Decarbonization with Induced Technical Change: Exploring the Niche Potential of Hydrogen in Heavy Transportation

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Abstract

Fuel cells and electric batteries are competing technologies for the energy transition in heavy transportation. We explore the conditions for the survival of a unique technology in the long term. Learning by doing suggests focusing on a single technology while differentiation and decreasing return to scale (cost convexity) favor diversification. Exogenous technical change also plays a role. The interaction between these factors is analyzed in a general model. It is proved that in absence of convexity and exogenous technical change, only one technology is used for the whole transition. We then apply this framework to analyze the competition between fuel-cell electric buses (FCEBs) and battery electric buses (BEB) in the European bus sector. There are both learning by doing and exogenous technical change. The model is calibrated and solved. It is shown that the existence of a niche for FCEBs critically depends on the speed at which cost reductions are achieved. The speed depends both on the size of the niche and the rate of learning by doing for FCEBs. Public policies to decentralize the socially optimal trajectory in terms of taxes (carbon) and subsidies (learning by doing) are derived.

Keywords: energy transition; learning by doing; fuel-cell electric vehicles; battery-electric vehicles; competing green technologies
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1 Introduction

The objective to achieve Net Zero Emissions by 2050 is now widely shared. In most sectors, several cleaner technologies are in competition, and their development requires huge investments. A key question for climate policies is the determination of which technologies to support. In this context, there are significant risks, such as making wrong decisions, firms delaying commitment due to the 'valley of death' phenomenon, and government agencies being captured by private interests (Rodrik, 2014). It is worthwhile to provide sound economic reasoning to throw some light on the stakes. This paper attempts to do so in the mobility sector.

In this sector, two prominent technologies are electric vehicles based on fuel cells or batteries. These two technologies require large and sunk investments in production facilities and charging infrastructure. A brief survey of past developments illustrates the significance of these investments and the difficulty in selecting a good strategy. For battery electric vehicles, a detailed evaluation of the celebrated Norway achievement by Figenbaum (2017) reveals that public support had started as early as 1990 and involved recurrent large subsidies for vehicles and infrastructure, but the demand remained sluggish until the middle of the 2010s. For fuel cell vehicles, the investment in infrastructure is particularly high and risky if demand does not materialize. Indeed, the profitability of hydrogen retail stations seems problematic in many areas Hydrogen Insight (2023). Which technology will eventually dominate on which market segment remains an open question.

The costs of low-carbon technologies are expected to decrease along their deployment paths thanks to learning by doing, which would justify focusing on one technology. In contrast, market differentiation and decreasing returns to scale (cost convexity) favor diversification. This paper investigates these intricate issues through a dynamic partial equilibrium model, discussing conditions for the survival of only one technology in the long term in a general framework. We then apply the model to the European bus market for the competition between battery-electric buses (BEBs) and fuel-cell electric buses (FCEBs).

The choice of focusing on BEBs and FCEBs in our model over other less polluting alternatives to diesel, such as Compressed Natural Gas (CNG), Liquefied Natural Gas (LNG), synthetic fuels, and biofuels, is primarily driven by their greater potential for significant greenhouse gas emissions reduction in the bus sector, as highlighted in Chapter 10 of IPCC (2022). While alternatives like CNG and LNG offer some emissions benefits, they do not contribute substantially to decarbonization goals and might impede the adoption of zero-carbon options. Synthetic fuels, although promising in reducing emissions, are currently hindered by high production costs and lower energy efficiency compared to electric vehicles. Biofuels, despite being a credible alternative, face complexities related to land use, environmental impact, and production costs. In contrast, BEBs and FCEBs, both characterized by negligible tailpipe emissions, represent a more direct route towards achieving stringent decarbonization targets in the transport sector. Additionally, the debate between FCEVs and BEVs is a well-established topic in transportation and economic literature, particularly in the bus market, underscoring the relevance of this comparison in a model assessing competing low-carbon technologies. This paper aims to determine the critical factors for the existence of a niche for FCEBs.

BEBs are currently leading the transition, progressively closing the gap with the total cost of ownership (TCO) of diesel vehicles. Thanks to quick progress in lithium-ion battery technology (Schmidt et al., 2017), the global increase in production volume has lowered battery unit costs and increased the implementation of subsidies in many countries (IPCC, 2022). According to International Energy Agency (2021), over 600,000 battery-electric buses were on roads worldwide in 2020, demonstrating that BEB deployment has been effective for some years. FCEBs are currently one of the most expensive bus options, mainly because of the higher capital expenditure of the vehicle itself (IPCC, 2022); however, research and development (R&D) efforts around fuel cells and cost reductions associated with mass production (IPCC, 2022) could make FCEBs cost-competitive with BEBs. FCEBs benefit from a much shorter refueling time and more extended autonomy, especially in rough topographic and weather conditions (International Energy Agency, 2019). These advantages give an edge to FCEBs for some uses. International Energy Agency (2019) estimated the total fleet of FCEBs at 500 units worldwide in 2019, with at least 11 manufacturers. In Europe, the two programs under the Joint Initiative for Hydrogen Vehicles across Europe have financed the deployment of approximately 300 FCEBs from 2017 to 2023 (Meunier et al., 2022).

We model the transition of a fleet of vehicles in a dynamic setting, where non-emitting "green" vehicles should replace a given number of polluting ones. Two green technologies are considered, the costs of which decrease thanks to learning by doing (i.e., depending on cumulative volumes) and exogenous technical change (i.e., depending on calendar time). The social cost of carbon (SCC) grows at the discount rate, and the social planner minimizes the discounted cost of the fleet, including pollution. In section 2, we analytically characterize the optimal deployment path for both technologies (Proposition 1). We elucidate the impacts of convexity and learning by doing on deployment paths, demonstrating that only one green technology will be selected if costs are linear and there is no exogenous technical change (Proposition 2). This illustrates how learning by doing encourages specialization in one technology: with linear costs, it is most effective to deploy only one technology to maximize the speed of endogenous cost reduction. The optimal trajectory is fully derived under a linear cost specification, integrated with a standard learning by doing formulation (Proposition 3). This clarifies that the decision between two green technologies hinges on comparing not only their short-term and long-term costs but also the rate of cost reductions. This rate is influenced by the learning rate and the market size. A technology with higher short-term costs should only be chosen if its long-term costs are lower and the rate of cost reduction exceeds a specific threshold.

In section 3 we apply this framework to investigate the transition of the European bus sector. A number of specific assumptions are introduced. Most importantly there are two market segments. In the main market, BEBs have a cost advantage in both the short and long term. In the niche market, BEBs are cheaper in the short run but more expensive than FCEBs in the long run. This cost structure implies that the main market is favorable to BEBs while the niche market is potentially favorable to FCEBs. We introduce inertia in the early deployment phase (convexity at low production rates), learning by doing and exogenous technical change so that Proposition 3 does not hold. The optimal deployment trajectory is derived numerically. Clean buses are deployed on different dates in the main and niche markets. Ordinarily, it is optimal to deploy BEBs immediately in the main market; whether FCEBs or BEBs should occupy the niche in the long run depends on the calibration of the model. If FCEBs are eventually deployed in the niche, they will occupy the whole niche in the long run.

With the baseline calibration, FCEBs should be deployed in the niche market. The transition of 180,000 diesel buses in Europe to 80% BEBs and 20% FCEBs requires incremental financial costs of 34.8 billion euros (EUR) and will exhibit 27.4 million tons (Mt.) of carbon dioxide (CO_2) emissions until completion. The optimal launch date of FCEBs is 2030, and their deployment will be completed in 2040, ending the whole transition. A transition solely based on BEBs would cost (including emissions) an additional 0.8 billion EUR breaking down into 0.9 billion EUR additional costs in the niche market but a gain of 0.1 billion EUR in the main market due to learning spillovers from the niche. We further investigate the role of technical change and its two channels. Without technical change, only BEBs are used, doubling the transition cost. Whether the technical change is entirely exogenous or endogenous implies different deployment strategies. We also investigate the influence of three key parameters on the deployment of FCEBs: the cost penalty of BEBs in that niche, the size of the niche and the rate of technical change.

The present work is related to the economic literature on induced technical change and climate policy. This literature is vast and mostly concerns replacing a polluting technology with a green one. For instance, Grimaud and Rouge (2008) and Acemoglu et al. (2012) consider endogenous growth models where a final good is produced using polluting and clean sector inputs. In this context, the primary issue is to direct research toward the clean sector in the most efficient way. A recurrent criticism of marginal abatement cost is the lack of integration of dynamic effects (Gillingham and Stock, 2018). In presence of technical change Goulder and Mathai (2000) characterize how learning benefits should be introduced in the abatement cost all along the deployment trajectory of the clean technology. Creti et al. (2018) provide a practical procedure to integrate the future learning benefits into the computation of the abatement cost of a given trajectory of a fleet of vehicles.

The role of network effects in the energy transition has also been studied. Learning by doing shares similarities with network effects, whether direct or indirect. In both cases, the cost of a technology decreases with the number of users. If network effects are sufficiently strong it can imply multiple equilibrium and a risk of lock-in at a suboptimal equilibrium. Farrell and Klemperer (2007) explore the implications of network effects on industry equilibrium and the risk of lock-in. In the transportation sector, network effects describe situations in which a user's utility is affected by the number of users. Indirect network effects occur through a complementary good (e.g., stations), the supply of which increases with the number of users of the primary good (e.g., vehicles). Indirect network effects may arise from the interaction between the fleet and the refueling network. The deployment of clean vehicles might be hindered by a chicken-and-egg problem: there are few clean vehicles because there are few charging stations and vice versa. These network effects might justify additional subsidies to install a critical mass of stations, to overcome the chicken-and-egg problem, and complement carbon taxes. This issue has been investigated formally by Greaker and Heggedal (2010); Meunier and Ponssard (2020); Greaker (2021) and empirically by Zhou and Li (2018) with a single technology.

