown in Fig. 22. As it is possible to notice from the histogram about two thirds of the surveyed people have a yearly driving distance lower than 20,000 Km and only very few people drive more than 50,000 per year. The driving distance can be thus transformed into a variable between 0 (few short trips) and 1 (many long distant trips) and this is done drawing the value of driving pattern of each consumer from a lognormal distribution with mean -0.85 and standard deviation 0.65, limiting the value of the drawn number to 1.

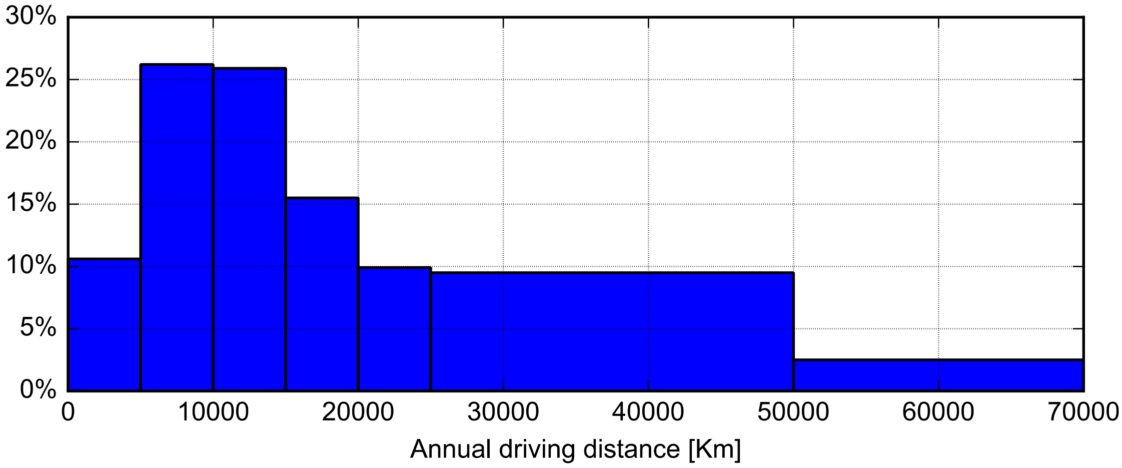

Fig. 22: Distribution of driving distance in Germany for the year 2008

Following (M. Schwoon, 2006) the fuel availability factor is set to -3.

5.1.5 Total demand

Total demand, computed through (24), is determined by two parameters: size of the segment in monetary terms (M_0) and the segment elasticity of demand. (Bordley, 1993) calculates a total market elasticity of -1: since the chosen market segment is rather broad the segment elasticity is set to be equal to that of the total market, thus -1. As regards M_0, this is calibrated in such a way as to have a number of consumers that buy a car each quarter in the base case that scaled up, corresponds to the total sold cars in the German compact car segment. In 2014 compact car sales in Germany added up to 801,441 units: this corresponds to 1540 sold cars per quarter, scaling down to the number of agents in the model. It should be noted that it is necessary to make a choice between having a realistic price or a realistic quantity of sold cars per quarter: if one is set, the other will be determined by the equilibrium of the model. Since having a reasonable scaled amount of car sales is considered more important, the price is set as to get the realistic scaled number of total sold cars in a quarter. In 2014 the average price in the compact car segment was about 25,000€ (ADAC, 2014), yet the equilibrium price reached in the model base case without a tax is about 16,000€. Using the latter value in the determination of the market size a value of about 24.6 M€ per quarter is obtained.

Table 1 Parameter values

Parameter	Description	Central case value	Sensitivity analysis	
General				
n_j	Number of car features	4		
M_0	Market segment size [M€]	2,900		
ϵ_{seg}	Demand elasticity of the segment	-1		
t_{repay}	Average repayment duration on the financial market (quarters)	40		
Producers				
n_i	Number of producers	12		
$c_{v,ICEV}$	ICEV variable costs [€]	13,000		
Δc_v	Difference in variable costs between FCVs and ICEVs	10%	5%	15%
η	Weight function scaling	5	3	7
A	Productivity of capital for ICEVs	0.0000625		
ΔA_{FCV}	Reduction of capital productivity for FCVs	-25%		
r	Interest rate	0.025		
δ	Depreciation rate	0.012		
μ	Share of maximum debts relative to capital	0.3		
φ	Ratio of R&D expenditures relative to capital	0.0012		
σ_1	Parameter 1 for scaling of R&D success	1		
σ_2	Parameter 2 for scaling of R&D success	0.001		
Consumers				
n_k	Number of consumers	90,000		
γ	Fuel availability factor	-3	-2	-4
β_k	Weight of own preference against social need	~Un[0.4,1]	~Un[0.2,1]	~Un[0.6,1]
ζ	Speed of preference convergence	0.99		
ϵ_{own}	Own price elasticity of car	-3	-2.5	-3.5
H_2 Infrastructure				
$s_{H_2,0}$	Initial share of H_2	3%	1%	5%
$g_{H_2}^{exog}$	Exogenous growth of the share of H_2 stations	0	0.15%	0.3%
$g_{H_2}^{exog}$	Maximum growth of the share of H_2 stations	1.5%		
ν	Impact of FCVs penetration on the H_2 infrastructure	1.5		

6 Simulation and results analysis

In this chapter the model is used to investigate the effect that different policies meant to foster the diffusion of FCVs have on producer decisions and on the observed FCVs

penetration rate. The combination of two incentive types, their shock or gradual nature and the different infrastructure scenarios give a total of 12 different combinations that will be analysed here. Due to the random nature of some of the input variables and the random order in which agents interact, each one of the plots in this chapter represents an average across 100 runs.

6.1 Tax scenarios

In the shock tax scenario a 40% tax on ICEVs is applied from the beginning of 2020 and it stays constant until the end of the simulation. In the gradual tax case the tax increases by 1% each quarter, starting from the same year, until it reaches the maximum value of 40%: after that it stays constant until the end of the simulation. The value of the tax across the simulation is shown in Fig. 23.

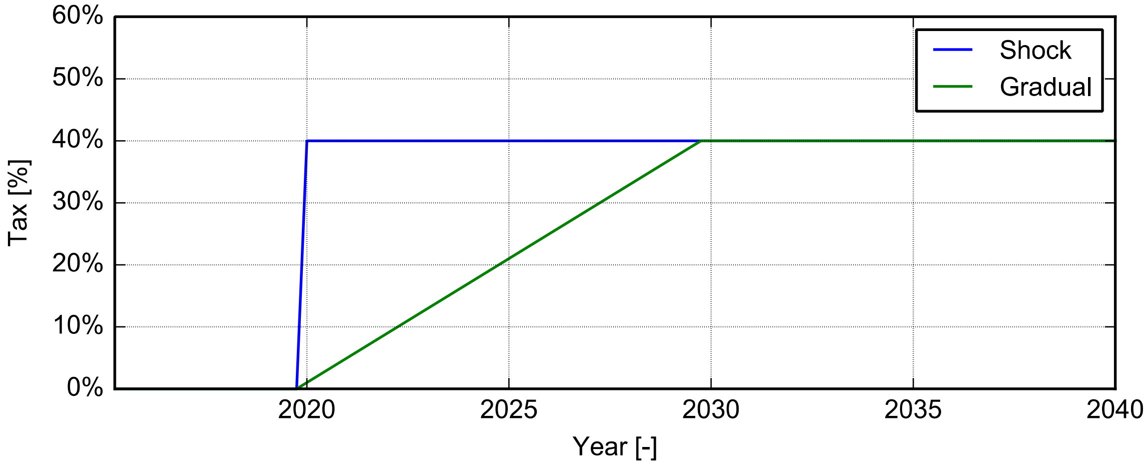

Fig. 23: Evolution of the tax

6.1.1 Effect of the tax on the system as a whole

One of the most important variables in determining the success of the introduction of fuel cell vehicles in the market is their share in the new car sales. Fig. 24 shows this share for the compact car segment in case of a tax. As it can be seen, in all three shock tax scenarios, at least one producer switches to FCVs and manages to find customers when the tax is introduced. Only after a couple of years it is possible to notice a difference in the three infrastructure scenarios: as expected, the presence of an exogenous expansion of the refuelling infrastructure results in a higher penetration rate and a slightly higher final value.

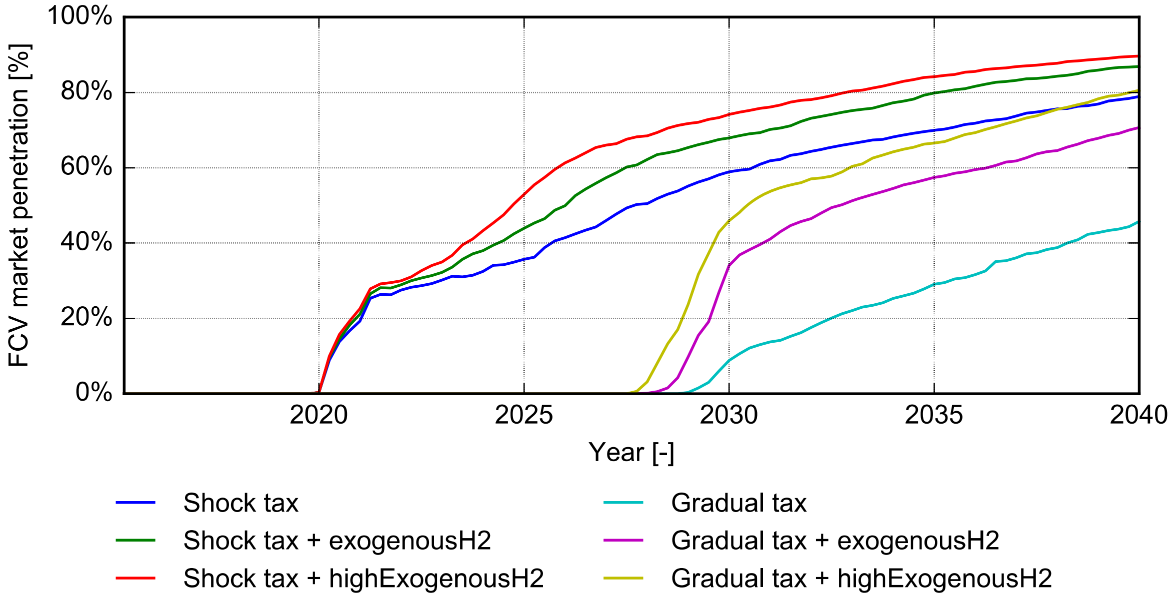

Fig. 24 Share of FCVs sold in the compact car segment with tax

In case of a gradual tax it is evident that no effect is visible until a value of the tax above 30% is reached, when producers gradually start switching. Here the difference between the effect of an exogenous build-up of the infrastructure is more evident than in the shock tax scenarios: in the case without exogenous build-up FCVs start being produced later and reach a final penetration that is significantly lower than the one observed in all other scenarios. The high exogenous development of the hydrogen infrastructure, on the other hand, guarantees a final penetration amount very close to that of the shock tax. Fig. 25 shows how the hydrogen infrastructure develops in the analysed tax scenarios.

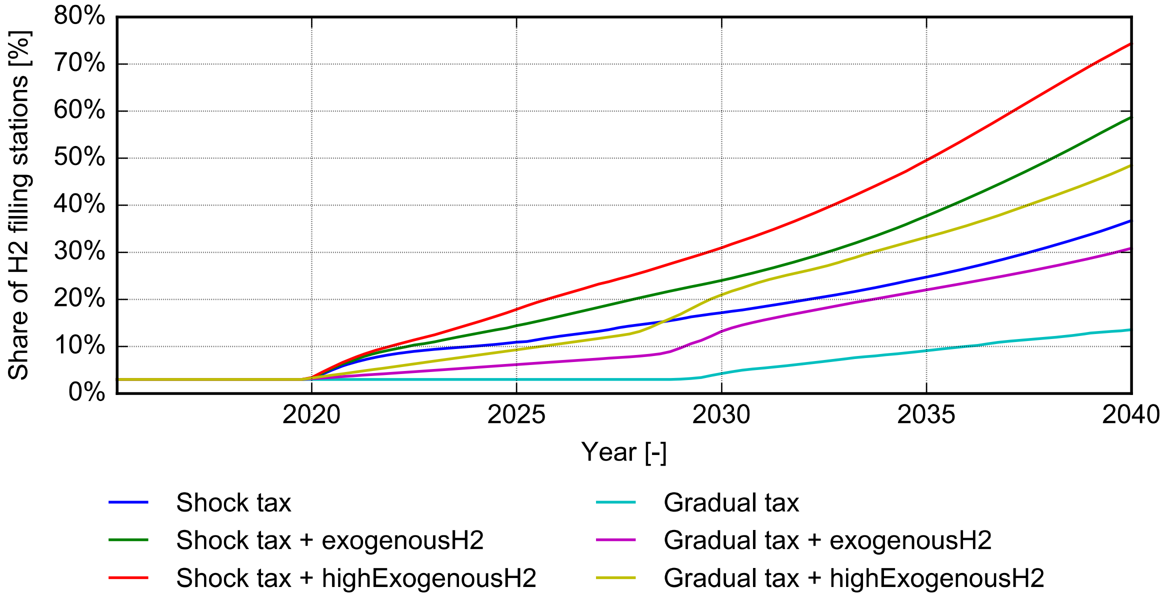

Fig. 25 Share of filling stations that sell hydrogen with tax

Here it becomes clear how FCVs market penetration and the hydrogen filling stations (HFSs) share are part of a positive feedback loop, in which FCVs sales cause an increase of the share of filling stations that sell hydrogen and this in turn leads to higher FCVs sales in the next quarter. The current results suggest that, in case of a high enough tax, the chicken and egg problem can be overcome and a successful market penetration of the new drivetrain technology can be achieved. It should be noted that while the market penetration of FCVs is only considered in the compact car segment, the response of the refuelling infrastructure is determined by the share of FCVs in the whole car market.

6.1.2 Effect of the tax on producers

As more FCVs are sold and the infrastructure develops, more and more producers decide to switch. In order to identify the effect of market share on the decision to switch two representative groups of producers are considered: large producers and small producers, which are respectively the 3 producers with the highest and lowest market share in the quarter before the introduction of the tax. As illustrated in Fig. 26 large producers are more likely to switch to FCVs for both shock and gradual tax and start switching before small producers. There are three main motivations for these differences:

- The productivity of capital decreases upon switching to FCVs, so that the capital must be expanded through investments if the current market share is to be maintained. This gives a clear advantage to large producers, that have a higher investment potential due to their higher available capital. It can actually be observed, analysing the model output in detail, that producers often make investments upon switching to FCVs
- Large and small producers give a different importance to market share in choosing the car price: small producers give a higher weight to market share since they aim at staying in the market, while large producer tend to focus more on income. Since switching to FCVs most likely results in a drop in market share, small producers are less likely to do it
- Large producers have a higher impact on the average market price and average market competitiveness: as a consequence they are better at predicting the quantity of cars sold if they decide to switch

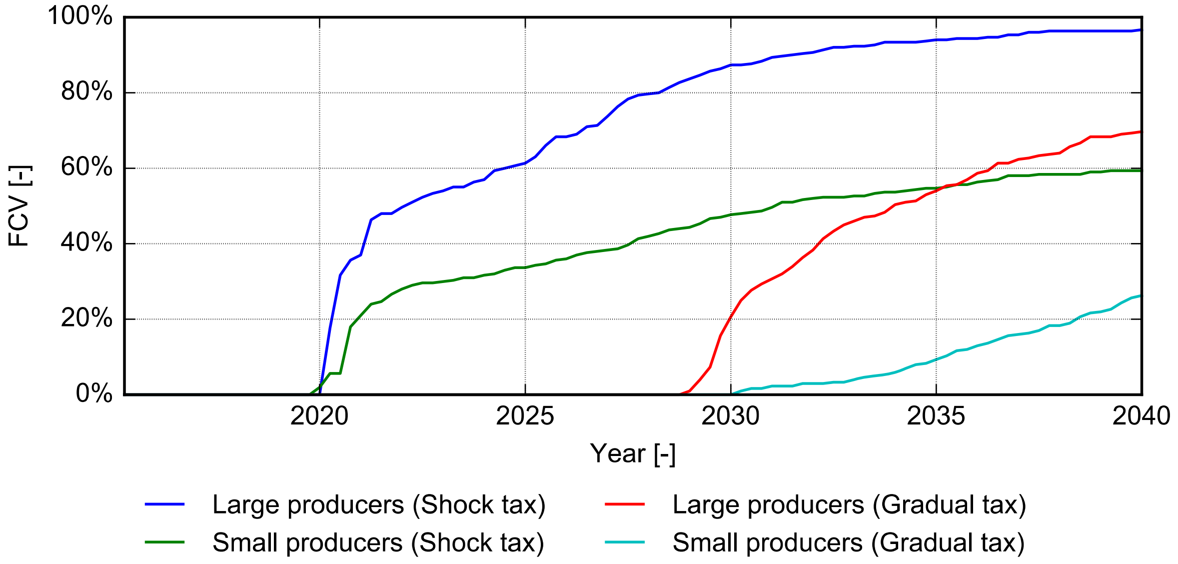

Fig. 26: Share of FCVs producers with tax

A major effect of the advantages of larger producers is that they expand their market shares after switching at the expenses of small producers, that, due to the reasons listed above, are stuck at manufacturing conventional vehicles. This effect can be quantified introducing the concepts of market concentration and the Herfindahl index. In economics, market concentration measures to what extent a small number of producers account for a large portion of a certain good or service provision (Khemani & Shapiro, 1993). If concentration is low the industry is competitive, otherwise it is said to be oligopolistic or monopolistic. A high market concentration is undesirable for several reasons: among these are a low incentive for large producers to cut costs and improve the product, higher product prices and lower consumer welfare.

A commonly accepted measure for market concentration is the Herfindahl index, defined as:

$$H = \sum_{i=1}^{n} s_i^2 \tag{26}$$

where n is the number of producers in the market and s_i is the market share of the i-th producer. The value of the Herfindahl index lies between $1/n$ and 1, with the extreme cases of perfect competition when the index value is $1/n$ and monopoly when it is equal to 1. In Fig. 27 the Herfindahl index is plotted to quantify how the tax scenarios affect the market concentration of the industry at hand.

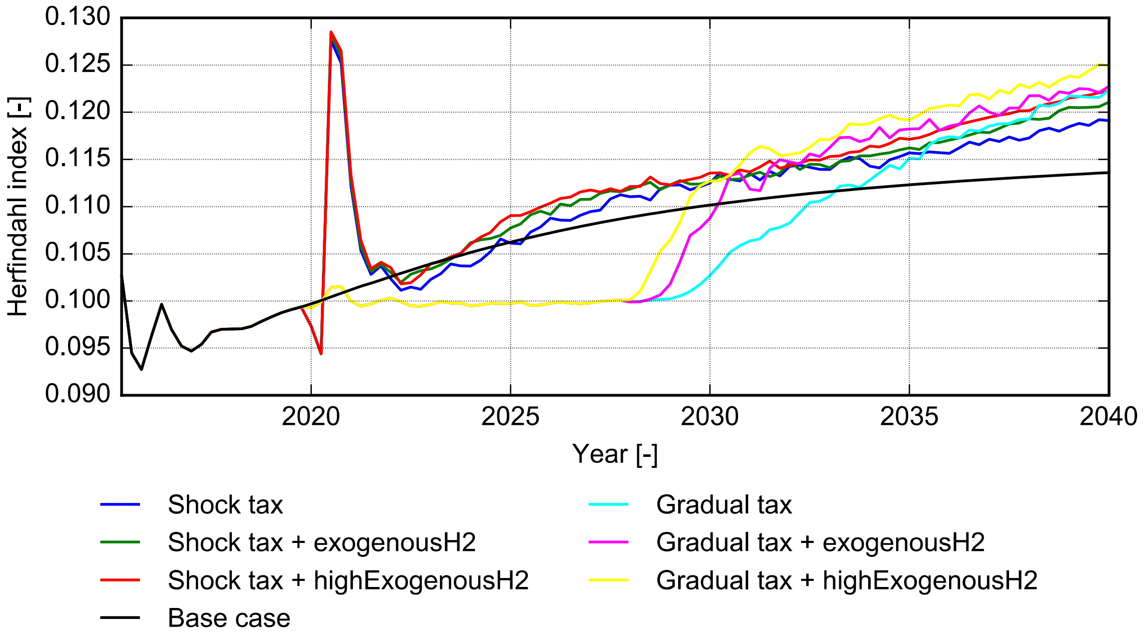

Fig. 27: Herfindahl index with tax

This plot shows that even in the base case, in which no tax is applied, the Herfindahl index increases throughout the simulation: this is a result of the effect that large producers have on consumer preferences through the mere exposure effect, in that they have a great influence on the features of the average car thanks to their high market share. Looking at the shock tax scenario it is possible to observe that the Herfindahl index presents a peculiar trend: it first decreases, since producers lower their prices very close to variable costs to compensate the sudden consumer price increase and very close prices cause a more equitable redistribution of market share. In the following tick one or two large producers switch to FCVs and their market share sharply rises due to their price advantage. After that other producers adapt to the new prices and regain market share, causing the Herfindahl index to drop back to the value it would have in the base case scenario. For the rest of the simulation concentration increases constantly and is always higher than that of the case without any tax: it can thus be inferred that the introduction of the tax intensifies the imbalances that were present in the market before its introduction. The trend is rather different for the gradual tax, with the Herfindahl index initially staying constant below the value of the base case scenario, due to a low tax that causes a drop in demand but is not enough to cause any producer to switch: in this conditions small producers choose very low prices and increase their market shares. When producers start switching the Herfindahl index rapidly increases and the final values are higher than those of the shock tax with the same infrastructure scenarios. This can be readily explained looking at the gradual tax scenarios in Fig. 26: as it can be seen here the probability of small producers to switch to FCVs is a lot lower than in the shock tax scenarios, thus implying a higher disadvantages for small producers in gradual scenarios. This might be a sign that small producers switch in the shock tax scenarios due to the high uncertainty caused by changes in market prices and that they would probably not make the same choice if conditions changed in a more gradual manner.

Fig. 28 shows how much the total profit of the three largest producers changes with respect to the base case without a tax. In the shock tax scenarios there is a large loss of profit just after the introduction of the tax, but after five to eight years the profit is higher than the base case, meaning that large producers gain from the shock tax. The gradual tax presents similar features but the profit loss period is much longer.

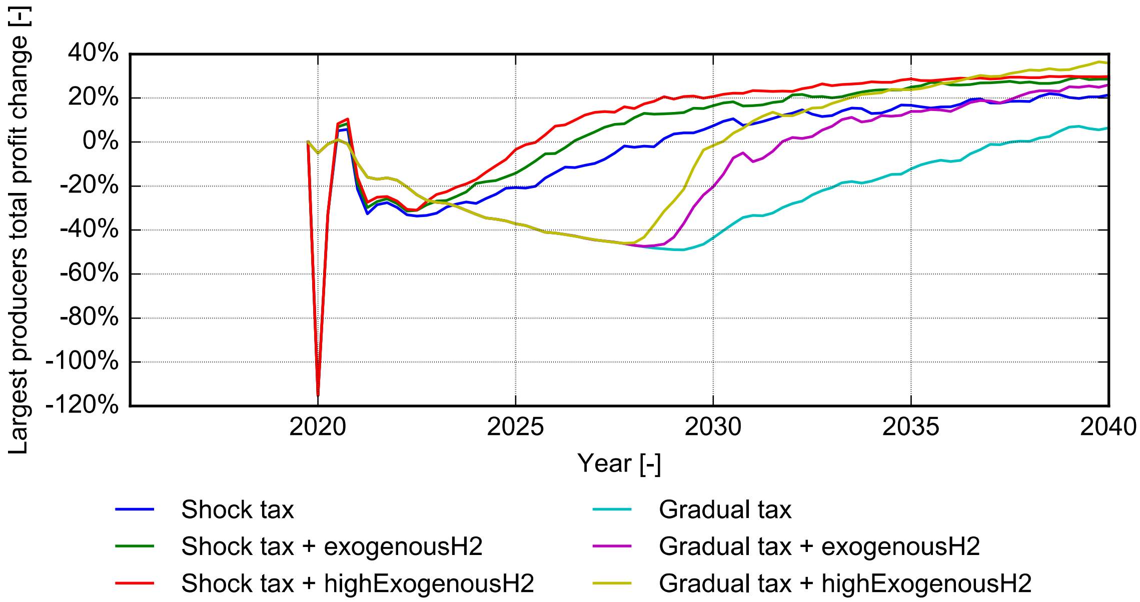

Fig. 28: Largest producers total profit with tax

Fig. 29 shows the same information for small producers, for which all tax scenarios bring about substantial losses. In the shock tax cases the profit loss can be partially recovered after the first five years, whereas profit changes are always negative in gradual ones.

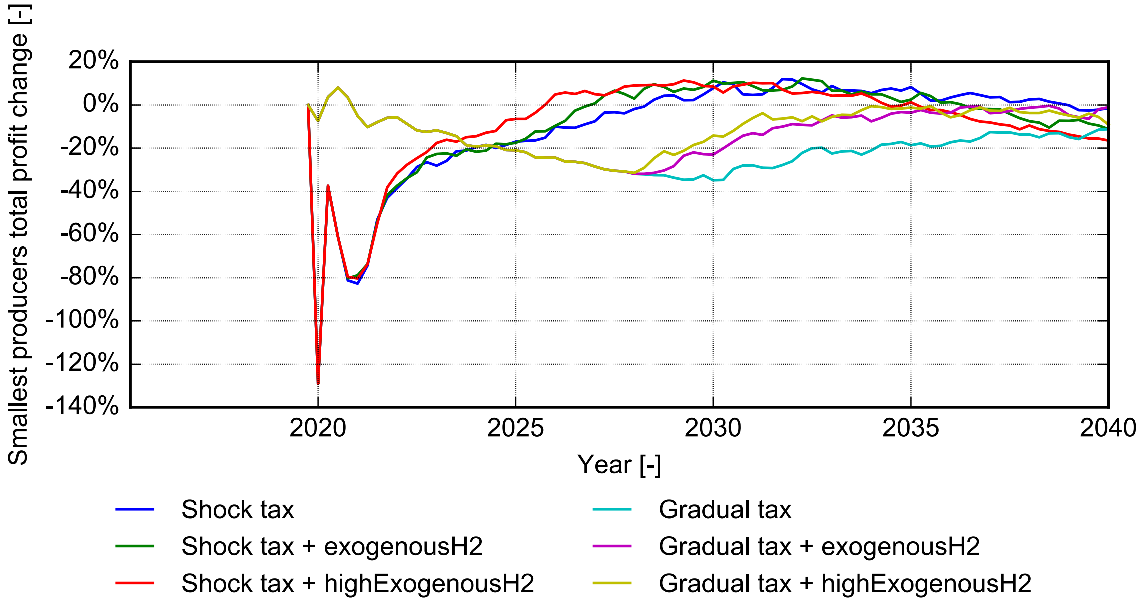

Fig. 29: Smallest producers total profit with tax

6.1.3 Effect of the tax on consumers

Turning now to consumers, Fig. 30 shows how the number of cars sold in the compact car segment changes in the regarded scenarios with respect to the base case. First of all it is possible to see that consumers do not benefit directly from any one of the scenarios: the total demand decreases due to increasing average prices and this means that many consumers that would have bought a car in the base case scenario will not do it due to the tax. Producers, in turn, lower the quantity of production because they predict a lower demand. In the case of a shock tax there is a sudden 40% drop in sales, which goes back to 23% in about two years; after that the sales slowly increase as prices go down when more and more producers switch to FCVs. For the gradual tax scenarios the decrease in sales is gradual and steady, but at the end of the simulation sales are roughly 5% lower than the corresponding shock scenarios.