Competition among green technologies subject to learning-by-doing or network effects has only been studied in few articles. Cost convexity and market differentiation are key in the results. Kverndokk and Rosendahl (2007) consider a dynamic setting with learning by doing and two green technologies with different degrees of maturity. The authors analyze how a myopic policy, which only supports a mature existing green technology, slows down the deployment of the green "challenger" technology. In their setting, the two green technologies coexist, because of convex investment costs. Bramoullé and Olson (2005) also analyze whether only one or two abatement technologies subject to learning by doing should be used in a dynamic setting. Contrary to us, in their model, green technologies do not compete in the same market. Consequently, the two technologies might be jointly deployed even with linear costs in their setting, contrary to ours. Andreassen and Rosendahl (2022) analyze the issue of co-existence of two green technologies (hydrogen and battery) in the transportation sector. They consider imperfect substitution and indirect network effects related to the charging infrastructure. The fact that consumers value the density of the charging infrastructure induces a form of scale economies that pushes for using only one technology. They show that both technologies should be deployed only if they are sufficiently differentiated. This result aligns with the ones obtained in our illustration for the bus sector, though cost and consumer preferences are modeled differently; the analysis in Andreassen and Rosendahl (2022) is static, while ours is dynamic.

From a public policy perspective, the present paper provides some ground for local and national authorities to design efficient public support. First, we must identify the conditions for a hydrogen niche in the bus sector. Most techno-economic studies on the cost-effectiveness of the hydrogen bus sector rely on Total Cost of Ownership (TCO) analysis, examining the breakdown of costs associated with vehicle use, such as Capital Expenditures (CAPEX), Operational Expenditures (OPEX), and fuel costs. An increasing number of studies have been conducted by research organizations (e.g. Baccelli, 2021; ADEME, 2018; Loszka et al., 2022) and international organizations (e.g. International Energy Agency, 2019), providing current and sometimes future estimates of TCO for these vehicles. A significant limitation of these studies is their failure to consider factors that determine the sustainability of the niche identified in our analysis: (1) the short-term and long-term costs; (2) the relationship between the speed of cost reduction and the trajectories of technology deployment; and (3) the bus market segmentation influenced by the relative advantages of each technology.

Finally, several studies compare the benefits of deploying Fuel Cell Electric Buses (FCEBs) and Battery Electric Buses (BEBs). Most of them evaluate different technological options in terms of environmental benefits (Logan et al., 2020), particularly at the local level in a specific geographical area (Stempien and Chan, 2017; Jelti et al., 2021). Notably, Karlström (2005) indicates that while the environmental advantages of fuel cell buses in Sweden were modest compared to their costs in 2005, mass production could change this results. Moreover, Siddiqui et al. (2024) introduce a social dimension to standard cost-benefit analysis in public transportation. Other studies comparatively assess BEBs and FCEBs, examining technology adoption. Wang et al. (2023) proposes a discrete choice model between FCEBs and BEBs and test the impact of policy, such as subsidies for hydrogen buses or support to hydrogen station, on the adoption of cleaner technologies. Hensher et al. (2022) highlights the potential for emission reductions and the cost implications of transitioning to different bus fleets, either BEBs or FCEBs, across various scenarios. Our analysis, differing from typical environmental studies, centers solely on direct emissions. Unlike these studies, we propose a dynamic analysis where the costs of technologies evolve depending on the choices made in adopting these technologies. This approach provides a different perspective on the long-term policy implications of transitioning to cleaner bus technologies.

This paper is organized as follows. Section 2 introduces the general model and provides some theoretical results. Section 3 presents additional assumptions to make the model more relevant for analyzing the bus market, and the completed model is calibrated, which indicates a niche for FCEBs exists. An extensive sensitivity analysis is made to test the robustness of this result. Section 4 discusses policy implications, and Section 5 concludes.

2 From one to two green technologies: some analytical results

2.1 The general framework

This section focuses on the case of one market segment and extends two propositions obtained by Creti et al. (2018) from one to two green technologies. This is an interesting benchmark to study the case of two market segments explored in the simulation section.

We consider a dynamic model of substituting a dirty, polluting technology with two clean technologies subject to learning by doing and exogenous technical change. We start with a general formulation before studying a specification better adapted to the bus sector.

Time is continuous, going from $t = 0$ to $t = +\infty$. There is an inelastic demand for N vehicles at all times. Three technologies are available: a dirty one and two green ones, denoted $i = 1, 2$. At time t, $x_{i,t}$ green vehicles are produced with technology $i = 1, 2$, and the remaining $N - x_{1,t} - x_{2,t}$ are produced with the dirty technology. Units are normalized so that a dirty vehicle emits one unit of CO_2 per unit of time.

The cost of dirty vehicles is assumed to be constant and normalized at zero. The cost of a green vehicle is decreasing with respect to the stock of units produced at time t (learning by doing) and with respect to time (exogenous technical change). It is increasing and convex with respect to production. The accumulated production with technology $i = 1, 2$ is $X_{i,t} = \int_0^t x_{i,u} du$, and its cost function $C_i(X_{i,t}, x_{i,t}, t)$. It is assumed to be non-negative, decreasing and convex with respect to $X_{i,t}$, and increasing and convex with respect to $x_{i,t}$. The marginal cost is decreasing with respect to time. A last assumption required is that $\partial C_i / \partial X$ is concave with respect to x. It means that the effect of accumulated production on the marginal cost is increasing with respect to the quantity produced.

The social discount rate is denoted r. The social cost of carbon at time t is denoted p_t^{CO2} and assumed to grow at the rate r, i.e $p_t^{CO2} = p_0 e^{rt}$ which is efficient in the presence of a carbon budget according to Hotelling's rule.

The social planner aims to minimize the discounted cost of operating the fleet of N vehicles. Let Γ denote this cost; it is as follows:

$$\Gamma = \int_0^{+\infty} e^{-rt} \left\{ p_t^{CO2} N - \sum_{i=1,2} \left[p_t^{CO2} x_{i,t} - C_i(X_{i,t}, x_{i,t}, t) \right] \right\} dt \tag{1}$$

to be minimized under the following constraints:

$$\dot{X}_{i,t} = x_{i,t},\ X_{i,0} = 0,\ x_{i,t} \geq 0 \text{ for } i = 1, 2 \text{ and } x_{1,t} + x_{2,t} \leq N.$$

A first proposition holds regarding the phasing of the transition from dirty vehicles to green ones. It is a direct consequence of the increasing total cost of dirty vehicles since p_t^{CO2} goes to infinity with t.

Proposition 1 *Denoting* $(x_{1,t}^*, X_{1,t}^*)$ *and* $(x_{2,t}^*, X_{2,t}^*)$ *the optimal productions and stocks along the optimal deployment trajectory, there exist two dates,* T_{in} *and* T_{out}*, such that three deployment phases can be identified:*

$$\begin{aligned}
&\textbf{\textit{Pre-transition phase :}} \quad \textit{for } 0 \leq t \leq T_{in} \textit{ we have } x_{1,t}^* = 0 \textit{ and } x_{2,t}^* = 0 \\
&\textbf{\textit{Transition phase :}} \quad \textit{for } T_{in} < t < T_{out} \textit{ we have } 0 < x_{1,t}^* + x_{2,t}^* < N \\
&\textbf{\textit{Post-transition phase :}} \quad \textit{for } t \geq T_{out} \textit{ we have } x_{1,t}^* + x_{2,t}^* = N.
\end{aligned}$$

The proof is given in Appendix A. Only qualitative aspects of the transition can be assessed without further specifying the cost functions. The three key aspects of cost functions are learning by doing, convexity, and exogenous technical change.

Learning by doing, or, more generally endogenous technical change, is at the root of the policymaker's difficulty. We use "learning by doing" and "endogenous technical change" indifferently to refer to the reduction of cost with respect to the total accumulated production, even though a number of phenomena can explain that relationship, not only learning by doing but also learning by using, R&D, direct and indirect network effects (investment in complementary infrastructure). Indeed, not all those mechanisms call for a subsidy, only the spillovers from one firm to the other require a subsidy. It induces a form of scale economies that explains that the choice between the two technologies might necessitate comparing competing whole trajectories. The conditions satisfied along the trajectory provide a preview of that issue that will be further investigated.

During the transition phase, if a green technology $i = 1, 2$ is used, the marginal cost is equal to the carbon price plus the learning benefits (arguments are omitted to alleviate notations):

$$\frac{\partial C_i}{\partial x} = p_t^{CO2} - \int_t^{+\infty} e^{-r(\tau - t)} \frac{\partial C_i}{\partial X} d\tau. \tag{2}$$

It is a well-known result in the literature on learning by doing that learning benefits (last term above) should be taken into account when deciding to produce, it is not specific to climate policy (Thompson, 2010).

In our scenario of competing green technologies, a key dilemma emerges: if there is an anticipation that a technology will not be deployed, the absence of learning benefits and potentially high marginal costs might prevent its deployment. This risk is less pronounced with only one technology, as it will eventually be deployed. However, with two technologies, there is a significant risk of lock-in on the wrong technology. Several local optima may exist, some of which may involve only one technology being deployed. Therefore, it is crucial for policymakers to accurately identify and select the most effective technology before fine-tuning its deployment. The multiplicity of local optima reflects the potential multiplicity in market equilibrium.