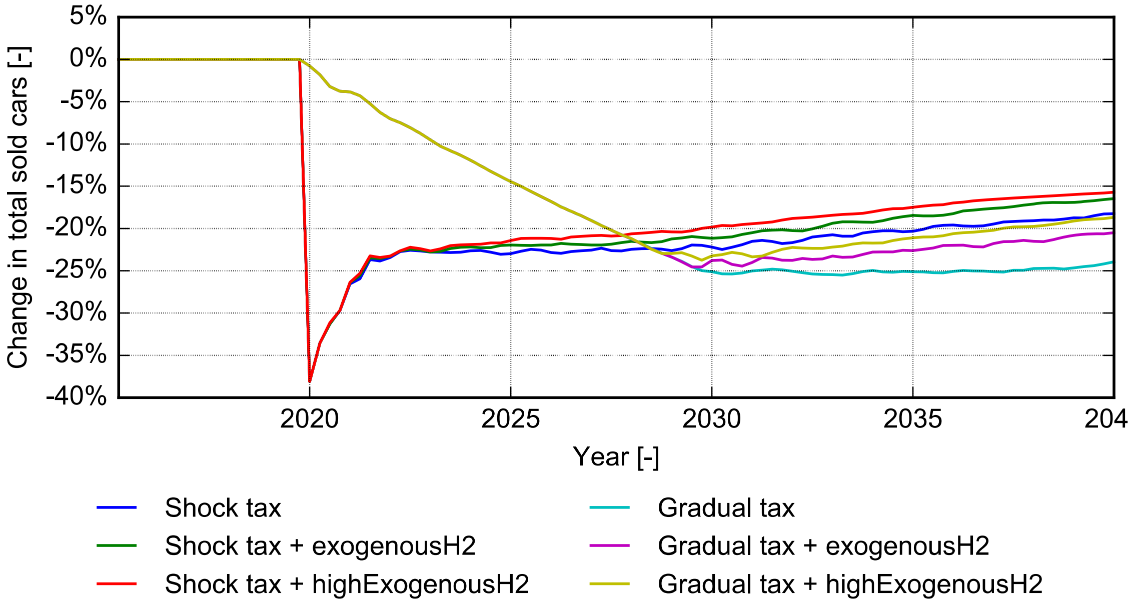

Fig. 30: Total sold cars change

6.1.4 Effect of the tax on the government

Finally the perspective of the government is taken, for which the tax represents revenue. Fig. 31 shows the total tax-generated income that can be earned each quarter in each scenario and Fig. 32 the cumulated revenue.

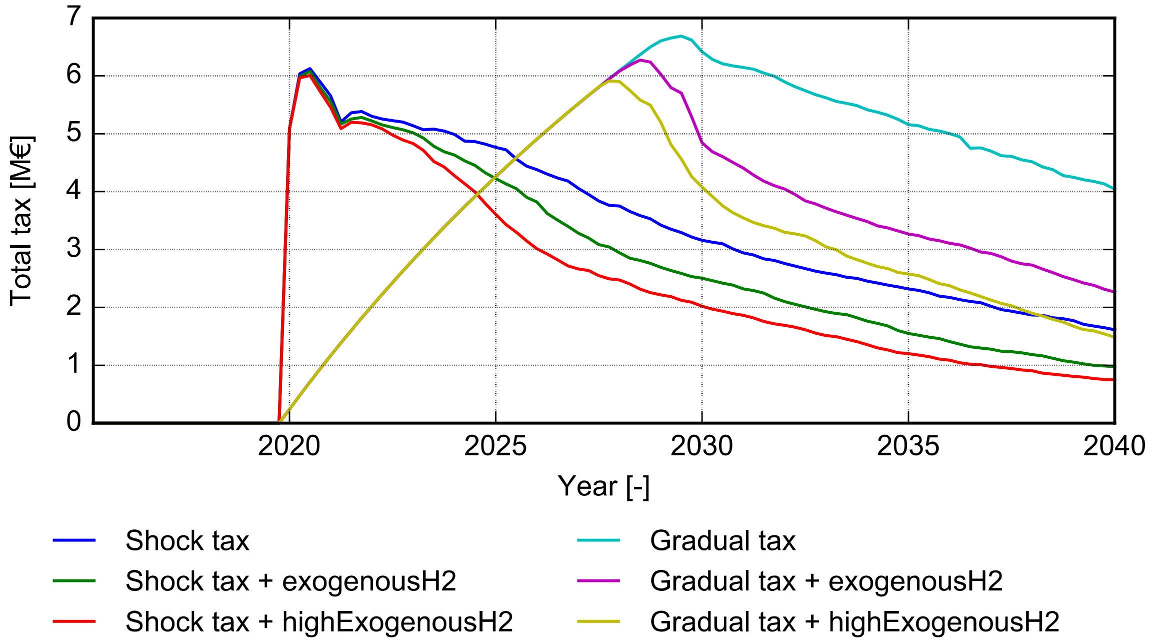

Fig. 31: Total revenue from tax

As it can be seen from these two plots the revenue from the tax is higher when the tax is less effective, and is the highest in the scenario with gradual tax and no exogenous infrastructure development. It should be clear to the reader that the revenue values are scaled down to the number of consumers in the model and are thus not to be taken as a reference to compare it to reality.

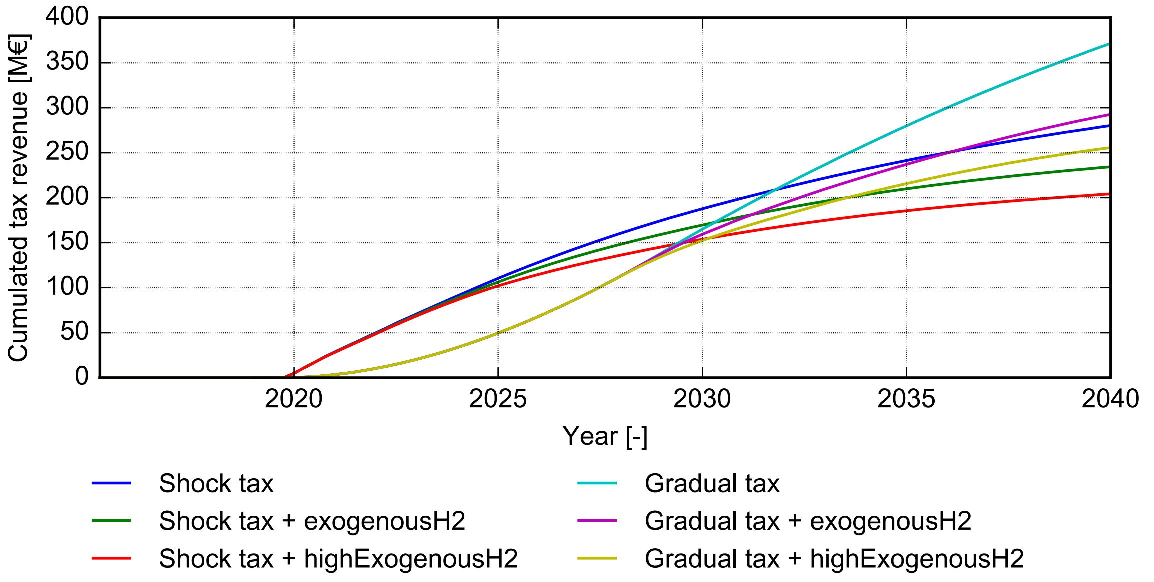

Fig. 32: Cumulated revenue from tax

6.2 Subsidy scenarios

In the subsidy scenarios a subsidy is applied on the purchase price of FCVs starting from the year 2020. The consumer decision on drivetrain technology mainly depends on the relative price of FCVs with respect to ICEVs and a subsidy of the same amount of the tax used in the tax scenarios would give a greater advantage to FCVs (the relative price is 1.4 in the case of the shock tax and 1.67 in the case of the shock subsidy).

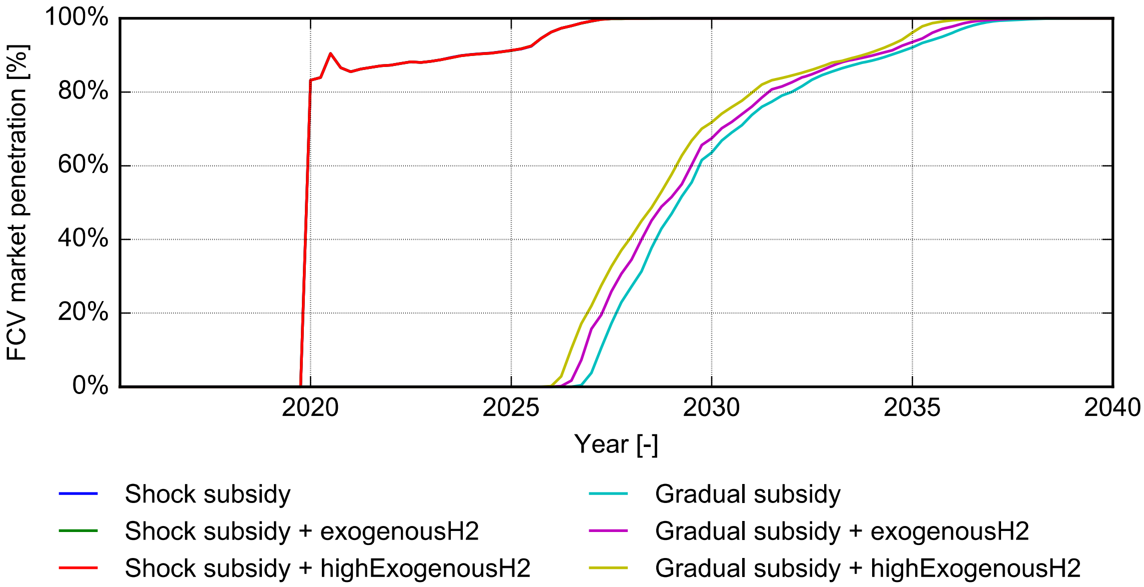

Fig. 33: Share of FCVs sold in the compact car segment with 40% subsidy

With such a high relative advantage of FCVs a sudden diffusion of the new technology is observed, in which about 80% of the producers switch to FCVs regardless of initially-low share of HFSs and the infrastructure scenario.

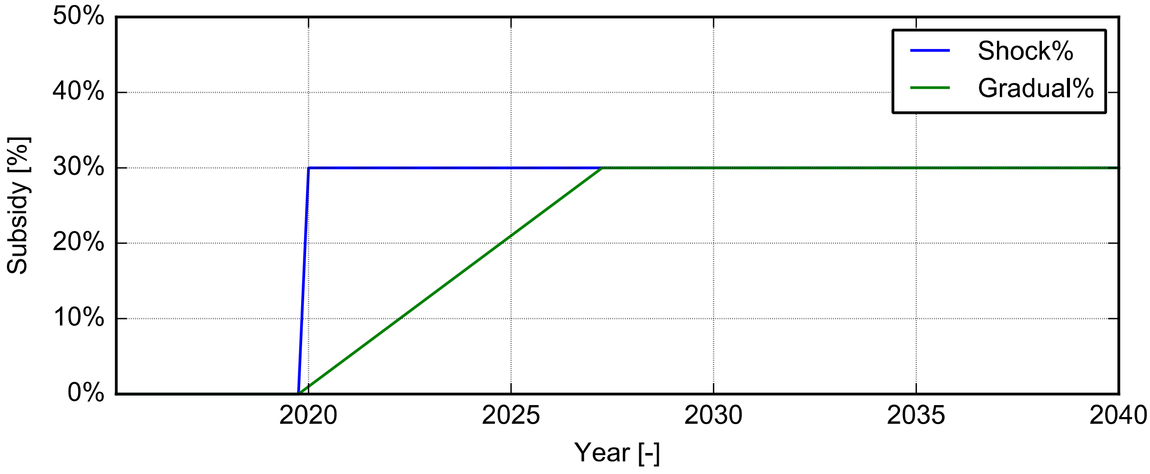

Fig. 34: Evolution of the subsidy

Since the results of such a scenario are hardly justifiable, a scenario with a 30% subsidy is analysed instead, in order to obtain a relative price that is almost identical to that of the tax.

6.2.1 Effect of the subsidy on the system as a whole

As it can be seen in Fig. 35 the market penetration of FCVs evolves in a way that closely resembles that of the tax scenarios. The only difference is that the gradual subsidy scenarios cause a faster penetration if compared with the gradual tax ones: this is easily explained considering that the relative price when the tax/subsidy reaches the maximum value is the same, but by increasing 1% each quarter the gradual subsidy reaches the maximum value 10 quarters before the gradual tax.

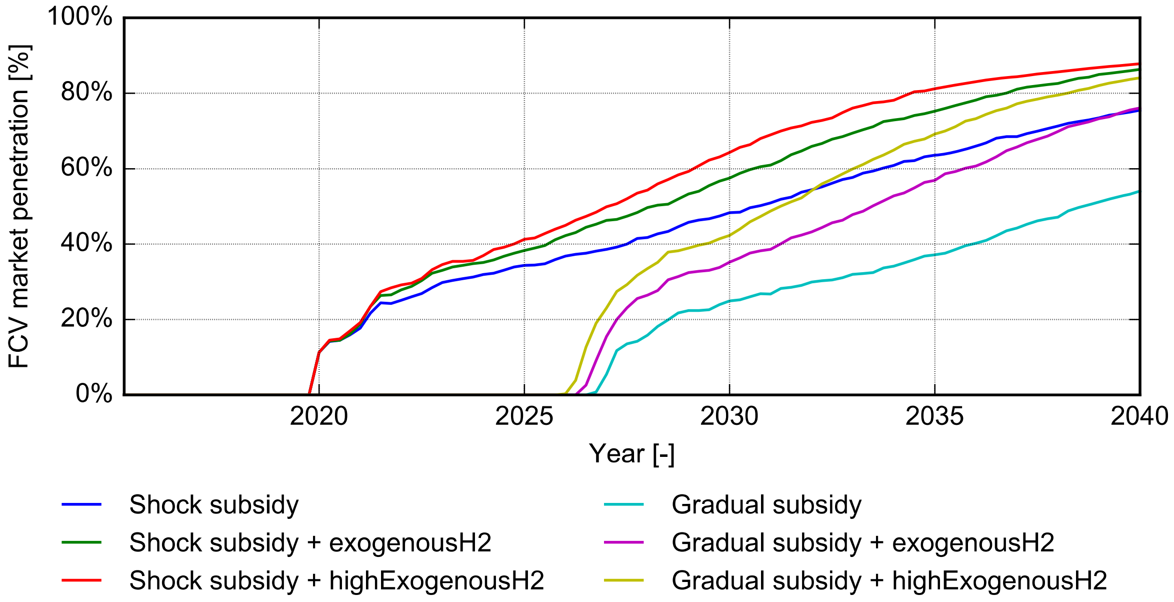

Fig. 35: Share of FCVs sold in the compact car segment with subsidy

Apart from this small difference the general result of the model in these scenarios are similar to those of the tax. Now it is interesting to compare how two different scenarios bring an almost identical results. The development of the infrastructure is closely interconnected with the FCVs market penetration and is thus very similar with the tax scenarios.

6.2.2 Effect of the subsidy on producers

The market concentration in Fig. 36, however, presents some features of interest. Here the increase in market concentration when the shock subsidy is introduced is a lot less disruptive than that in the corresponding tax scenarios: this is due to the fact that here producers that haven’t switched yet do not face such a great disadvantage as in the tax case, in that total demand actually increases due to falling prices. In the long run however, the increase in market concentration is not dissimilar from the tax scenarios.

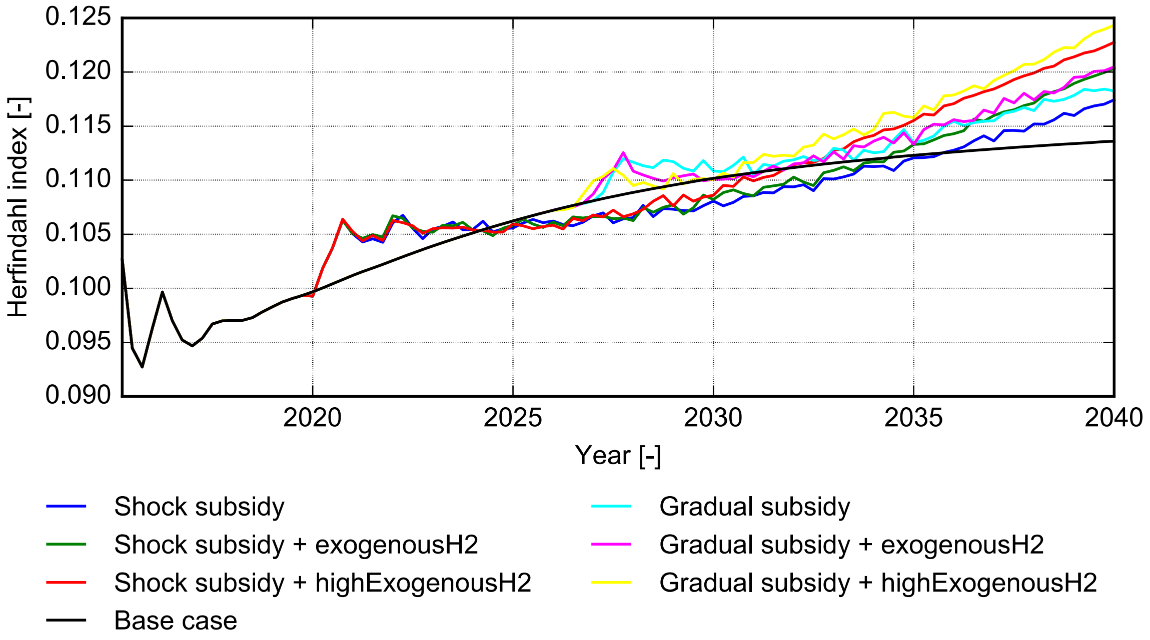

Fig. 36: Herfindahl index with subsidy

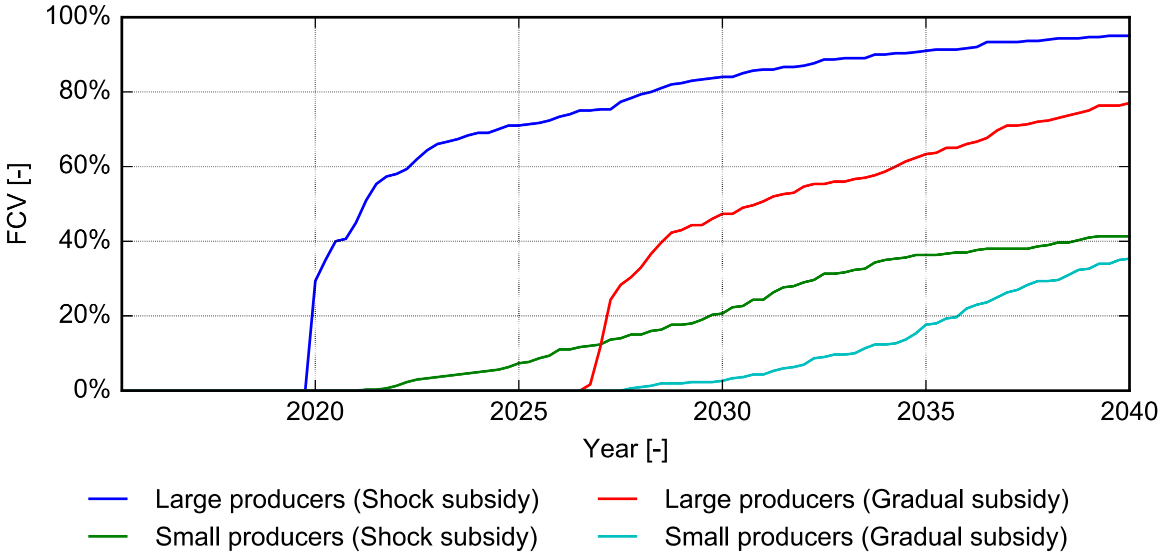

Fig. 37: Share of FCVs producers with subsidy

As illustrated by Fig. 37 even in the subsidy scenarios small producers are a lot less likely to switch to FCVs, and in this case it is clear that none of the smallest producers switches due to uncertainty when the shock subsidy is introduced: this causes a lower FCVs penetration among small producers if compared to tax scenarios.

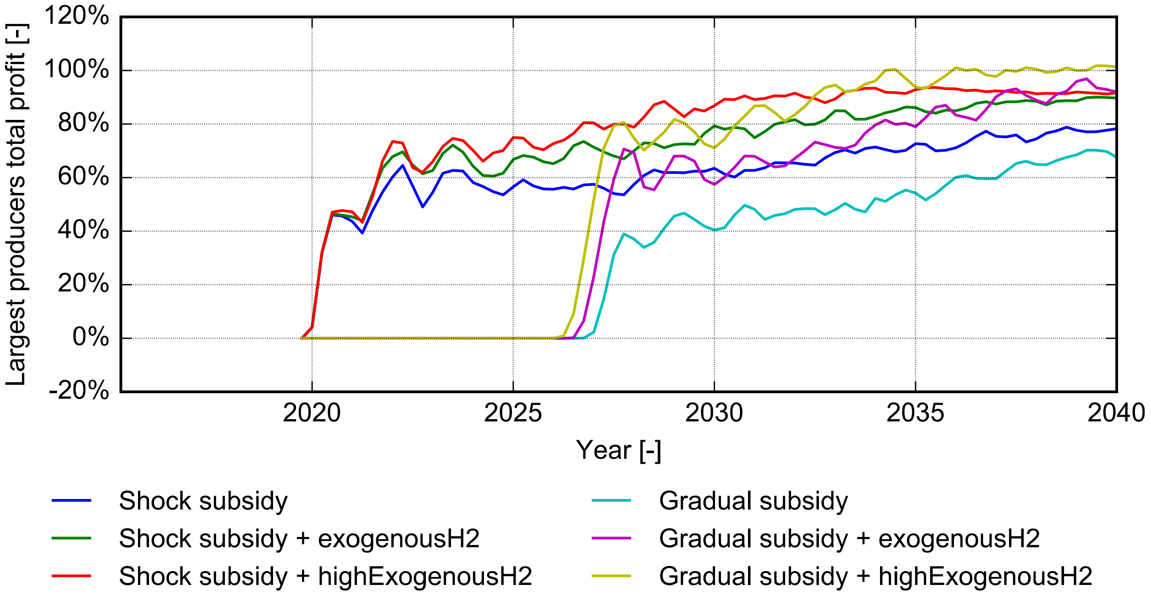

Fig. 38: Largest producers total profit with subsidy

Fig. 39 shows how the subsidy affects the total profit of the largest and smallest producers compared to the base case scenario: for the largest producers it is in any case convenient to have a subsidy for FCVs, because they will likely switch and benefit from both price advantage and increase in demand. This is even more so if an exogenous infrastructure build-up is realised by the government. The situation is a little bit different for small producers: they are more likely than not to be stuck with ICEVs production and will benefit from the demand increase in the short run. In the long run however their profit will start to decrease due to the fact that most of the other producers switch to FCVs, causing a drop in average price they cannot compete with.

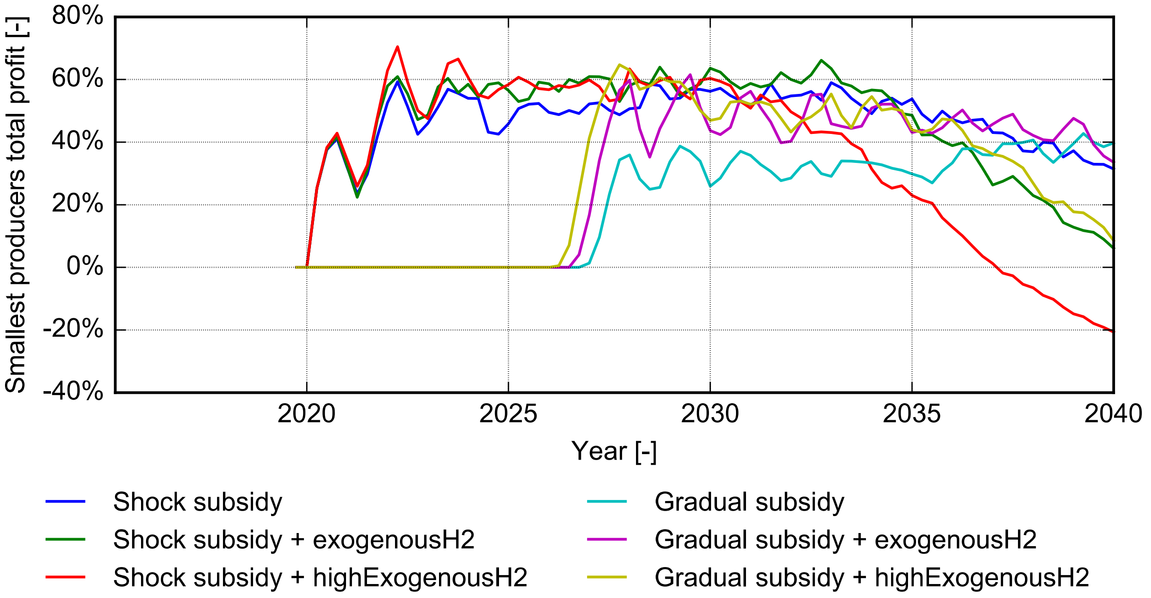

Fig. 39: Smallest producers total profit with subsidy

6.2.3 Effect of the subsidy on consumers

Seen from a consumer perspective all subsidy scenarios present an advantage. Fig. 40 shows the change in the total number of cars sold every quarter: after an initial oscillating behaviour the number starts increasing steadily and does so until the end of the simulation. This is caused by the decrease in consumer prices made possible by the subsidy. As can be expected the situation is even more convenient for them if there is an infrastructure build-up combined with the subsidy.

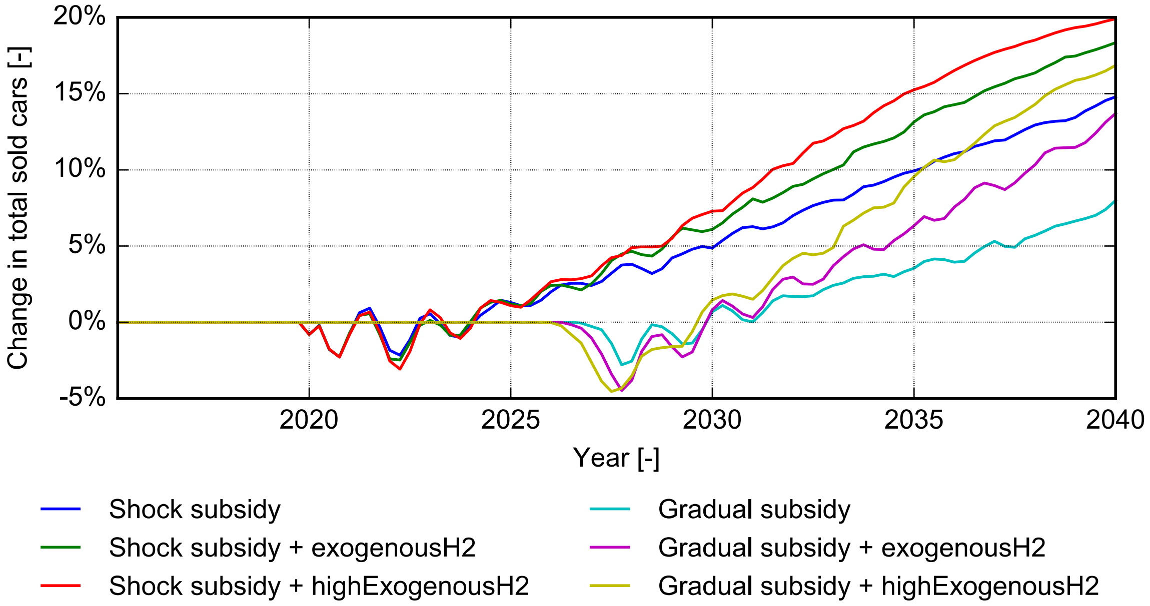

Fig. 40: Total sold cars change with subsidy

6.2.4 Effect of the subsidy on the government

Lastly in Fig. 41 the government effort in making subsidies available to consumers in the different scenarios can be compared. It is interesting to notice that the gradual subsidy case with exogenous and high exogenous growth respectively result in an equal and higher penetration rate if compared with the shock subsidy scenario without exogenous infrastructure and this is obtained with a lower expenditure on the government side. It should yet be considered that two important aspects are not considered in this comparison: the exogenous growth needs to be payed for by the government and while the penetration results at the end of the simulation are comparable, the number of existing FCVs in the shock subsidy scenarios is still higher than the two considered gradual tax scenarios. This could be taken into account in future versions of the model, in which filling station owners would also be represented as single agents and they could receive subsidies if they decide to add an hydrogen outlet to their filling station.