During the post-transition phase, if both technologies are used, the allocation of N among the two technologies is described by the following equation:

$$\frac{\partial C_1}{\partial x} - \frac{\partial C_2}{\partial x} = \int_t^{+\infty} e^{-r(\tau - t)} \Big[\frac{\partial C_2}{\partial X} - \frac{\partial C_1}{\partial X}\Big] d\tau \tag{3}$$

Equation 3 illustrates the key difference between our work and Bramoullé and Olson (2005); the two green technologies are competing for the same market, and increasing the production of one requires reducing the production of the other and losing the associated learning benefits. Market shares of the two green technologies evolve during that phase. One technology might be only temporarily used before being phased out of the market, while the other progressively moves down the learning curve.

Finally, learning by doing is also a possible justification for subsidizing a technology for two reasons. First, the market might imperfectly internalize learning, spilling from one firm to another. Second, as mentioned, it is also a kind of scale economy that might induce a lack of profitability along the optimal path and a need for compensation. As no demand function exists, the price is not explicitly determined; however, one can assume it is equal to the cost of the marginal technology. According to the principles of Pigouvian taxation, if producers do not internalize learning benefits, the optimal transition can be decentralized by combining a Pigouvian tax on emissions with a subsidy for learning benefits. This subsidy should be set equal to

$$s_{i,t} = -\int_t^{+\infty} e^{-r(\tau - t)} \frac{\partial C_i}{\partial X}(X_{i,\tau}, x_{i,\tau}, \tau) d\tau \tag{4}$$

Convexity of the cost function, with respect to production, is necessary for both a progressive transition and the coexistence of green technologies. Convexity can be due to the scarcity of some inputs or limited production capacity. It can also be related to some demand side aspects; if the user cost of a technology varies among users, it is *as if* the cost of the technology is convex.

With convexity and without learning, along the transition, the marginal cost of both technologies is equal to the SCC, and the deployment is progressive until all units are clean.

The transition is immediate without convexity, and only one green technology operates at each date; if there is no exogenous technical change, only one technology is used. The cost of the whole transition with each should be compared to assess which technology should be deployed. It is done in the next section for a specific case.

Proposition 2 *If cost functions are linear, $\partial C_i / \partial x^2 = 0$: the transition phase is instantaneous, i.e., $T_{in} = T_{out}$.*

Furthermore, if the cost functions are time-independent ($\partial C_i / \partial t = 0$) only one technology is used for the whole transition, and the other is never used.

The proof is in Appendix B.

Exogenous technical change plays an important role in our study of the bus market because some reductions of costs will likely originates from the deployment of battery and hydrogen in other markets.

Analytically, exogenous technical change is materialized in the model through the dependence on t of the cost functions $C_i(X_{i,t}, x_{i,t}, t)$.This dependence is not easy to handle, even with a simple specification. For instance, with exogenous technical change and without learning or convexity, multiple switches between technologies may occur along the optimal path, as illustrated in Appendix C with a simple function. Unlike learning by doing, exogenous technical change has relatively light policy implications since the policymaker has only to wait for the cost to decrease.

2.2 Solving a specific case: absence of both convexity and exogenous technical change

As mentioned above, convexity in the cost functions plays a key role in intertwining the joint deployment of the two green technologies. It also greatly complicates the resolution of the analytical model. To get some insights, we consider here two technologies with neither convexity nor exogenous technical change. This section draws on Meunier and Ponssard (2022).

Let us consider the cost functions of the form:

$$C_i(X_{i,t}, x_{i,t}) = [\underline{c}_i + (\overline{c}_i - \underline{c}_i)e^{-\lambda_i X_{i,t}}]x_{i,t} \tag{5}$$

For $i = 1, 2$, the parameter λ_i represents the learning rate of technology i, and $\underline{c}_i$ and $\overline{c}_i$ are the short-term and long-term marginal costs, respectively.

As shown in Proposition 2, the transition is instantaneous and involves only one of the two green technologies. Proposition 3 describes which technology should be selected.

Proposition 3 *With the specification (5) of the cost functions, the optimal technology to be selected is the one that would have the earlier launch date.*

Proof. T_i is the date at which technology i would replace all polluting vehicles if it is used. K_i is the discounted cost of the post-transition phase of a fully clean fleet; it is as follows:

$$K_i = \int_0^{+\infty} e^{-rt} C_i(tN, N)dt = \underline{c}_i \frac{N}{r} + (\overline{c}_i - \underline{c}_i)\frac{N}{r + \lambda_i N}$$

The total discounted cost with technology i is Γ_i:

$$\Gamma_i = \int_0^{T_i} e^{-rt} P_t^{CO2} N dt + e^{-rT_i} K_i$$

which is minimized for T_i such that

$$P_0^{CO2} e^{rT_i} = \frac{rK_i}{N}.$$

which implies that at the optimal launch dates (using Hotelling's rule):

$$\Gamma_i = p_0^{CO2} N T_i + p_0^{CO2} \frac{N}{r}.$$

The second term of this latter expression is independent of the technology, and the first term gives the social cost of emissions until the optimal launch date. ■

Observe that
$$\frac{rK_i}{N} = \overline{c}_i \frac{r}{r+\lambda_i N} + \underline{c}_i \frac{\lambda_i N}{r+\lambda_i N}$$
may be seen as a weighted average between two static marginal abatement costs: one with the short-term marginal cost $\overline{c}_i$, and another one with the long-term $\underline{c}_i$. The weights depend on the speed of cost reductions that is, the rate of LBD λ_i times the size of the market N relative to the discount rate. The higher the speed, the lower rK_i/N, which eventually converges into the static long-term abatement cost. On the contrary, if the speed is null, it coincides with the standard short-term marginal cost, whatever the size of the market. Altogether Proposition 3 states that the technology with a higher short-term cost should be selected if and only if its long-term cost is lower and its speed for cost reductions is above a certain threshold.

These results also illustrate the potential for lock-in in the wrong technology. There are an infinite number of possible transitions. The first-order conditions do not characterize a unique optimum but rather two local optima, each deploying only one technology. This leads to a risk of lock-in at each of these local optima, making it essential to compare them for the best decision. Additionally, the issue of path dependency arises: if the a priori sub-optimal technology has been utilized for a sufficiently long time, it might become optimal a posteriori once its current cost has been sufficiently reduced through learning by doing. If technology i has been used for T years, the future discounted cost of using it is $K_i(T) = \underline{c}_i \frac{N}{r} + (\overline{c}_i - \underline{c}_i) e^{-\lambda_i T N} \frac{N}{r+\lambda_i N}$ which could become lower than K_j, which could become lower than K_j after a sufficiently long time T.

3 A deployment perspective for BEBs vs FCEBs

The analytical framework is used to analyze the competition between BEBs and FCEBs in a niche market. Additional assumptions are introduced; most notably, the bus sector is divided into a main market and a niche market. A discrete version of the previous dynamic model is calibrated and solved numerically. The results obtained with the baseline calibration are presented, and a sensitivity analysis of the key parameters is conducted. Finally, implications for public policy are derived in the last part.

3.1 Additional assumptions

Specification of the cost function In the numerical application, the cost function is specified as follows:

$$C_i(Z,z,t) = (\underline{c_i} + \overline{c_{endo,i}} e^{-\lambda_i Z} + \overline{c_{exo,i}} e^{-\mu_i t}) z \text{ for } i \in \{BEB,\ FCEB\} \tag{6}$$

with $\overline{c_{endo,i}}$ the potential of endogenous cost reduction, i.e., costs that can be nullified thanks to learning by doing, and $\overline{c_{exo,i}}$ the potential of exogenous cost reduction, i.e., costs that will be nullified over time independently of production, thanks to spillovers from other markets. Thus, $\overline{c_i} = \underline{c_i} + \overline{c_{endo,i}} + \overline{c_{exo,i}}$ is the short-term marginal cost of technology i and $\underline{c_i}$ the minimal achievable cost for technology i.

This function is linear with respect to production, implying an unrealistic sudden transition of one technology on the whole market. Two additional features are introduced to model the imperfect substitution between green technologies and the inertia of the transition.

Imperfect substitution of technologies FCEBs have a longer range and a shorter refueling time than BEBs. Uneven topographical landscapes, such as mountains and extreme temperatures, also represent advantages for FCEBs (Meunier et al., 2022). These advantages translate into additional costs for BEBs for some usages, either in terms of opportunity cost (the recharging time of the electric vehicle) or the number of vehicles (more than one BEB or more powerful batteries are needed to replace a single FCEB operating on a long route). This suggests introducing horizontal differentiation between technologies. To simplify, we consider two types of users: the total number of buses N is the sum of N_{main} standard users and N_{niche} niche users, with $N_{main} > N_{niche}$.

- **Main market segment** N_{main}: The cost of the two technologies is given by Equation (6). BEBs are less expensive than FCEBs on this segment; that is, $C_{BEB}(Z, z, t) < C_{FCEB}(Z, z, t)$ for all Z, z.
- **Niche market segment** N_{niche}: For N_{niche} niche users, the cost of BEBs is higher than in the main market. The cost of FCEBs is still C_{FCEB} and the cost of BEBs is $C_{BEB} + d$ with $d > 0$ the cost penalty for BEBs in the niche market.

The cost penalty d of BEBs on the niche market plays a central role in our numerical investigation. For some values of d to be determined, it may be beneficial to launch FCEBs in the niche market.

Exogenous transition duration: A form of inertia in the deployment of green buses is introduced, modeled by a constraint on the time derivative of the production of low-carbon technologies. This approach is equivalent to imposing that the deployment time of the green technology i from zero to the entirety of one of the two markets is D_i. The technology deployment trajectory is assumed to be linear for simplicity and is related to the technology and not the market segment. We assume more inertia exists in the transition with FCEBs than with BEBs, $D_{BEB} < D_{FCEB}$. The inertia constraint is defined in Appendix D.

3.2 Two types of optimal strategies

A discrete dynamic optimization problem is solved with the Python package "Pyomo" to determine the optimal transition. The code is available upon request to the authors. This corresponds to a discretized version of problem (1), to which the above-mentioned additional assumptions are added. The time horizon for this optimization is 100 years. The explicit minimization program is detailed in Appendix D.

The parameters of this optimization program are calibrated in the next section. Within the scope of eligible values for these parameters, some deployment strategies cannot be optimal.

FCEBs are never deployed in the main market and are never used temporarily in the niche market. Consistently with Proposition 2, only one technology is used in the niche in the long run, even though the deployment pace constraint explains temporary coexistence in some cases. The optimal transition will be of one of two types: B-B or B-FC (representing the long-run combination of technologies in the main and the niche market).

- **B-B type**: BEBs are used in both the main and the niche markets. FCEBs are never used.
- **B-FC type**: BEBs are used on the main market. FCEBs are used on the niche market. BEBs might be used temporary on the niche market.

These two types of strategies schematically represent the two possible options in the presence of several competing green technologies. As stressed in Section 2, with linear costs, only one technology is used in each market segment in the long run.

The first option focuses on a single technology to maximize learning by doing, even if it means using it for less appropriate uses. The second is the diversification strategy, where technologies are adopted to meet user needs. It is worth stressing that the long-run market share of FCEBs does not evolve continuously concerning the various parameters. In the long run, FCEBs either occupy the whole niche or are not used at all.

3.3 Calibration

We distinguish between two sets of parameters depending on their influence on the result, given the underlying uncertainty on their calibration. The first set (the basic ones) remains unchanged over the simulation. The second set (the key ones) is used to test the robustness of the results through a sensitivity analysis.

3.3.1 Basic parameters

Table 1 gives the numerical values of the basic parameters for this market: the constant average TCO for diesel buses c_0, the short-term marginal cost $\overline{c_i}$ for BEBs and FCEBs, the total market size N, the discount rate r, and the SCC of a diesel bus p_0. The latter is derived from the CO_2 emissions of a diesel bus per kilometer and the social cost, both of which are reported in Table 1. The social cost of local pollution of a diesel bus is also reported; the reference year is 2020.

We now further detail the calibration for the parameters and the corresponding sources.

Market size Based on data from the European Automobile Manufacturers' Association (ACEA) (2021) and Ministère de la transition écologique (2021), we estimate the number of medium and heavy city-bus registrations in the European Union to be 12,000 in 2020. We assume that these registrations correspond to the number of buses built for the European market and that this number remains stable over time. Although the number of registration includes all types of city buses (8m, 12m, and 16m), we assume that the distribution of buses is centered around the 12m bus so that it is possible to study the average cost of the fleet from the cost of the 12m bus.

Basic parameters	**Value**
Market size N (volume of vehicles)	12 000
Cost of diesel vehicles (c_0) (EUR /km)	0.9
Short-term marginal cost of FCEBs $\overline{c_{FCEBs}}$ (EUR /km)	2.2
Short-term marginal cost of BEBs $\overline{c_{BEBs}}$ (EUR /km)	1.1
Discount rate r (%)	4.5
Tank-to-wheels emissions of diesel buses ($tC0_2$/100km)	0.09
Social cost of carbon in 2020 (SCC) (EUR /$tC0_2$)	160
Social cost of carbon in 2020 per diesel km (p_0) (EUR /km)	0.15
Social cost of local pollution per diesel km (p_{loc}) (EUR /km)	0.2

Table 1: Estimated values for basic parameters

Cost of vehicles The cost of vehicles corresponds to the Total Cost of Ownership (TCO) of the buses for the different technologies in 2020. The TCO takes into account fixed capital, maintenance, fuel and charge without tax. The estimated values are the authors' estimates based on the following sources: public reports (International Energy Agency, 2019; Baccelli, 2021; ADEME, 2018; Commissariat Général au Développement Durable, 2018; Loszka et al., 2022; Meunier et al., 2022) and interviews of experts. These data are summarized in Table 2.

	Diesel	FCEB	BEB
Fixed capital (EUR/km)	**0.3**	**0.7**	**0.6**
Corresponding purchase price (EUR)	250 000	500 000	450 000
km/year	50 000	50 000	50 000
life duration (year)	15	15	15
Maintenance (EUR/km)	**0.3**	**0.4**	**0.2**
Fuel & charge (no tax) (EUR/km)	**0.3**	**1.1**	**0.3**
Levelized cost of fuel (EUR/L, kgH2 or kWh)	0.8	8.0	0.10
Levelized cost of infrastructure (EUR/L, kgH2 or kWh)	-	5.0	0.05
Unit price at pomp (EUR/L, kgH2 or kWh)	0.8	13.0	0.15
Consumption (L, kgH2 or kWh per 100km)	46.0	9.0	160.0
TCO (EUR/km)	**0.9**	**2.2**	**1.1**

Table 2: Total cost of ownership (TCO) components of a fuel-cell electric bus (FCEB), battery-electric bus (BEB) and diesel bus in 2020

Social discount rate and social cost of carbon The calibration is based on values discussed in Quinet et al. (2019). The social discount rate is taken at 4.5%. The SCC for 2020 is valued at 88 EUR/tCO_2; however, it does not grow at the social discount rate. We keep the Hotelling assumption and use a value for the SCC in 2020 at 160 EUR/tCO_2, in line with a value of 250 EUR/tCO_2 in 2030 as established in the economic models reported in Quinet et al. (2019), and growing at 4.5 %. In Quinet et al. (2019) the 2020 value resulted from political constraints to start at a low level.

Social cost of tank-to-wheels emissions and local pollution of diesel buses Only direct CO_2 emissions are considered in this paper. For diesel buses in urban areas, based on several studies (ADEME and Scania, 2018; The International Council of Clean Transportation, 2023), we estimate the tank-to-wheel emissions at 0.09 tCO_2/100km, which translates into a value for $p_0 = 0.15$ EUR /km for $SCC = 160$ EUR /tCO_2. FCEBs and BEBs do not emit greenhouse gases. Considering the life cycle assessment of the emissions associated with the French electric mix in 2020, the social cost of "Well to Wheels" emissions would be 0.007 EUR/km for BEBs and 0.020 EUR/km for FCEBs (ADEME, 2018). We consider these amounts negligible compared to the TCO of these vehicles.

We integrate the cost of local pollution (NOx and PM 2.5 emissions) generated by diesel vehicles. Estimates of this cost depending on the area concerned (urban, suburban) and the corresponding density of inhabitants (Quinet, 2013). A cost of 0.2 EUR/km is added to the TCO of diesel buses. This cost is considered fixed over time.

3.3.2 Key parameters

Table 3 gives the numerical values of the key parameters : the long-term marginal cost $\underline{c_i}$ for BEBs and FCEBs, the associated exogenous and endogenous technical change rates μ_i, λ_i, the relative market size of the niche market $\theta = N_{niche}/N$, the additional cost for BEBs on the niche market d and the exogenous transition duration D. The reported values of these parameters are our own best estimates and should be regarded with particular caution.

Key parameters	FCEBs	BEBs
Long-term marginal cost $\underline{c_i}$ (EUR /km)	1.0	0.8
Endogenous cost reduction potential $\overline{c_{i,endo}}$ (EUR /km)	0.6	0.1
Years of production to reach LBD cost reduction potential	20	20
Exogenous cost reduction potential $\overline{c_{i,exo}}$ (EUR /km)	0.6	0.2
Years to reach exogenous cost reduction potential	2040	2040
Niche market relative size θ (N_{niche}/N) (%)	20 %	
Additional cost for BEBs on the niche market d (EUR /km)	0.4	
Inertia to deploy technology D_i (years)	10	5

Table 3: Estimated values for the key parameters

Long-term marginal cost We estimate the so-called long-term costs of low-carbon vehicles based on data and estimates from many sources, including public reports (notably Loszka et al., 2022; Baccelli, 2021; E4Tech, 2021) and interview of experts. In the literature, these are mostly costs that can be achieved by 2040–2050 under certain assumptions. We consider these data as floor costs, i.e., the minimum cost that could be reached by low-carbon vehicles. These long-term costs are detailed in Table 4.

	FCEB	BEB
Fixed capital (EUR/km)	**0.4**	**0.3**
Corresponding purchase price (EUR)	300 000	250 000
km/year	50 000	50 000
life duration (years)	15	15
Maintenance (EUR/km)	**0.2**	**0.2**
Fuel and charge (no tax) (EUR/km)	**0.4**	**0.3**
Levelized cost of fuel/charge (EUR/L, kgH2 or kWh)	4.0	0.15
Levelized cost of infrastructure (EUR/L, kgH2 or kWh)	3.0	0.03
Unit price at pomp (EUR/L, kgH2 or kWh)	7.0	0.18
Consumption (L, kgH2 or kWh per 100km)	6.0	160.0
TCO (EUR/km)	**1.0**	**0.8**

Table 4: Estimated long-term total cost of ownership (TCO) analysis of fuel-cell electric bus (FCEB) and battery-electric bus (BEB)

Endogenous and exogenous technical change First, we identify which elements of the cost of a bus are more likely to decrease thanks to endogenous or exogenous technical change. We make the following assumptions for the European bus market: The elements of the TCO concerned by an exogenous cost decrease are the batteries and the hydrogen fuel. The elements concerned by an endogenous decrease in costs are the fuel cell, the hydrogen tank, maintenance, and the other elements of the fixed capital.