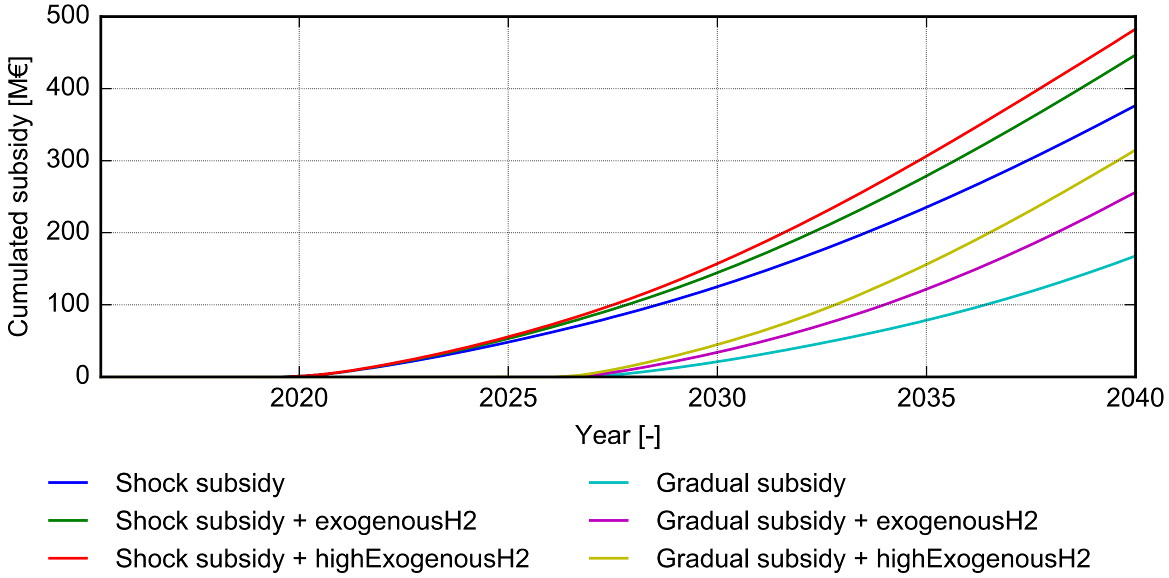

Fig. 41: Cumulated expenditures for subsidy

6.2.5 Comparison with the tax scenarios

Comparing the results that have been obtained analysing the tax and subsidy scenarios it is now possible to sum up the advantages and disadvantages of both approaches. It should by now be clear that the use of a subsidy presents several advantages over a tax, namely:

- A 30% subsidy has roughly the same effect of 40% tax, due to the different effect on relative price
- A shock tax causes a sharp increase in market concentration, that is not there in case of a subsidy (although the final concentration has a similar value)
- In tax scenarios all producers experience profit losses, while in subsidy scenarios their profit increases
- In case of a subsidy consumers can benefit from lower prices, whereas the opposite happens in case of a tax

Another great advantage of the subsidy, which affects both consumers and producers, is what happens in case the policy does not work. If a tax is applied and no effect on FCVs penetration is observed, producers and consumers will still experience all the drawbacks of this solution. On the other hand, if a subsidy is applied and the policy fails no side effect is experienced by the actors involved. It should taken into consideration, however, that while a tax represents income for the government, a subsidy implies great investments on its part.

6.3 Environmental benefits

From the results of the simulated scenarios it is now possible to estimate the corresponding environmental benefits that would derive from the market penetration of FCVs in the German compact car segment. For the sake of simplicity this is only done for tax scenarios, but the results are similar in subsidy ones. While the success of market penetration of FCVs is measured in terms of share of FCVs in the quarterly sales, environmental benefits depend on the share of FCVs in the compact car fleet. As shown by Fig. 42, this share is always lower than 50% at the end of the simulation: even with a very high market penetration in terms of sales, it takes time for all ICEVs to be replaced.

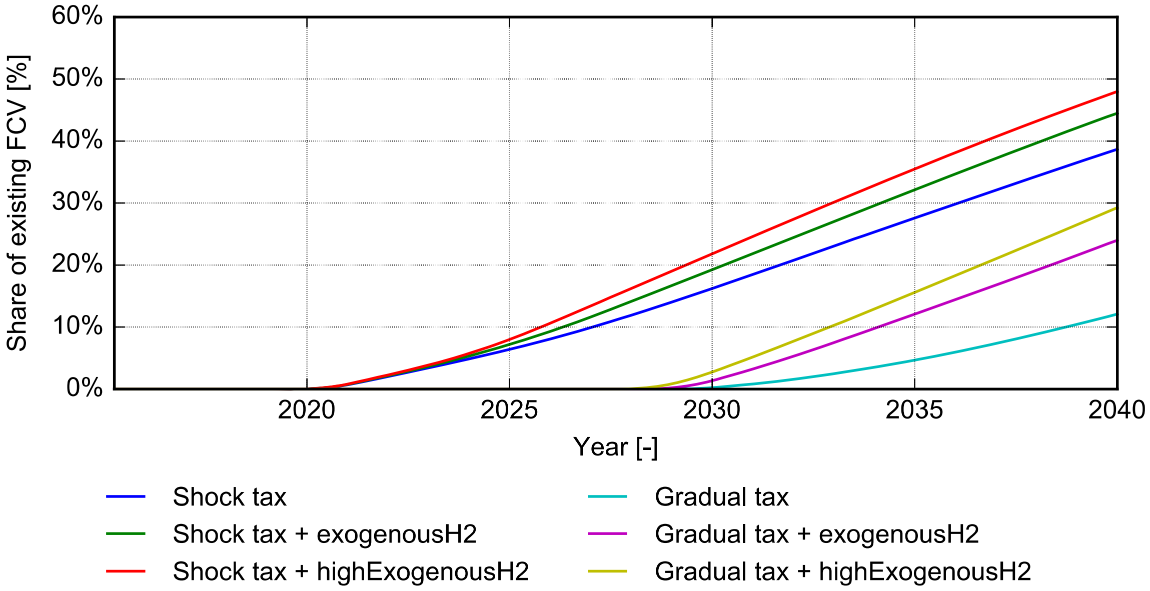

Fig. 42: Share of FCVs in the compact car fleet with tax

Making assumptions about greenhouse gas (GHG) emissions and the energy consumption of a compact car it is now possible to calculate the environmental benefit associated to FCVs penetration in terms of used renewable surplus energy, saved primary energy and saved GHG emissions. It should be clear to the reader that the results discussed in this section should not be interpreted as a prediction, but as what the environmental benefits could be in case the previously-discussed results of the model were true.

6.3.1 Main assumptions

In order to take GHG emissions and energy consumptions of a compact car into account the whole process that starts with production of the fuel and ends with the usage of the car must be considered. This can be done using the results of the Well-to-wheel analysis provided by the Joint Research Centre of the European commission (JRC, 2014). This study provides with estimates of the well-to-tank and tank-to-wheel energy consumption and GHG emissions for ICEVs and FCVs after 2020, that corresponds with the time in which policy is introduced in the model. The curb weight of the car used as a reference for these estimates also lies in the range of compact cars.

The following assumptions were made to calculate the energy consumption and the GHG emissions per Km for FCVs and ICEVs:

- Hydrogen is produced in large-scale electrolysers exclusively from wind power plants and distributed to hydrogen filling stations via pipeline
- Since no distinction is made in the model between gasoline and diesel ICEVs, average values must be used. The average values for ICEVs are weighted by the share of gasoline and diesel cars in the whole German car market, which is roughly 68% and 32% respectively for the year 2015 (Kraftfahrt-Bundesamt, 2015). Others types of vehicle are not considered in the estimate
- The average value of the annual mileage is used, which was estimated by (INFAS, 2009) to be 14,360 Km per vehicle per year in Germany. It is here assumed that the driving distance of consumers does not change if they buy a FCV. Yet, It should be noted that since consumers with a low driving distance are more likely to buy a FCV in the model, using the average value leads to an overestimation of the environmental benefit
- Due to the restriction of the model to the compact car segment, the evaluation of the environmental benefits is also restricted to this segment only

Table 2 summarizes the estimates for well-to-wheel energy consumption and GHG emissions per kilometre that were obtained applying the above-mentioned assumptions to the data provided by the JRC report.

Table 2: Results of well-to-wheel analysis

	ICEV	**FCV**
WTW Energy Consumption (MJ / Km)	1.598	1.077
WTW GHG emissions (g CO_2, eq / Km)	119.082	7.001

6.3.2 Results of the estimates

In this section the results of the estimates of the environmental benefits are discussed. The results presented here are scaled up to the number of compact cars owners in Germany, so that these figures can be compared to the actual values of primary energy consumption and CO_2 emissions in the segment. Fig. 43 shows the yearly amount of excess energy needed to produce enough hydrogen to cover the demand generated by the existing FCVs. The trend of this graph is similar to that of the share of existing FCVs, since using an average annual driving distance makes the used excess energy directly proportional to the latter value. Yet, the annual driving distance of early adopters of FCVs is likely to be less than average: as a consequence the real value of used excess energy would be lower than that of Fig. 43 when the tax is introduced and the curve would be steeper afterwards. In the case of the shock tax, the required energy in the year 2025 is about 4 TWh: this is 1/3 of the excess energy estimated by (Bartels, 2016) for that year.

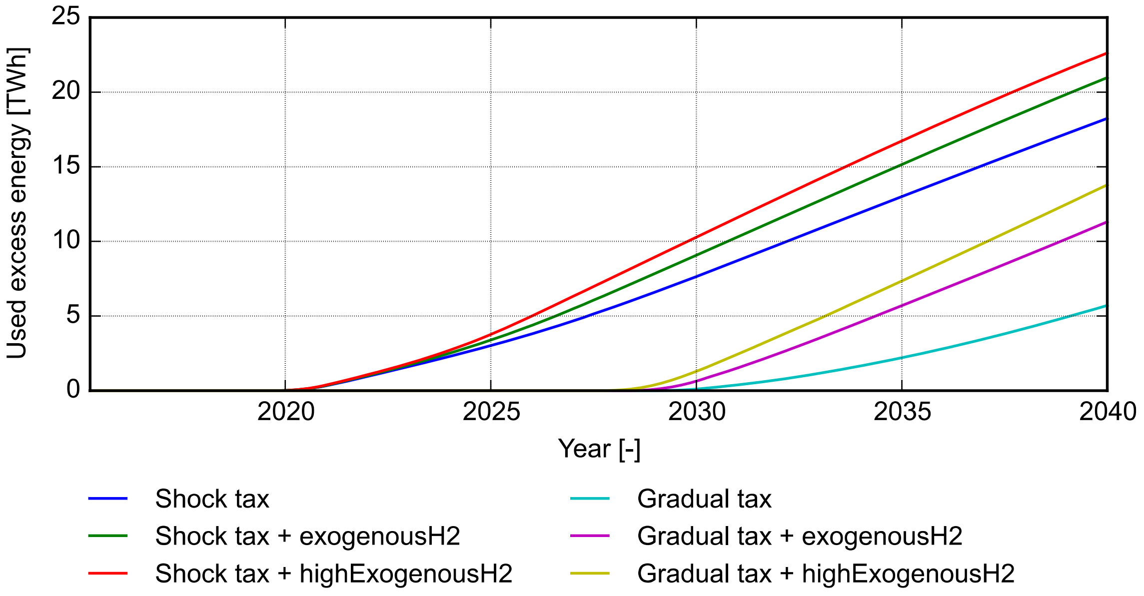

Fig. 43: Yearly amount of excess energy used to produce hydrogen

In Fig. 44 the primary energy consumption of all the compact cars is shown. From the graph it is possible to see how primary energy consumption decreases as ICEVs are replaced by FCVs. This is easily explained considering that a FCV is about twice as efficient as an ICEV (JRC, 2014): as a consequence, a lower amount of primary energy is needed for the same driving distance.

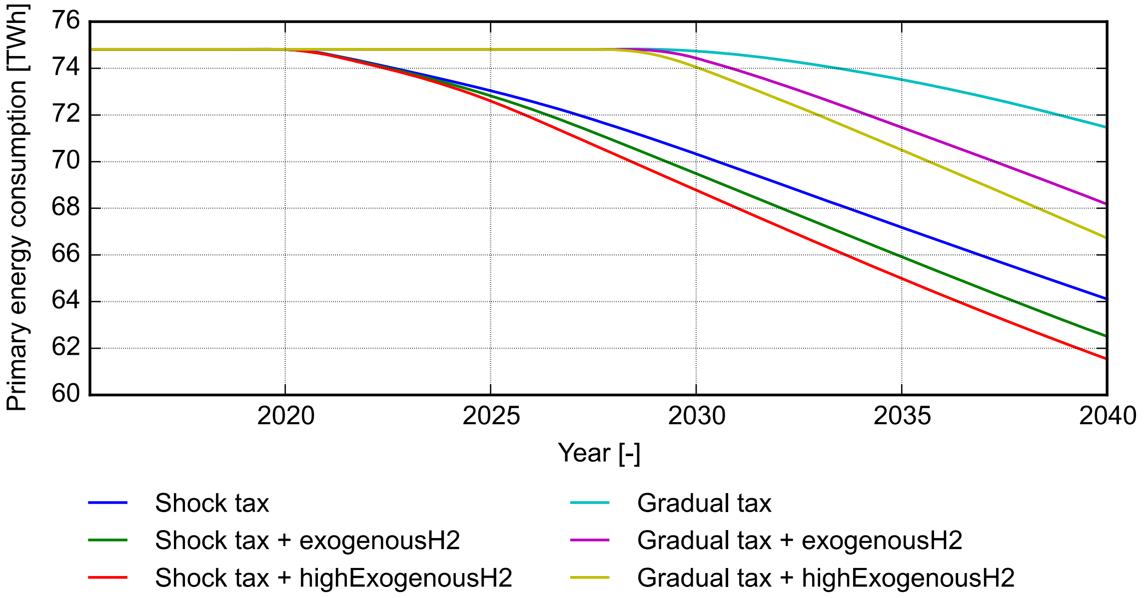

Fig. 44: Yearly primary energy consumption of existing cars in the compact segment

Finally, the amount of saved GHG emissions can be estimated. As shown by Table 2 the well-to-wheel GHG emissions of FCVs are two orders of magnitude lower than those of ICEVs, because hydrogen is produced from wind and there are no tailpipe emissions. This implies that substituting ICEVs with FCVs allows to lower the total GHG emissions of the segment. Fig. 45 shows how the total avoided GHG emissions develop as FCVs penetrate the market. To put the numbers into perspective, the total amount of emissions when all the vehicles of the segment are ICEVs is about 20 Mio.t $CO_{2,eq}$. As a consequence, by 2040 a 35% to 45% GHG emissions reduction is observed in the shock tax scenarios.