Second, the short-term cost $\overline{c_i}$ is decomposed in 3 components: the long-term cost $\underline{c_i}$, the exogenous cost reduction potential $\overline{c_{exo,i}}$, the endogenous cost reduction potential $\overline{c_{endo,i}}$, such as $\overline{c_i} = \underline{c_i} + \overline{c_{exo,i}} + \overline{c_{endo,i}}$.

Third, to calibrate the rates of endogenous and exogenous technical change, we assume:

- 95% of the endogenous potential is achieved after 20 years of full-time deployment in their respective markets. Thus, $\lambda_{BEV} = \frac{1}{N_{main}20} \ln(\frac{100}{5})$ and $\lambda_{FCEB} = \frac{1}{N_{niche}20} \ln(\frac{100}{5})$.
- 95% of the decrease in the exogenous potential will be achieved in 2040; thus, $\mu_i = \frac{1}{(2040-2020)} \ln(\frac{100}{5})$.

The relative size of the niche market in the bus sector According to CGDD (2018), 20% of bus journeys are made at the peripheries of large cities. We assume that a potential niche for hydrogen buses exists in this segment.

Additional cost for BEBs in the niche market According to ADEME (2018), BEBs currently offer an average range of 200 km for a standard bus, while the range of hydrogen vehicles is between 300 and 500 km. For simplicity, we assume that vehicles need a range of 400 km per day in the interurban market niche. Different charging strategies are available to travel this distance with a BEB. We evaluate the additional cost of the different charging options on the TCO.

- The most expensive option is to own a second BEB to make the same journey that a single FCEB could travel in a day. The additional cost would then be equal to the capital expenditure (CAPEX) cost of a second BEB. For simplicity, we take the average CAPEX, i.e., 0.5 EUR/km. This assumption ignores that technical change also affects these additional buses.

- The two other options considered are to either increase the size of the batteries in buses (overnight charging) or to install ultra-fast charging stations allowing BEBs to recharge in 15–30 min at regular intervals (opportunity charging). Transport & Environnement (2018) estimates the additional cost of these two options to be approximately the same. Based on our calculations, we estimate the additional battery cost of doubling the range of BEBs at EUR 0.3/km.

We take the average value between these two estimates, i.e., $d = 0.4$ EUR/km, for our baseline scenario and then perform sensitivity analyses on this parameter.

Exogenous transition duration Several empirical factors constrain the deployment of green buses, such as the need to deploy infrastructure, the potential synergies with other deployments in green energy production, and the availability of funding. This paper assumes that the transition duration is longer for FCEBs than for BEBs, requiring $D_{BEB} = 5$ years and $D_{FCEB} = 10$ years.

3.4 The optimal deployment strategy

Figure 1 depicts the optimal evolution of technology shares in the main and niche markets for the calibrated model (denoted the baseline scenario). Table 5 introduces a set of indicators to describe the optimal deployment of low-carbon technologies for the calibrated model. The optimal strategy is of type B-FC (described in column 1) and is compared with the optimal strategy of type B-B (column 2) for the baseline scenario. Total costs (line 1) correspond to the minimal discounted social cost of deploying B-B or B-FC relative to the cash cost of diesel buses. These total costs are decomposed into the discounted cash cost for the transition (line 2) and the cost of emissions. The latter is the accumulated amount of emissions (line 3) multiplied by the value of the SCC. Costs on the main and niche market (lines 4 and 5) and the corresponding optimal launch dates on N_{niche} of BEBs and FCEBs (lines 6 and 7) are also reported.

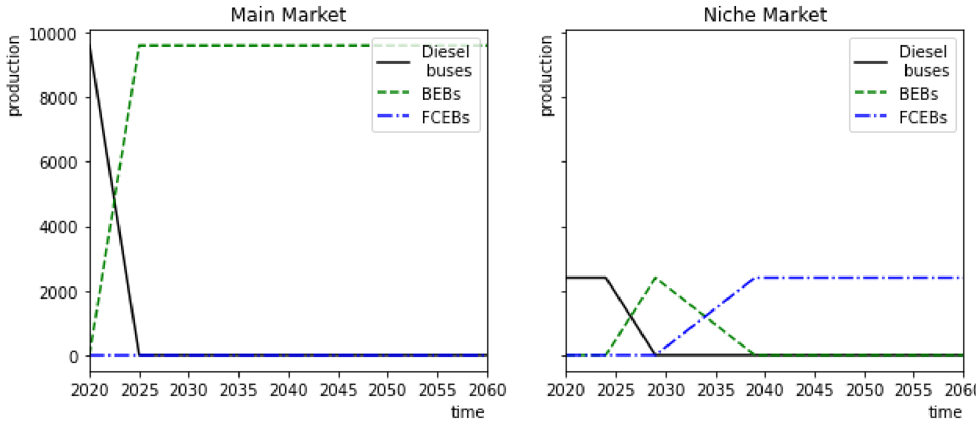

Figure 1: Deployment of battery-electric buses (BEBs) and fuel-cell electric buses (FCEBs) in the main and niche market for the baseline scenario (production over time)

Strategy type	**B-FC**	**B-B**
Total Costs (Bn. EUR)	**34.8**	35.6
Cash Costs (Bn. EUR)	**29.7**	30.5
CO_2 emissions (M. tCO_2)	**27.4**	27.4
Costs on the main market (Bn. EUR)	**17.5**	17.4
Costs on the niche market (Bn. EUR)	**17.3**	18.2
Launch year of BEBs in the niche	**2025**	2025
Launch year of FCEBs in the niche	**2030**	/

Table 5: Indicators for deployment of type Battery-Battery (B-B) and Battery-Fuel Cell (B-FC) under the baseline scenario

In the baseline scenario, the optimal deployment trajectory belongs to the B-FC strategy. The optimal transition of a European bus fleet of about 180,000 diesel buses into 80% BEBs and 20% FCEBs results in a total discounted cost of 34.3 billion EUR. In the main market, BEBs are launched immediately, which means that all the buses renewed in this market after 2025 are BEBs. In the niche market, BEBs will not be deployed until 2025 because of the additional cost of d in this market. The launch of FCEBs in the niche market will occur in 2030, and from this date, FCEBs replace BEBs. The decarbonization of the niche market will be achieved in 2040. The most cost-effective B-B alternative, i.e., the scenario that would optimize costs if FCEBs were not available, is also described for comparison. A transition solely based on BEBs would cost (including emissions) an additional 0.8 billion EUR breaking down into 0.9 billion additional costs in the niche market but a gain of 0.1 billion EUR in the main market due to learning spillovers from the niche. In the absence of exogenous technical change and transition inertia, the cash cost of strategies should be equal, and the cost difference should be entirely captured by the cost of pollution (based on Proposition 3). Here, decarbonization starts on the same date, so emissions are the same between the two strategies.

Table 6 makes apparent the role of technical change in the search for the optimal strategy. Three alternative scenarios are considered. In the "No TC" scenario, the costs of low-carbon vehicles remain constant ($\lambda_i = \mu_i = 0$). In the "Exo only" scenario, technical change is exogenous, i.e., low-carbon technology's cost falls over time independently of production. The cost of low-carbon technology i becomes $C_i(x_t, X_t) = \underline{c_i} + (c_{endo,i} + c_{exo,i})e^{-\mu_i t}$. In the "Endo only" scenario, technical change is only endogenous. The cost of low-carbon technology i becomes $C_i(x_t, X_t) = \underline{c_i} + (c_{endo,i} + c_{exo,i})e^{-\lambda_i X_t}$. Note that in all the scenarios, the timing of deployment of BEBs on the main market does not vary from the baseline scenario.

Scenario	**Optimal Strategy type**	**Total costs (Bn. EUR)**	**Cash cost (Bn. EUR)**	**CO_2 emission (M. $t_{eq}CO_2$)**	**Launch year of BEBs in the niche**	**Launch year of FCEBs in the niche**
No TC	B-B	77.3	68.2	49.0	2040	/
Exo only	B-FC	30.8	25.4	28.5	2026	2027
Endo only	B-B	37.6	33.5	21.6	2021	/

Table 6: Indicators of optimal strategies under alternative scenario regarding technical change

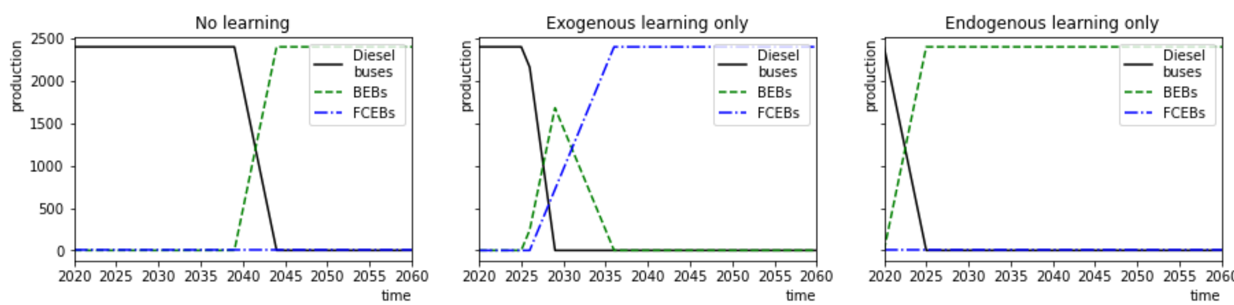

Figure 2: Deployment of green technologies in the niche market under alternative scenarios regarding technical change (production over time)

Without technical change, only BEBs are used since they are cheaper than FCEBs in both markets. The optimal launch date for BEBs would be 2040, which would increase CO_2 emissions by 78% compared to the baseline scenario. The gain from technical change is around 42 billion EUR, a 54% cost reduction.

Whether the technical change is entirely exogenous or endogenous drastically impacts the optimal strategy. If technical change is solely exogenous, FCEBs are deployed earlier than in the baseline scenario (2027). The transition cost is 12% lower. In other words, if technical change were mistakenly considered entirely exogenous, as in most TCO studies, the transition costs would be underestimated by 12%. If technical change is solely endogenous, only BEBs are used, and the transition in the niche takes place earlier (2021). The costs of the transition are then 8% larger than in the baseline scenario.

With only exogenous technical change, no scale effect is associated with technical change, which favors the challenger technology FCEB. Endogenous technical change justifies focusing on a single technology (cf Proposition 2) and thus favors the dominant technology BEB which benefits from the main market. If technical change is entirely endogenous, the niche is too small to justify the deployment of FCEBs. In the baseline scenario, the balance between the two sources of technical change is such that FCEBs are used in the niche.

Interestingly when one moves from Exo only to Baseline to Endo only, increasing the importance of endogenous technical change, the transition cost is higher, but the transition in the niche starts earlier, and emissions decrease. With the endogenous technical change, clean technologies should be deployed earlier to trigger cost reductions, and initial units are costly, which explains the higher cost of the transition. It illustrates that endogenous technical change justifies deploying technologies early, not waiting for their cost to spontaneously decrease, and possibly focusing on dominant ones. Mistakenly attributing cost reduction to exogenous factors would inefficiently delay deployment and favors niche technologies.

This discussion suggests that it is important to investigate further the impact of technical change on the long-term evolution of the cost in this market. In the final section, we examine how much comes from exogenous factors (from other market segments) or from learning by doing due to bus volumes.

3.5 The impact of the key parameters

3.5.1 The impact of the long-term marginal cost of FCEBs

The long-term marginal cost of FCEBs $\underline{c_{FCEB}}$ is certainly the most debatable key parameter of the model. We explore its impact by identifying the threshold values of its respective components for which FCEBs would no longer be deployed.

	Baseline	Threshold value
Long-term marginal cost of FCEBs $\underline{c_i}$ (EUR /km)	1.0	1.06
Fuel cell (EUR 2019/kW)	300	650
$LCOH_2$ (EUR 2019/kg)	4.0	5.0
Grid electricity price (centralized H2 production) (EUR 2019/MWh)	150	100
Grid electricity price (on-site H2 production) (EUR 2019/MWh)	150	20

Table 7: Threshold values of the main components for the long-term cost of fuel-cell electric buses (FCEBs)

FCEBs are deployed up to a long-term TCO of 1.06 EUR /km. Loszka et al. (2022) state that the long-term competitiveness of FCEBs depends mainly on the future cost of hydrogen and fuel cells. We detail the analysis through the threshold for these components (Table 7).

All else equal, the levelized cost of hydrogen ($LCOH_2$) must be less than EUR 5/kg for FCEB to be deployed. The threshold value for $LCOH_2$ is EUR 7/kg for the exo-only scenario and EUR 3.5 /kg for the endo-only scenario. As in Section 3.4, the exo-only scenario gives too high threshold values for $LCOH_2$, inducing excessive optimism about the competitiveness of FCEBs. Similarly, the long-term price of fuel cells needs to remain lower than EUR 650/kW. These critical values are contained in the range estimated by Loszka et al. (2022).

We also analyze the impact of the price of electricity on the competition between BEBs and FCEBs. Note that we consider a higher grid electricity price in the long-term than in the short-term in our TCO calibration. We consider two scenarios for hydrogen deployment: the first one is decentralized hydrogen production, with small-scale on-site production of H_2 with a strong dependency on the retail grid price (80% of $LCOH_2$); the second one is centralized hydrogen production with a large-scale electrolyzer, less dependent on the retail grid price (30% of $LCOH_2$). In our model, as grid electricity price directly impacts the recharging of BEBs, a lower grid electricity price favors the B-B scenario, particularly in the centralized H_2 production scenario. The two threshold values for the electricity price are 100 and 20 EUR/MWh for centralized and decentralized H2 production.

3.5.2 Impact of the other key parameters

The other major source of uncertainty concerns the cost penalty d of BEBs in the niche market. The estimation of this parameter is difficult and requires further scrutiny.

If $d = 0$, the best strategy is clearly of the type B-B, and there a threshold d^* exists above which FCEBs are deployed. We derive the threshold value as a function of another key parameter, i.e., the rates of exogenous or endogenous technical change and the size of the niche. For the baseline calibration, the threshold is $d^* = 0.29$.

Exogenous and endogenous technical change Here, we are concerned with the speed of technical change, not the size of cost reduction potentials. We analyze how the threshold cost penalty varies with the rate of endogenous (λ_{FCEBs}) or exogenous (μ_{FCEBs}) technical change. Figure 3 shows that the rate of exogenous technical change has little impact on the type of optimal strategy. If exogenous cost reduction is achieved later, the deployment of FCEBs is delayed but not canceled. The deployment of FCEBs is more sensitive to the rate of endogenous technical change.

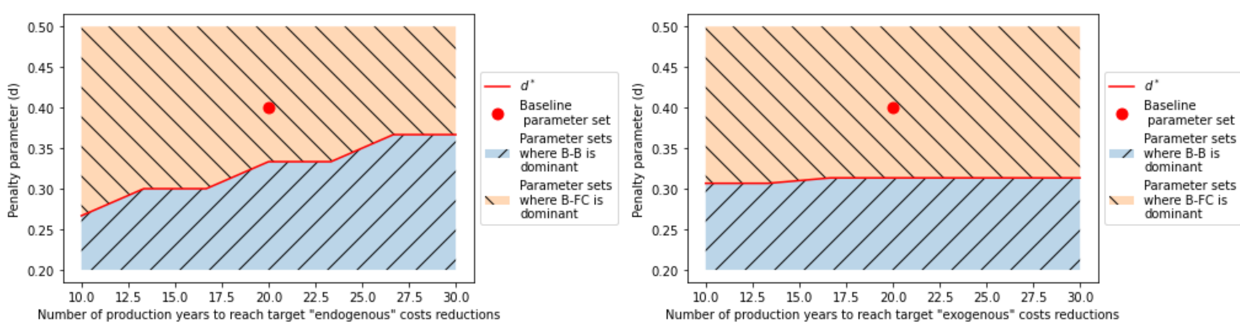

Figure 3: Evolution of d^*, threshold cost penalty of battery-electric buses (BEBs) ensuring the deployment of fuel-cell electric buses (FCEBs) on the niche, as a function of the endogenous and exogenous rates of technical change of FCEBs. The rates are derived from the number of years of production at scale to achieve 95% of the endogenous cost reduction potential for FCEBs (left panel), or the target year where 95% of the exogenous cost reduction potential is achieved for FCEBs (right panel).

Niche market size The joint calibration of these two parameters is important, as niche size and niche penalty are correlated. We have distinguished between a niche market and a main market for simplicity, whereas there is a continuum of bus users with specific uses. The more the niche is restricted to long and flexible travel, the greater the penalty for

BEBs. On the contrary, if the long-distance niche market is considered in a broader sense, the penalty applied to BEBs is less important because solutions for operating BEBs in that niche increases.

The influence of the size of the niche is due to learning by doing. Figure 4 shows that d^* decreases from 0.37 to 0.22 as the size of the niche market goes from 10% to 30%. The total size of the bus market affects this trade-off in the same way. If the bus market is large, FCEBs are more likely to be deployed because the hydrogen market niche is large enough for the costs of the hydrogen technology to decrease.

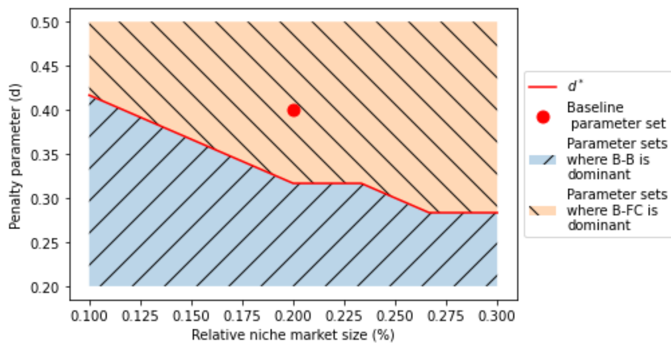

Figure 4: Evolution of $d*$, threshold cost penalty of battery-electric buses (BEBs) ensuring the deployment of fuel-cell electric buses (FCEBs) on the niche, as a function of the relative niche market size (in % of the total market)

4 Policy implications

Policy implications will be discussed first from a theoretical perspective and then in implementation.

Optimal policy level The optimal regulation combines taxes on diesel buses and subsidies on BEBs and FCEBs. The taxes on diesel buses (or on fuel consumption) should be equal to the marginal social cost of global and local air pollution. Similarly, optimal subsidies to clean buses should equal the external learning benefits associated with learning by doing.

Carbon tax: Concerning the global and local external costs generated by diesel buses, carbon taxes on diesel implemented are lower than the SCC in most countries. For instance, in France, in 2022, the carbon tax was around EUR 50/tCO_2; the difference with the national estimates for the SCC was EUR 110/tCO_2, or EUR 0.1/km, growing exponentially over time (Quinet et al., 2019). Second, the local social cost of air pollution from diesel buses (0.2 EUR/km) should also be incorporated. In total, diesel buses should be taxed at a rate of 0.35 EUR/km in 2020 and then $0.2 + 0.15e^{rt}$ EUR/km for year t.