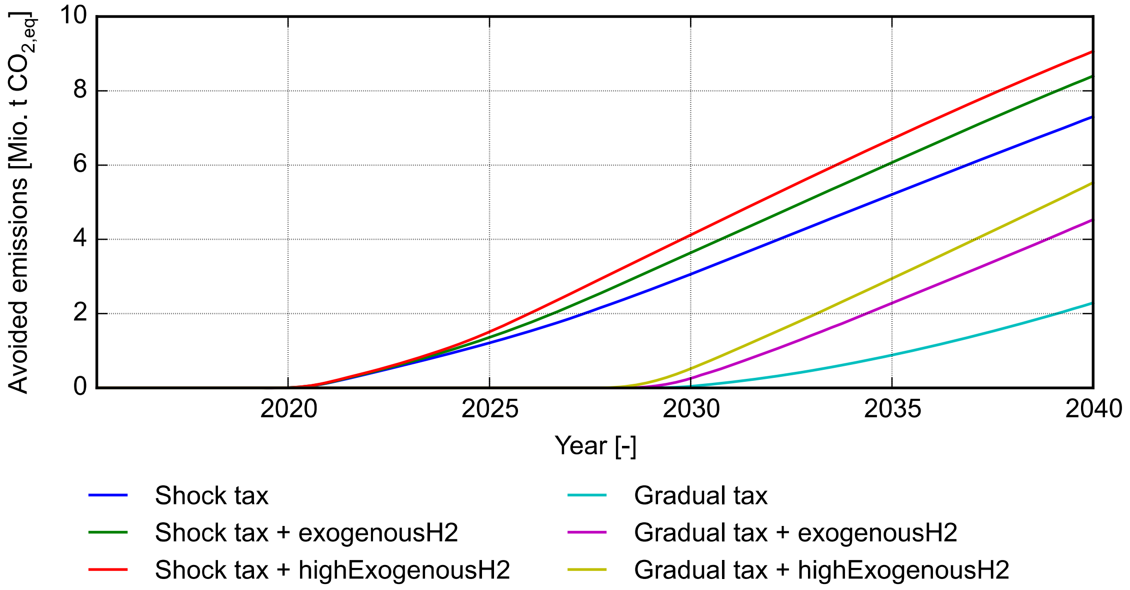

Fig. 45: Yearly avoided CO_2 emissions

6.4 Sensitivity analysis

Given the large amount of input parameters used to describe agent behaviour in the model, a sensitivity analysis is needed to understand the robustness of the results described above. In the following section the crucial parameters are let vary one at a time within reasonable boundaries and the effect of this variation on the market penetration of FCVs is observed. In order improve the readability of the graphs only the tax cases without any exogenous infrastructure build-up are considered, although the conclusions reached here also extend to the other tax and subsidies scenarios.

6.4.1 Parameters that influence consumers' buying decisions

Four main parameters that affect consumer's choice and in turn also the price setting procedure of producers:

- Own price elasticity (ε_{own})
- Amount of tax (tax_{max})
- Fuel availability factor (γ)
- Initial hydrogen filling stations share ($s_{H_2,0}$)

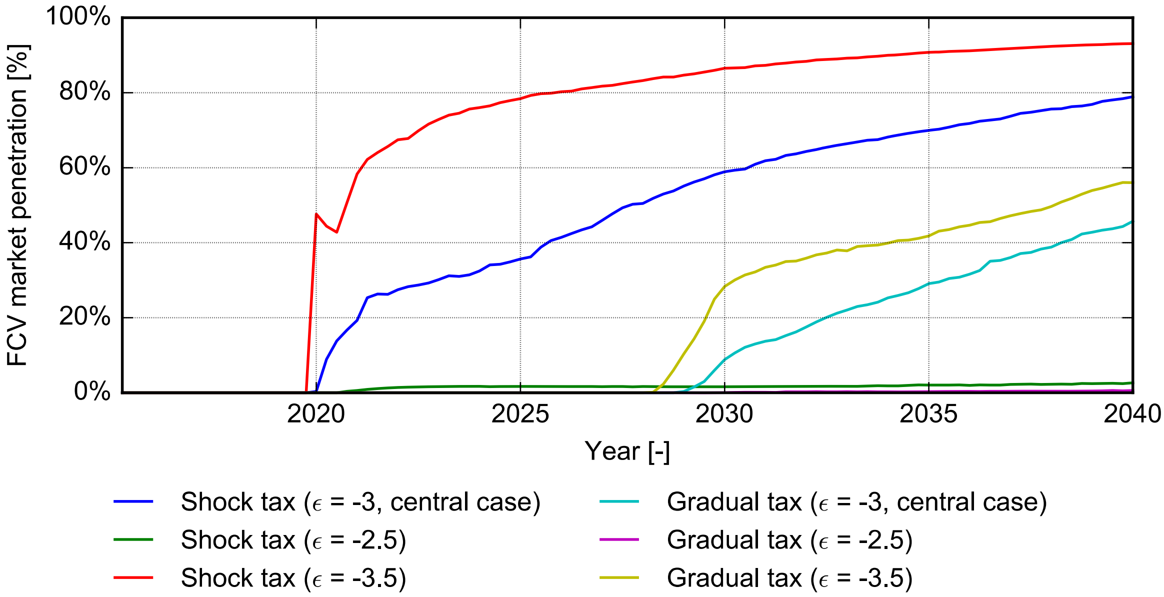

Fig. 46: Sensitivity with respect to own price elasticity

One of the most decisive parameter as regards consumer decision is own price elasticity: this parameter represents the importance of price in the consumer buying decision and, due to the structure of Eq. (4), the relative importance of refuelling effect, car features and social need. The value of the parameter is set to -3 in the central case. Fig. 46 makes it clear that the results of the model are highly dependent on ε_{own}, since a change of ±0.5 makes the difference between a very abrupt penetration and almost no penetration at all. This is not so surprising considering that a tax on ICEVs only acts on the price in order to promote the diffusion of FCVs and its effect mainly depends on this parameter. This also means that a high uncertainty on the consumers' sensitivity to price would imply a high risk in implementing a tax that could have no effect on the market penetration of FCVs, but would in any case bring about several disadvantages for consumers and producers alike.

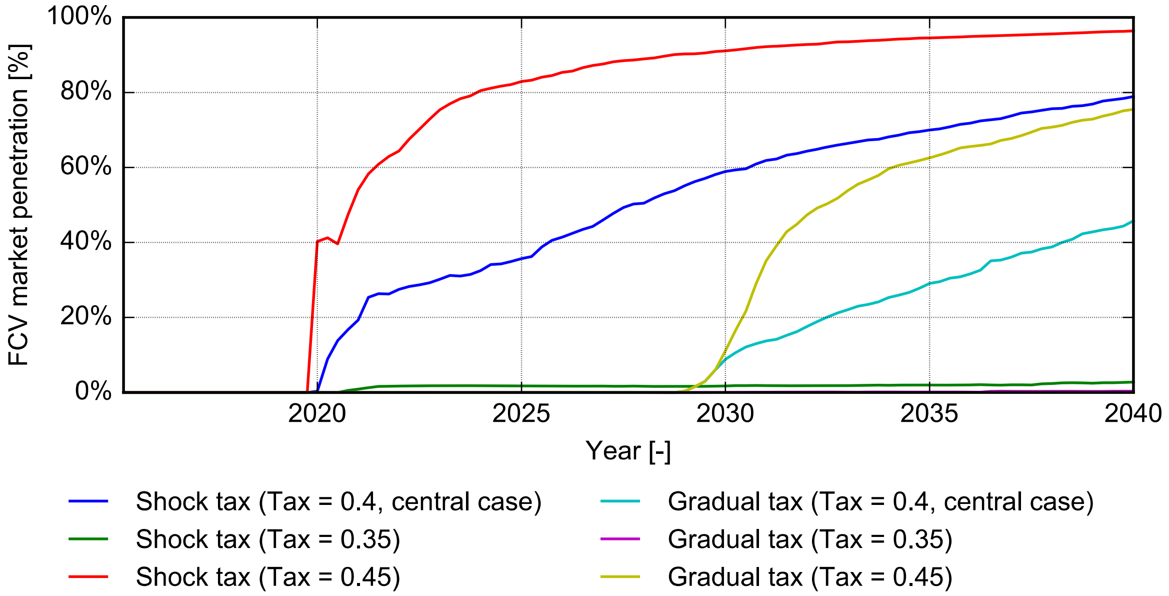

Fig. 47: Sensitivity with respect to the amount of tax

No less important is the value of the tax itself, that is set to 40% in the central case for the shock tax and as a maximum for the gradual tax. As illustrated by Fig. 47 the FCVs market penetration changes dramatically when the tax is increased or lowered by 5% and this makes the amount of tax, together with consumer price elasticity, the most sensible

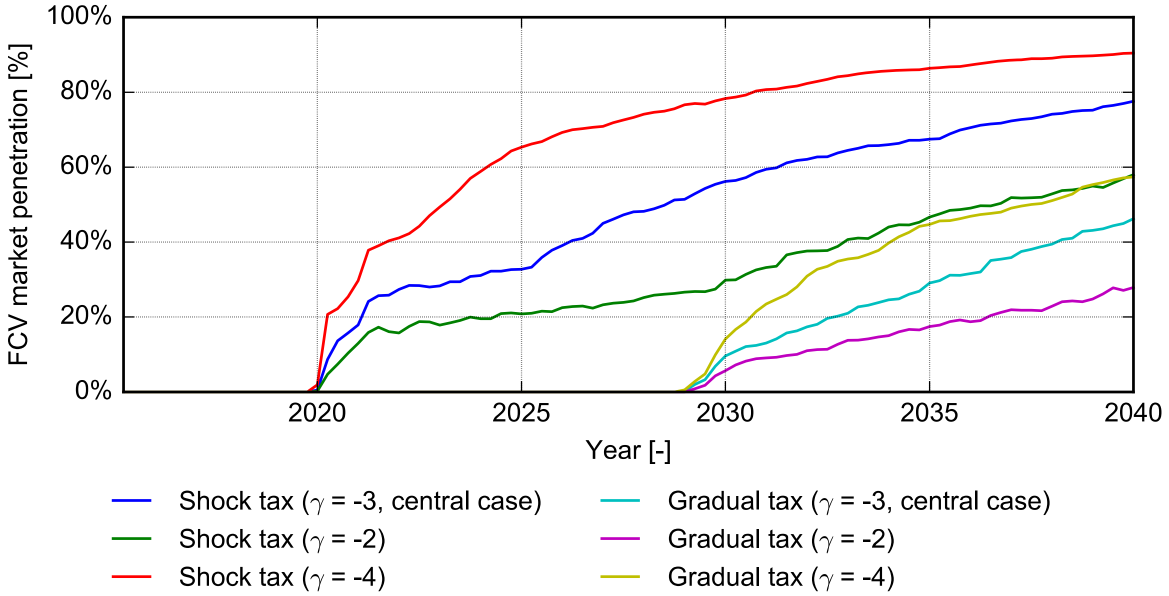

Fig. 48: Sensitivity with respect to fuel availability factor

As regards the refuelling effect, this is directly affected by the initial hydrogen filling stations share and the fuel availability factor. Fig. 48 shows the effect of change in the latter on market penetration. This parameter expresses the importance that consumers assign to the share of existing hydrogen filling stations in the evaluation of a FCV and is set to -3 in the central case. A lower absolute value of γ implies a higher importance of the share of hydrogen filling stations in the evaluation of the refuelling effect and vice versa. Hence, as expected, FCVs penetration is higher for a higher absolute value and lower for lower absolute value of the parameter. While the value of the fuel availability factor affects FCVs penetration throughout the whole simulation, the initial amount of FSs that sell hydrogen mainly affects consumers' and in turn producers' reaction when the tax is introduced: Fig. 49 shows how increasing the share from 3% (as it is set in the central case) to 5% causes about 30% of producers to switch in the first half year after the introduction of the shock tax, when the same value is only reached after 3 years in the central case and in 8 years in the case with 1% HFSs as a starting value. A higher initial HFS share causes a faster penetration and a higher final value, yet it is reassuring to see how even starting with a low value as 1% a successful penetration is observed. An equivalent effect of these two parameters can be observed in the gradual tax scenario.

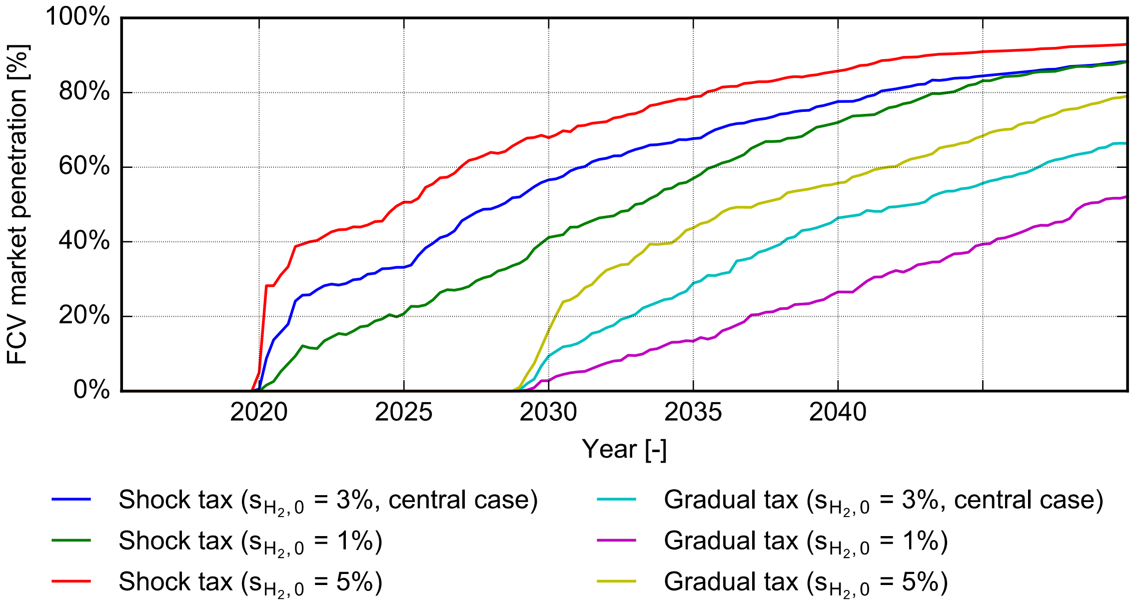

Fig. 49: Sensitivity with respect to initial share of hydrogen filling stations

6.4.2 Parameters that influence producer behaviour

Besides the indirect effect of the parameters discussed above producers' price and quantity choice are also directly affected by:

- Variable costs difference between FCVs and ICEVs (Δc_v)
- Producer's objective (η)

Fig. 50 illustrates how the increment in variable costs when switching to FCVs affects the decision of producers and in turn market penetration. As expected a 5% decrease in variable costs leads to a much faster and abrupt market penetration compared to the central case; a 5% increase however completely hinders any diffusion of FCVs. The latter result highlights one of the great limitation of the model in its current implementation, namely the fact that the learning curve effect has not been considered and variable cost increment is taken as constant. Considering this effect would probably give a successful, even if slower, penetration of FCVs even in the case of higher variable cost difference. This is one of the problems that could be solved in a future and more realistic version of the model.

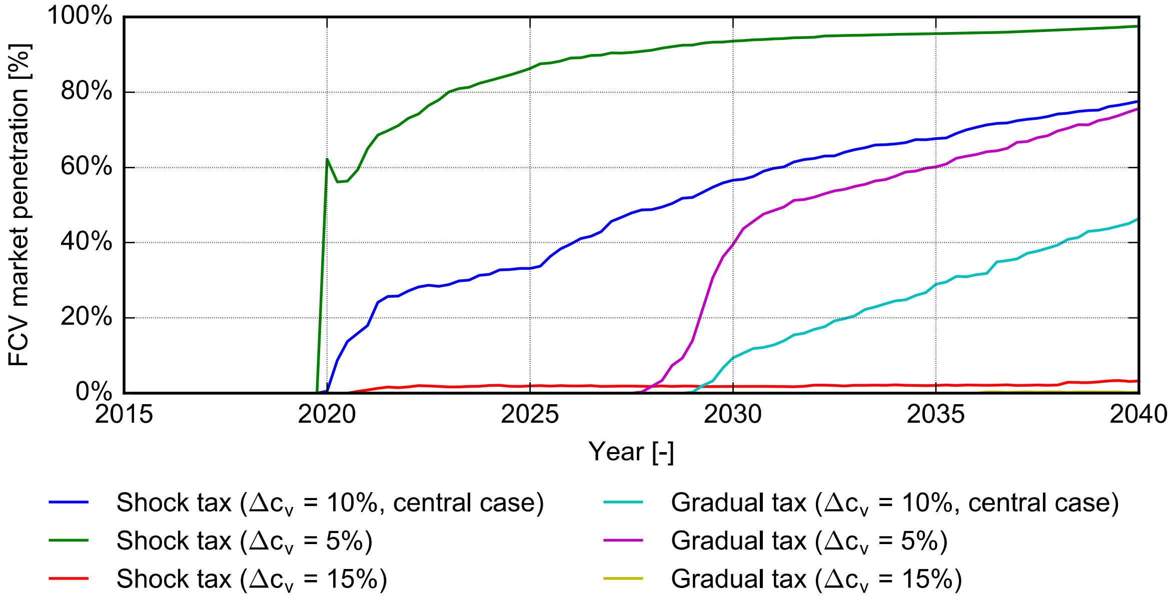

Fig. 50: Sensitivity analysis with respect to FCV variable cost increment

In the following plot the effect of the weight in the objective function is analysed. The weight function determines to what extent producer focus lies on market share: the closer its value is to 1, the more important is market share in the optimization. The value of the weight is in turn determined by the expected market share and by a scaling factor (η), so that the higher the expected market share the lower the focus on it.

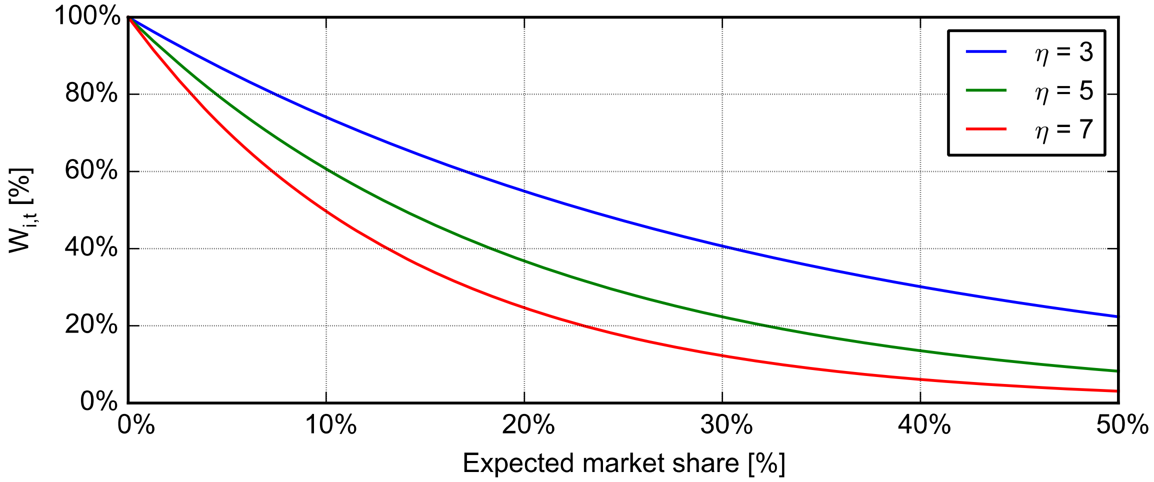

Fig. 51: Weighting function with different scaling parameters

As shown in Fig. 51 a higher scaling factor implies a relatively lower focus on market share and this effect increases with increasing market share in the left side of the plot. The main effect of increasing η on penetration of FCVs can be seen in Fig. 52: when producers focus more on income rather than on market share, as in the case with η = 7, they have a higher probability of switching and the penetration is clearly higher. This can be easily explained considering that, due to a lower capital productivity, producers can only manufacture a limited number of cars if they switch to FCVs and as a consequence they will have a lower market share after the switch. This is why, when the focus on market share is lower, the penetration is higher. Comparing the two cases with η = 7 and η = 3 in the shock tax scenarios we can furthermore distinguish two group of producers. The first group is represented by the ones with the highest market shares and highest capital availability, that switch during the first 5 years after the tax is introduced regardless of the scaling parameter value: these producers can most probably get enough capital through investment to maintain or even increase their market share after the switch (and are those that cause the increase in market concentration immediately after the introduction of the tax). The second group is made up of those producers whose market share would be decreased switching to FCVs: their decision to switch strongly depends on the value of the scaling factor and if they switch they only do it after year 2025 . It is very unlikely for them to switch when η = 3 but they almost always switch when η = 7, since a market share reduction is not so important in that case. The central case is halfway between these two extremes. In the gradual tax scenario a higher focus on market share almost completely hinders diffusion, while in the other two cases the behaviour is similar to that of the shock tax scenario.

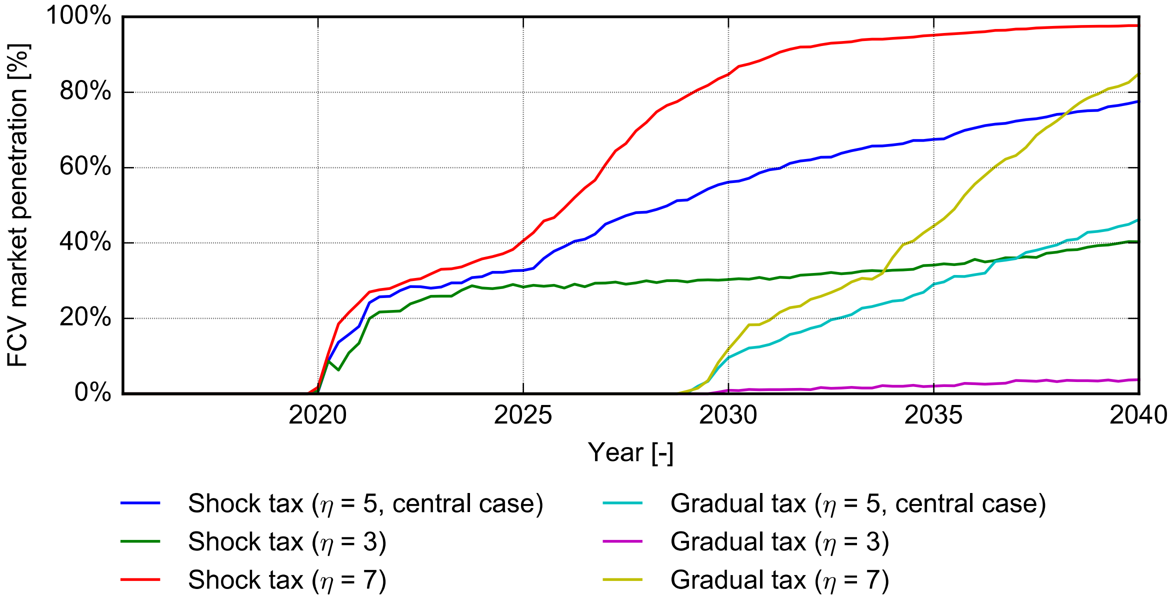

Fig. 52: Sensitivity analysis with respect to weight function scaling

6.5 Comparison with the original model

6.5.1 Differences in implementation

The implementation of this model is similar to the one described in (M. Schwoon, 2006), yet some of the assumptions about agent behaviour are different: in this section the motivations for these differences are explained and their effects on the model results are discussed.

First of all, the original version of the model considers the phenomenon of imitation among producers. This implies that when a producer has a very low market share, defined as being lower than half of the market share producers would have if market shares were equitably distributed, it imitates what the largest producer is doing: if it has already switched to FCVs, then the producer imitates the largest one regardless of what the value of the objective function would suggest. This simulates the cognitive process of imitation, used when the producer faces high uncertainty and part of the consumat approach and described in section 3.2.1. The threshold for imitation is half of the market share that the producer would have if customers were equally distributed among producers. Implementing this behaviour in the model causes, however, small producers to make the wrong choice and consequently an unjustified increase in market penetration of FCVs, and this is why imitation was not included. Analysing the market share of the largest producer across multiple runs it was possible to determine that the largest producer in the quarter before the tax is introduced is the one that is most likely to switch first and usually maintains the status of largest producer after the switch. At the same time, due to the introduction of the policy and especially in case of a shock tax, small producers suffer a loss of market share, that for some of them means reaching a value below the imitation threshold. As a consequence, if imitation is active, they switch to FCVs in the first three years after the policy introduction: when they do this they always perform worse than they would have done if they hadn't switched, indicating that they actually make the wrong choice. Fig. 53 shows this effect on the market penetration, comparing the shock and gradual scenarios without exogenous infrastructure growth in the cases with and without imitation. Here it is possible to see how, after about two years from the introduction of the shock tax, the penetration with imitation presents a sudden increase due to the small producers that switch. As expected, the general effect of imitation is a higher FCVs market penetration, since small producers, that would not have switched otherwise, start producing FCVs because of it.

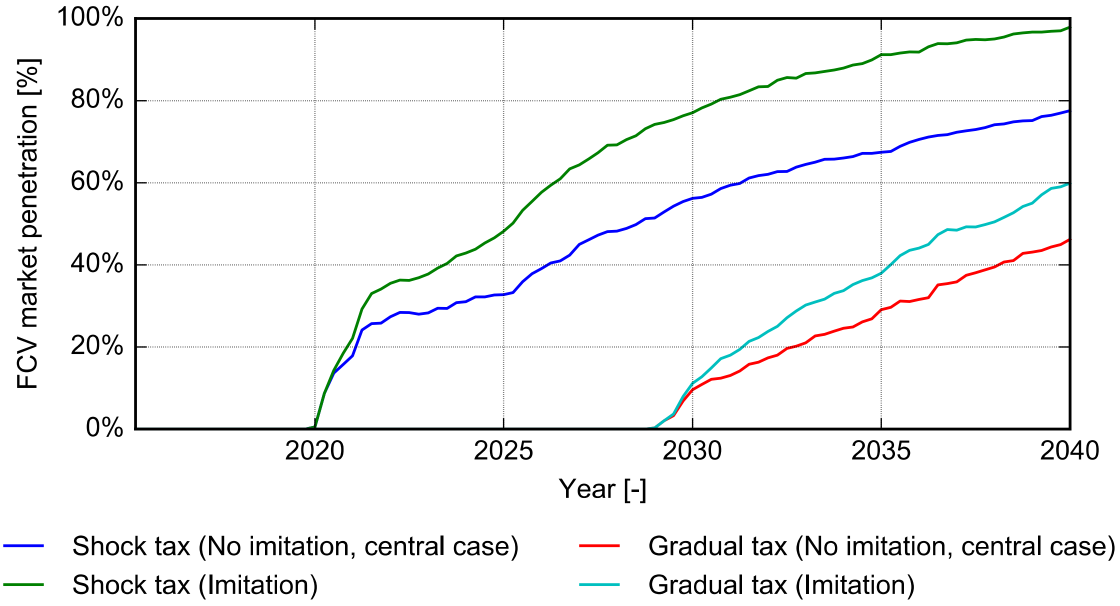

Fig. 53: Effect of imitation among producers on FCVs market penetration

Another change that has been made to the original model regards the way in which producers estimate the social need of their potential customers in order to evaluate the competitiveness of their car model. In the original model this was done assuming that the share of FCVs sold in the previous quarter could also be found in the individual customer's neighbourhood (referred to as optimistic approach): as discussed in section 3.3.2 this is rather unrealistic and causes producers to overestimate expected sales for FCVs. An approach in which the share of FCVs in the average neighbourhood is considered was used instead (referred to as realistic approach). In Fig. 54 the effect of the two prediction strategies on market penetration is shown: it is clear that the market penetration of the product is a lot faster in the optimistic approach, both in shock and gradual tax scenarios. This happens because all the producers overestimate the social need of FCVs and switch because of this. Now, it might be surprising that consumers buy FCVs regardless of the producers' wrong predictions, but it should be remembered that, due to the structure of the matching of supply and demand, consumers are forced to buy a new car when selected to do so and would even buy their least favourite car if that is the only one that is still available. This unrealistic behaviour implies that when one or two producers switch following the tax introduction the market penetration increases above zero and in the next quarter more producer will switch because of the increase in overestimated social need: this creates a very fast feedback loop that brings market penetration to 100% already after two years in case of a shock tax. In case of a gradual tax it can be gathered from the plot that this feedback loop is slower than the one in the shock tax case and this is caused by a smoother initial value of the market penetration slope.

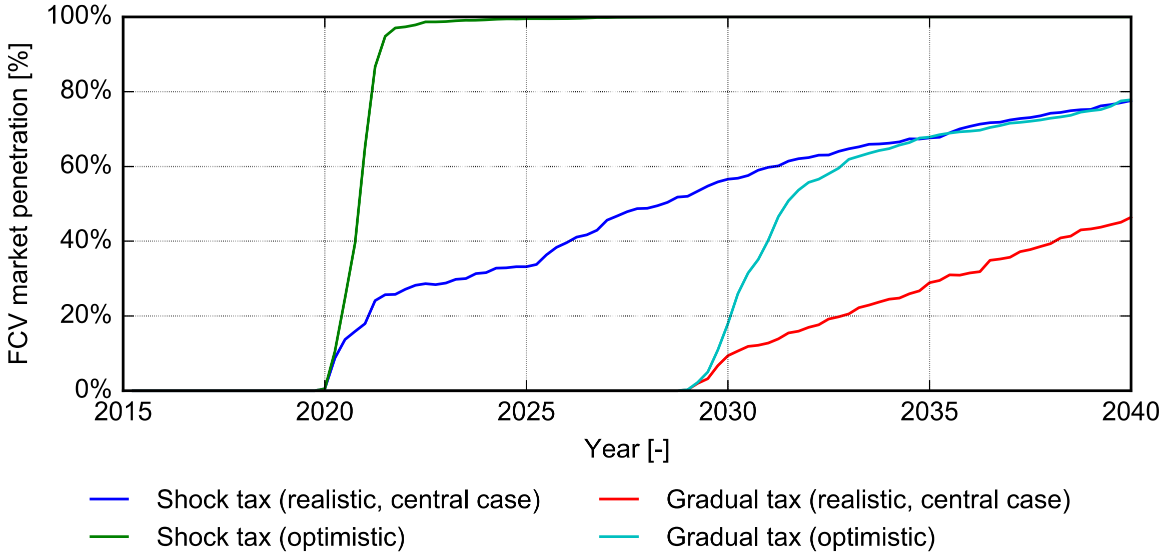

Fig. 54: Sensitivity analysis with respect to social need estimation method

Finally, in the original model, the phenomenon of social comparison, explained in the consumat approach section, is included in the sensitivity analysis. Social comparison has the effect of reducing the decision space of consumers if they experience high uncertainty, in that they only consider cars with the drivetrain technology that most of their neighbours use and the car on the market with the same brand as the one they already own. In order to calculate uncertainty they use the total expected utility of their old car and the one of the new one in formula (3): when the tax is introduced most of the consumers experience uncertainty due to a higher price for all the ICEVs on the market and some of them end up buying FCVs only because the producer that produced their old car is not producing ICEVs anymore. Social comparison should theoretically slow down the diffusion of FCVs, but in this particular case, due to the limitations of the model it actually ends up making it faster. Since this model behaviour is not justifiable social comparison was not included in the model. Its addition is only legitimate if producers have more than one production line, so that they can produce ICEVs and FCVs at the same time: in this scenario the consumers that do social comparison and then decide to buy the car of the same brand will not be forced to buy FCVs.