Green subsidies: The optimal subsidy for low-carbon technologies should be equal to the positive externality generated by learning by doing. If firms do not internalize any learning effect, the optimal subsidy is given by formula (4).

If bus producers internalize some learning benefits, the subsidy should be reduced accordingly. The situation is depicted in Figure 5. The left panel shows the evolution of the unit costs of the three technologies in the niche market (with the penalty on BEBs) in the baseline scenario along the optimal strategy B-FC. The costs of FCEBs decrease first through exogenous technical change and then after 2030 through the combined effect of exogenous and endogenous technical change. In the niche market, FCEB-diesel bus cost parity will be reached in 2037, and FCEB-BEB cost parity will be reached after 2040. The right panel shows the evolution of the optimal tax and subsidy levels. Subsidies for BEBs decrease quickly from 2020 onward, while subsidies for FCEBs increase until the launch date in 2030. At that date, subsidies for FCEBs reached almost 0.5 EUR/km, then decreased during deployment. Note that the subsidies keep growing for a couple of years past the launch dates of each technology, this is due to the inertia factor; without inertia they would immediately decrease.

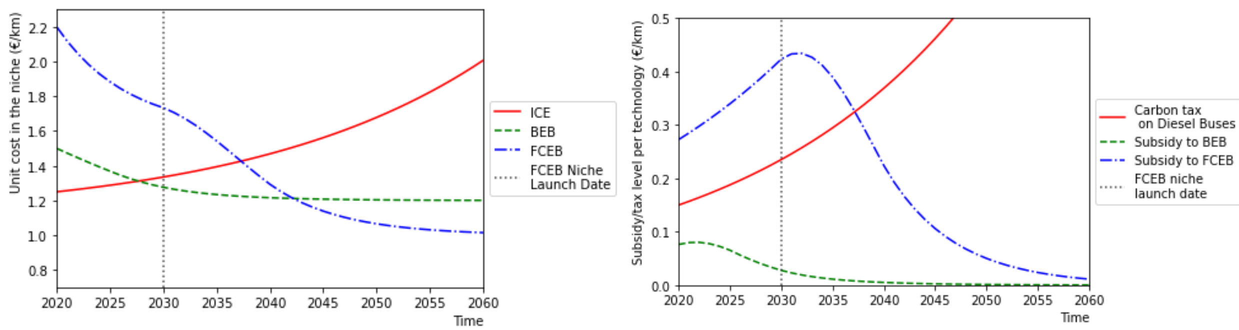

Figure 5: Evolution of unit cost of technologies in the niche over time (left panel) and optimal level of subsidy and tax over time (right panel) under the baseline scenario

This policy mix of tax and subsidies would achieve the socially optimal deployment path. If additional taxes on diesel buses are not feasible, the subsidies should be increased to fill the difference. In our simple model, without a smooth demand for buses and only two market segments, numerous combinations of taxes and subsidies could decentralize the first best. For instance, a subsidy constant through time for FCEBs would be sufficient to ensure a timely launch on the niche market. However, with additional market segments, a constant subsidy would trigger a too-early transition on some segments and a too-late transition on others.

Global and local policies Local public authorities (cities, regions), national agencies, and the EU Commission play a role in regulating the bus sector.‘ These entities have different objectives and levels of information. How could they use our model to design an efficient set of incentives?

We could decompose our model into several sub-models in which each would correspond to a city. The calibration of the sub-models would involve common figures, such as fixed capital of vehicles and learning rates. In contrast, other figures would be specific, such as pollution costs, depending on the availability of carbon-free sources of electricity, fuel, and charges, depending on potential synergies for sharing the fixed cost of logistics and infrastructure. One could also expect that the size of the local niche and the additional cost for BEBs on that niche be defined locally. In that framework, the transition on each local market would generate learning spillovers on other local markets. Part of the "exogenous" technical change in a local market would be generated in other local markets and be "endogenous" in the global bus market. This two-level model could be solved from a social point of view along the lines of Section 3. The local deployment strategies would depend on the cities' characteristics and the public policy's design. The main issue for public policy is to enhance technical change through efficient coordination between geographical markets and activities.

Consider first the coordination between geographical markets. The objective is to encourage credible demand projections from the cities to allow private companies to invest in BEBs and FCEBs based on consolidated volumes and benefit from learning by doing. Subsidies for vehicles (such as bonus deductible on the capital price) could be designed accordingly. The previous discussion provides some basis for the level of these subsidies. They increase up to the launch dates of each technology and then progressively decline until the respective TCO converges to one of the diesel buses. Observe that they are not technology neutral because of the different maturities of the technologies. Ordinarily, vehicle subsidies are identical at the national level, but additional local bonuses could be added. In line with our results, these bonuses could depend on the size of each city to reflect differences in the spillovers generated across geographical markets. It would make sense to have these additional bonuses designed and paid by the central authority.

Consider now the coordination across activities. This point is certainly more important for FCEBs than for BEBs. The infrastructure and fuel charges could depend on the commitments from potential local users outside FCEBs, such as other mobility segments and industries. For example, the European truck market is 10 times larger than the bus market (European Automobile Manufacturers' Association (ACEA) (2021)), which could lead to significant spillovers for FCEBs. In this respect, the existence and the scope of a hydrogen valley in a region would play a role in assessing the local spillovers in the underlying ecosystem (Clean Hydrogen JU (2022)). It may also be important to require that business plans elaborated by public transport operators integrate a general view of the region's future mobility plan, including inter-modal changes. Since these points are better known locally than centrally, the design of the corresponding subsidies should be left to local authorities.

Two papers illustrate the interest in pursuing these ideas further. The inefficiency of a pure global policy betting on endogenous technical change through a demand push for electric vehicles was analyzed for the US by Zhou and Li (2018). Rather than providing indiscriminate bonuses at the national level to acquire an electric vehicle, it would be better to consider the characteristics of local markets, some of which are large enough and do not need subsidies to develop. At the same time, some others are too small and wasteful to initiate since sustainability would require permanent subsidies. Furthermore, Meunier and Ponssard (2020) analyzed the complementary role of local and global policies through possible combinations of subsidies to infrastructure and vehicles as a function of the maturity of the technology through market size and potential learning by doing. Subsidizing infrastructure appears to be the dominant factor for emerging technologies such as FCEBs. It would be worthwhile to pursue these lines of research both at the empirical and conceptual levels based on the analytical framework developed in this paper.

5 Conclusion

This paper has three main contributions, which can be summarized as follows. Firstly, it examines the role of technical change in the competitive dynamics among cleaner technologies in a specific market. The decreasing costs of these technologies over time add complexity to identifying the most efficient option. This decrease may result from learning by doing, stemming from the volumes deployed over time in the market considered, or due to exogenous technical change from other markets where the technologies could be applied. We model the choice among competing cleaner technologies by considering factors like short-term and long-term cost differentials, cost convexity in the short-term, market size, and the learning rate of technologies. Focusing on the case where one of the cleaner technology has higher short-term costs but lower long-term costs than the other, this technology should prevail if both its learning rate and the market size reach a certain threshold level. The joint impact of these two factors has not been considered in previous papers.

The second contribution provides methodological insights for the effective design of cost-benefit evaluations of an activity. In this regard, the paper explicates two interrelated issues commonly overlooked in applied research: firstly, how to analyze one complete sectoral decarbonization, which involves integrating cost dynamics over time as a function of the transition's deployment; and secondly, how to accurately model technical change, including its impact on the cost dynamics of the activity through its relation with related markets and the components of value-added costs. This framework proposed in the paper provides a solid foundation for various applications.

The final contribution involves applying this theoretical framework to the competition between battery electric buses (BEBs) and fuel cell electric buses (FCEBs) in Europe's urban bus sector. While battery buses currently lead the energy transition due to their lower short-term costs, hydrogen buses might gain an advantage in niche markets characterized by longer routes and challenging topographic and climatic conditions. Our detailed model, incorporating technical change in cost dynamics, identifies three conditions for a sustainable market niche for FCEBs. Firstly, the niche market must be substantial, ranging between 10–20% of the overall bus market. Considering the current TCO of FCEBs is about twice that of BEBs (2.2 EUR/km vs. 1.1 EUR/km), the second condition is a significant long-term reduction in this gap (TCO around 1.0 EUR/km for FCEBs vs. 0.8 EUR/km for BEBs in the long-term), achievable through greater learning effects for FCEBs. This is more effective when the technical change is exogenous, as the niche's limited size is insufficient to spur endogenous technical change for FCEBs, and other heavy-mobility markets are more significant in volume. Finally, FCEBs must keep a substantial market advantage in the niche, stemming from factors like refueling time, autonomy, and adaptability to weather and topography, to offset the remaining TCO disparity. Our estimates indicate that this advantage needs to exceed 0.3 EUR/km for FCEBs to be competitive in the long term.

Three issues would require further investigations to assess the robustness of these results. The first issue is that our model currently only considers two low-carbon technologies and one carbon-intensive technology. Including partially decarbonized transition technologies, likes biofuel-powered buses, could significantly alter the competitive landscape between BEBs and FCEBs. Considering these transitional technologies might delay the decarbonization of the transport sector, but wouldn't result in a lock-in, as they would eventually be phased out.

This delay could impact the short-term niche market competition, potentially making BEBs more competitive in the long run due to learning effects, thereby preventing the adoption of FCEBs in the niche. This aspect remains an area for further research.