6.5.2 Differences in the results

Although most of the results obtained from the implemented model are in line with those presented in (M. Schwoon, 2006), there are some small differences worth mentioning. The main difference has been found in the switching behaviour of small producers: in the original model almost none of the small producers switches to FCVs in the tax scenarios and when some of them do this only happens when the market penetration of FCVs is rather high. On the contrary, in this implementation, the amount of small producers that do the switch is rather high. This phenomenon is particularly true for the case of the shock tax, in which small producers have a probability of switching within the first year after the introduction of the tax that is higher than 20%, as shown in Fig. 26. This difference in small producers' behaviour causes, in turn, a different trend of the Herfindahl index for the tax case: as shown by Fig. 27, after the initial peak that comes with the introduction of the tax the Herfindahl index goes down and then up again to end up having a similar value to the one of the corresponding gradual tax scenario. In the original model, on the other hand, there is a visible difference between gradual and shock tax scenarios, the latter ones having a higher Herfindahl index. This is a direct consequence of the different behaviour of small producers: they are not stuck with ICEVs and can now switch to FCVs. As a consequence, their market share does not suffer from the effect of the tax as much as it happens in the original model. This difference can be explained in terms of the initialization of the model, that is the only thing that is not thoroughly specified in (M. Schwoon, 2006). If, for example, a different assignment of the initial capital is used, in which the available capital is higher than the one producers need to cover current production, small producers would have extra capital available when the tax is introduced. Hence, having enough capital to cover the decrease in capital productivity, they are more likely to switch to FCVs.

6.6 Limitations of the model

Although the model captures the main dynamics of the FCVs diffusion process, it also presents limitations that constrain the conclusions that can be drawn from it.

The model only considers one segment of the German car market in order to guarantee comparability between different car models. It is generally agreed upon that buying decisions in different car segments are dominated by different factors: while for a small car the most important factors are size and price, for a luxury car status is more important. Nonetheless, cars of the small car segment could be considered substitutes of compact cars and this phenomenon is not considered in the model. Yet considering all these aspects requires simulating a multi-segment market that could complicate the model so much as to obscure the results.

In addition producers in the model only have the option of completely changing their entire production to FCVs and this is unlikely to happen in reality. This effect of the radical switch is partially mitigated by averaging the results over a large number of simulation runs. In order to relax this assumption more than one production line should be allowed for each producer so that cars with both drivetrain technologies can be manufactured simultaneously. This addition would require a way for producers to optimise the number of cars on two production lines, which is no trivial task.

Furthermore the model shows a high sensitivity with respect to the relative importance of price and fuel availability for consumers. Three crucial limitations exist at this level: the estimation of own price elasticity, the representation of the refuelling infrastructure growth and the perfect knowledge of consumers. As regards price elasticity, it has been discussed in section 5.1.4 how estimations from different sources provide a wide spectrum of possible values. The sensitivity analysis has then shown that this represents a crucial parameter in the decision of consumers and a variation of ±0.5 can lead to completely different results. As concerns the growth of the refuelling infrastructure it should be noted that, although CNG filling stations are the closest analogy, experience with a totally different fuel is absent. Investment costs to add hydrogen to an existing filling stations are likely to be a lot higher than the ones required to add CNG. Thirdly, consumers are assumed to have a perfect knowledge about prices and hydrogen infrastructure coverage. In the real world they might erroneously perceive coverage as being lower and prices of FCVs as being higher than they actually are. This phenomenon would cause a slower penetration compared to the one presented in the model results.

Another important limitation lies in the representation of the cost difference between the two drivetrain technologies. The costs considered in the model include both vehicle costs and fuel costs and the difference between FCVs and ICEVs is fixed during the simulation. Relaxing the first hypothesis means making assumptions about the price of hydrogen, which would probably change if this fuel is to be used in the transportation sector. The second one was relaxed in a later paper by the same author (Schwoon, 2008): in this work learning curves are added to the previous agent-based model to simulate reduction in costs that follows an increase in cumulated production quantity.

7 Conclusions

In this last chapter the main points of this master thesis project will be summed up and indications for future work on the model will be given.

7.1 Summary

In this master thesis an agent-based model based on (M. Schwoon, 2006) was implemented with the aim of demonstrating its use in analysing the diffusion process of fuel cell vehicles (FCVs) in Germany. The model was developed to gain insights into the dynamics of the system made up of car manufacturers (indicated as producers), consumers and refuelling infrastructure when a policy to foster the diffusion of fuel cell vehicles is introduced by the government. The analysed policies were a tax on internal combustion engine vehicles and a subsidy for fuel cell vehicles, coupled with different refuelling infrastructure development programs. Particular emphasis was laid on investigating possible negative effects that these policies could have on consumers and on the German automotive industry.

Agent-based modelling is a bottom-up modelling approach in which the behaviour of autonomous entities (indicated as agents) that make up a system and their interactions are simulated to study their effect on the system as a whole. The power to represent the heterogeneity of the actors and to capture their interdependence in a system makes agent-based modelling one of the best tools to study the problem at hand.

In the model, producers offer cars that are heterogeneous in terms of characteristics but can be considered close substitutes. In order to allow comparability between different car models the focus is restricted to one segment of the German car market and this segment is the one of compact cars. With 25% of sales, this is the largest car segment in Germany and consequently the one that would most likely generate enough demand for hydrogen if the diffusion of FCVs were successful. At the beginning of the simulation all producers sell internal combustion engine vehicles (ICEVs). During each quarter, each producer chooses the drivetrain technology and price for their cars that maximise a weighted average of expected income and expected sales, taking limited capital availability into account. As soon as FCVs are considered to be the best option the producer switches and will continue with FCVs production until the end of the simulation. The total demand for cars in one quarter is determined based on the average car price and the corresponding number of consumers is randomly selected to buy a car. Consumers evaluate each car on the market based on car features, price, social need and share of filling stations that sell the corresponding fuel. After that, they buy the car with the highest expected utility among the ones that are still available. When all the cars have been sold, the hydrogen refuelling infrastructure develops based on the share of FCVs in car sales.

The model was implemented using an object-oriented programming approach in the modelling environment Repast Simphony. A large part of the development effort was directed towards model verification, which was found to be one of the most important phases. Isolating producers and analysing the output of their production decision in varying conditions was crucial not only to make sure that there were no mistakes in the code, but also to gain a deeper understanding of their behaviour, which was in turn essential to interpret the behaviour of the model as a whole.

The model is run for 100 periods that represent quarters, corresponding to the timespan between 2015 and 2040, and the government introduces a policy in the year 2020. The policy can be either a tax on ICEVs or a subsidy for FCVs, and each one of them can be either introduced directly with its maximum value (shock) or increasing by 1% each quarter until the maximum value is reached (gradual). As regards the infrastructure three different scenarios were considered: in the base scenario the share of hydrogen filling stations increases in response to an increase in FCVs sales, while in the exogenous and high exogenous scenarios the government directly promotes a fixed amount of growth that is added to the endogenous one. The combination of three infrastructure scenarios with four different policies gives a total of twelve different cases that were analysed. The main benchmark to compare the different cases is the share of FCVs within the newly registered cars.

The model results are in line with those presented in (M. Schwoon, 2006). In all the analysed scenarios a successful FCVs market penetration can be observed, suggesting that the chicken-and-egg problem can be overcome with the help of policy. For all tax and subsidy scenarios the market penetration is always faster when the policy is of the shock type compared to the gradual one. The exogenous infrastructure build-up causes a faster penetration since the refuelling disadvantages of FCVs are reduced.

The fast penetration of FCVs in the market presents however some drawbacks when the effect on producers and consumers is observed. As regards producers, it is evident from the results of all tax scenarios that the policy emphasises the imbalances that were present in the market before its introduction: large producers can adapt better to the introduction of the policy and gain market share at the expenses of small producers, leading to an increase in market concentration. This suggests that small producers would probably oppose such a policy: if they had to choose one of the tax scenarios, however, they would prefer a gradual tax without infrastructure development, which is the one that damages them the least. In the case of a subsidy imbalances between large and small producers are a lot less severe than those in the tax case. Here, even small producers gain from the introduction of the policy, since an increase in demand brings higher profits.

As regards consumers, the introduction of a tax, be it shock or gradual, has the undesirable effect of increasing prices and causing a drop in demand: as a consequence consumers never gain directly from this type of policy. Subsidies, on the other hand, bring about lower prices and directly benefit consumers, besides fostering FCVs diffusion. Another important advantage of subsidies is that they do not cause any negative effects in case the market introduction fails, whereas all the disadvantages of a tax persist even if the diffusion of the new technology does not succeed. It should be remembered, however, that while taxes are collected from the government, subsidies have to be paid.

The sensitivity analysis, done only for the tax scenarios, showed that the results of the model are robust with respect to most of the parameters used. The results of the model show high sensitivity with respect to three parameters, namely the elasticity of demand

(ε_{own}), the amount of tax and the difference in variable costs between ICEVs and FCVs (Δc_v). The high sensitivity with respect to elasticity of demand and the amount of tax indicates that a subsidy would be a better choice if the knowledge of these parameters were not so accurate, in order to avoid the side effects of a tax besides the diffusion failure. The high sensitivity with respect to Δc_v points at one of the limitations of this model, namely the fact that the difference in variable costs between FCVs and ICEVs is taken as a constant. The constant difference rests on the assumption that cost reductions due to technological improvements and economies of scale have already been realised when the policy is introduced. The effect of cost reductions is however one of the most interesting dynamics that could be considered in future versions of the model.

Differences in implementation and results were present compared to (M. Schwoon, 2006). As regards implementation, a different and more realistic method was introduced in this model for producers to estimate the share of FCVs in the average consumer's neighbourhood, which caused slower diffusion. In addition, the process of imitation was not considered to avoid the linked negative effects on producers' performance. Concerning the model results a different behaviour of small producers was noticed: many more of them switch to FCVs compared to the original results. As a consequence the change in market concentration caused by the policy is more contained.

As shown by this master thesis, although the model presents several limitations, it also manages to capture the main dynamics of FCVs diffusion. Its analysis helped gathering insights into the effects that a policy would have on the car industry, showing who winners and losers would be. Experimenting with the model it became clear how subsidies could bring the same desired effects as a tax while limiting the drawbacks. Although none of these policies would be applied in such a simple way in reality, the study of these extreme cases opens a range of alternatives.

Having said this, it is very important to remind the reader of the proper interpretation of the results presented in this thesis. It should not be forgotten that the large number of parameters used, each of which rests upon assumptions and uncertainties, not to mention the simulation of human behaviour, restricts interpretation of the results to a qualitative level. Agent-based modelling is meant to increase the understanding that the modeller has about the system and not to make predictions: learning "what could go wrong" using a certain policy is, most of the times, the most precious piece of information the modeller can gather from it.

7.2 Future work

Considering the many parts the model is made up of, there are many possibilities for improvement or extension. Considering that a general-purpose agent-based model cannot work, any potential addition should be chosen with a specific question in mind. Here three suggestions are given: a more accurate description of consumer behaviour, producers with more than one production line and analysis of a more realistic policy.

Since this model focuses on the effect of policy on car manufacturers, the representation of consumers is simplified compared to the consumat approach (3.2.1). It follows that one improvement possibility is adding a more accurate representation of consumers' buying choices, using real car features as decision criteria or defining a lower threshold for total expected utility. The first option would give a specific meaning to car characteristics and would allow differentiating between FCVs and ICEVs features. This option requires either empirical work to calibrate the relative importance of different car characteristics in the buying process or to adapt the buying decision process to the data of an existing survey. The second option would make consumers' purchases more realistic, adding a minimum level of total expected utility in order to buy a car. In the current model selected consumers must buy a car that could be their least favourite if it is the only one available, while a real consumer would simply wait until the next quarter to get his favourite model. Yet, in order to relax this assumption, the way producers estimate sales should also be changed, taking a minimum value of utility into account. I should be considered however that both options present a risk: adding too much complexity on the consumer side could obscure model results. To compensate this, a simplification of producer's behaviour might be needed.

A second option is allowing car manufacturers to have more than one production line, so that they do not need to stop selling ICEVs when they start producing FCVs. This could allow for a more realistic representation of the behaviour of producers and to consider related consumer behaviours like social comparison. This addition transforms the production decision process in a multi-product pricing problem, which is in any case more complex than the current implementation.

Finally, the current model analyses tax and subsidy scenarios that represent extremes in the spectrum of policies and are not likely to be applied in reality as such. Another possibility for improvement is a policy scenario in which a high subsidy is initially applied for FCVs and the value of the subsidy decreases with time or based on the total number of sold FCVs. This scenario would be similar to what has been done in Germany with subsidies on solar panels. Yet, learning curves need to be implemented in the model in this case, so that the incentive can cause a reduction in costs and the sales of FCVs will not drastically drop when the subsidy decreases.

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List of figures

List of abbreviations

Abbreviation	**Meaning**
ABM	Agent-based modelling
CNG	Compressed natural gas
FCV	Fuel cell vehicle
GHG	Greenhouse gas
ICEV	Internal combustion engine vehicle
JRC	Joint Research Centre
RES	Renewable Energy Resources