The second issue concerns our assumption that the size of the niche and the market advantage are independent. Rather than considering an additional cost and the relative size of the niche market, as done in the sensitivity analysis, it may be more appropriate to introduce a demand function in which consumer preferences would advantage BEBs over a significant part of the demand. Thus, the advantage could be progressively reversed in favor of FCEBs on the remaining part. In this formalization, the consumer preferences and the relative competitiveness of the two technologies would interact to segment the market at each point. This formulation would allow for explicating the existence of a niche in the long run for FCEBs from more conceptual parameters.

The last issue concerns the dual role of endogenous and exogenous technical change. In the niche market, the TCO of BEBs is mostly reduced due to exogenous technical change, partly coming from its deployment in the main market. Conversely, the TCO decrease for fuel cell electric buses (FCEBs) is largely driven by learning-by-doing. The respective shares of exogenous and endogenous learning and their total magnitudes are subject to debate. To empirically validate the model, one approach could be to break down the TCOs into component costs (such as the fuel cell, tank, etc.) and consider the production volumes in each market segment that shares these components. Some components are common across light- and heavy-duty mobility segments, creating broader experience across the value chain. The production volume, and hence the economies of scale in manufacturing a component, are shared across different mobility sectors. For instance, the battery cost for BEBs is influenced by the cumulative production volume of battery-electric cars. Additionally, the costs of both BEVs and FCEVs are affected by the development and usage of low-carbon technologies in other sectors. For example, the cost of renewable hydrogen, likely to decrease with its large-scale production for industrial use, will indirectly influence the TCO of FCEVs. Incorporating these considerations into future research would be beneficial.

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A Proof of proposition 1

Optimality conditions

The Hamiltonian is

$$\mathcal{H} = p_t^{CO2}N - \sum_{i=1,2}\left[p_t^{CO2}x_{i,t} - C_i(X_{i,t}, x_{i,t}, t) + \lambda_{i,t}x_{i,t}\right] \tag{7}$$

with $\lambda_{i,t}$ the co-state variable of $\dot{X}_{i,t} = x_{i,t}$. The Lagrangian is

$$\mathcal{L} = \mathcal{H} - \theta_{1,t}x_{1,t} - \theta_{2,t}x_{2,t} + \eta_t(x_{1,t} + x_{2,t} - N) \tag{8}$$

With $\theta_{i,t}$ the Lagrange coefficient associated with the non-negativity constraint ($x_{i,t} \geq 0$) and η_t the fleet size constraint ($N \geq x_{1,t} + x_{2,t}$).

Apart from the slackness conditions, the optimality conditions are

$$p_t^{CO2} - \frac{\partial C_i}{\partial x} + \theta_{i,t} - \eta_t = -\lambda_{i,t} \text{ for } i = 1,2 \tag{9}$$

$$\dot{\lambda}_{i,t} - r\lambda_{i,t} = \frac{\partial C_i}{\partial X} \text{ for } i = 1,2 \tag{10}$$

Integrating Eq. (10) gives the expression of $\lambda_{i,t}$ as the present value of learning benefit:

$$\lambda_{i,t} = -\int_t^{+\infty} e^{-r(\tau-t)}\frac{\partial C_i}{\partial X}(X_{i,\tau}, x_{i,\tau}, \tau)d\tau \tag{11}$$

Monotonicity of the clean production

There are three technologies to produce the N units, 7 possible combinations are possible. The two main cases depends whether the fleet is not fully clean (Case 1) or whether it is (Case 2).

Case 1: The fleet is not fully clean, i.e., $0 \leq x_{1,t} + x_{2,t} < N$ so that $\eta = 0$.

- If technology $i = 1,2$ is not used, $\theta_i > 0$ and, from Eq. (9),

$$\frac{\partial C_i}{\partial x} - \lambda_{i,t} > p_t^{CO2} \tag{12}$$

  As $\dot{\lambda}_{i,t} - r\lambda_{i,t}$ is null ($\partial C_i/\partial X = 0$ for $x = 0$), λ_i grows at rate r.

- If technology i is used while the fleet is not completely clean, then $\eta_t = \theta_{i,t} = 0$ and

$$p_t^{CO2} - \frac{\partial C_i}{\partial x} = -\lambda_{i,t} \tag{13}$$

  Injecting Eq. (11) results in Eq. (2) in the main text.

Lemma 1 *If technology i is used while the fleet is not completely clean, then the quantity produced $x_{i,t}$ is strictly increasing with respect to time.*

Proof.

Differentiating Eq. (2) with respect to time

$$\begin{aligned} rp_t^{CO2} - \frac{\partial^2 C_i}{\partial x^2}\dot{x}_i - \frac{\partial^2 C_i}{\partial X \partial x}x_i - \frac{\partial^2 C_i}{\partial t \partial x} &= -\dot{\lambda}_{i,t} \\ &= -\frac{\partial C_i}{\partial X} - r\lambda_{i,t} \text{ using Eq. 10} \\ &= -\frac{\partial C_i}{\partial X} + r(p_t^{CO2} - \frac{\partial C_i}{\partial x}) \text{ using Eq. 9} \end{aligned}$$

gives the Euler equation for technology i:

$$\frac{\partial^2 C_i}{\partial x^2}\dot{x}_i = \left[\frac{\partial C_i}{\partial X} - \frac{\partial^2 C_i}{\partial X \partial x}x_i\right] - \frac{\partial^2 C_i}{\partial t \partial x} + r\frac{\partial C_i}{\partial x} \tag{14}$$

The bracketed term is non-negative by concavity of $\partial C/\partial X$ with respect to x. The right-hand side is positive, so that $x_{i,t}$ is strictly increasing. ■

Case 2: The fleet is completely clean.

- If both clean technologies are used, then $\theta_{1,t} = \theta_{2,t} = 0$ and $\eta_t > 0$. From Eq. (9), $\partial C_1/\partial x - \lambda_{1,t} = p_t^{CO2} - \eta_t = \partial C_2/\partial x - \lambda_{2,t}$, and injecting the expression (11) gives Eq. (3) in the main text. Furthermore, differentiating with respect to time, the corresponding Euler equation is :

$$\begin{aligned} &\frac{\partial^2 C_1}{\partial x^2}\dot{x}_{1,t} + \left[\frac{\partial^2 C_1}{\partial X \partial x}x - \frac{\partial C_1}{\partial X}\right] + \frac{\partial^2 C_1}{\partial t \partial x} - r\frac{\partial C_1}{\partial x} \\ =&\frac{\partial^2 C_2}{\partial x^2}\dot{x}_{2,t} + \left[\frac{\partial^2 C_2}{\partial X \partial x}x - \frac{\partial C_2}{\partial X}\right] + \frac{\partial^2 C_2}{\partial t \partial x} - r\frac{\partial C_2}{\partial x} \end{aligned} \tag{15}$$

  In that case $\dot{x}_{1,t} = -\dot{x}_{2,t}$.

- If the fleet is produced with technology $i = 1, 2$ alone, i.e., $x_{i,t} = N$.

$$\frac{\partial C_i}{\partial x} - \lambda_{i,t} = p_t^{CO2} - \eta_t < p_t^{CO2}$$

  As $\theta_j > 0$, with $j \neq i$,

$$\frac{\partial C_j}{\partial x} - \lambda_{j,t} = p_t^{CO2} - \eta_t + \theta_{j,t} > \frac{\partial C_i}{\partial x} - \lambda_{i,t}. \tag{16}$$

Proof of Proposition 1

The clean production is increasing through time because if it is positive ($\exists i, x_{it} > 0$) while the fleet is not completely clean it is strictly increasing (Lemma 1). Therefore, the fleet moves from fully dirty to partially dirty to fully clean.

The fleet is fully clean in finite time, otherwise the cost would be infinite because of the exponentially growing SCC. For instance, the cost of a fully clean fleet with technology 1 alone is finite.

The first proposition follows.

B Proof of Proposition 2

If cost functions are linear with respect to x, and given that $C_i(X, 0, t) = 0$, they can be written

$$C_i(X, x, t) = \gamma_i(X, t)x \tag{17}$$

with γ_i positive and decreasing with respect to both arguments. The following holds:

$$\frac{\partial C_i}{\partial X} = \frac{\partial^2 C_i}{\partial X \partial x}.x. \tag{18}$$

Instantaneous transition We prove the result by contradiction.
If a clean technology is used while the fleet is not fully clean, then it satisfies the Euler equation (14) in which the left-hand side and the bracketed term are null because of Eq. (18), then

$$\frac{\partial^2 C_i}{\partial t \partial x} = r\frac{\partial C_i}{\partial x} \tag{19}$$

The left-hand side is non-positive and the right-hand side is positive (since $x_{i,t} > 0$), which is a contradiction.

Therefore, either $x_{1,t} + x_{2,t} = 0$ or $x_{1,t} + x_{2,t} = N$. And the fleet moves from fully dirty to fully clean instantaneously at T_{out}.

Without exogenous technical change, only one clean technology is used forever
Once the fleet is completely clean, at date T_{out}, the two clean quantities minimize the cost of a fully clean fleet. Thus, $x_{1,t-T_{out}}$ solves the minimization problem:

$$\min \int_0^{+\infty} e^{-rt}[\gamma_1(X_{1,t}).x_{1,t} + \gamma_2(tN - X_{1,t})(N - x_{1,t})]dt$$

s.t. $\dot{X}_{1,t} = x_{1,t}$, $X_{1,0} = 0$ and $0 \leq x_{1,t} \leq N$. In the following, we analyze this minimization problem, the solution of which is denoted $x^*_{1,t}$.

We first establish that for all t, $x^*_{1,t}$ is either null or equal to N and then that it does not switch.

- $x_{1,t} \in \{0, N\}$:

  The proof is simpler by rewriting the cost of a clean fleet with the functions $s_i(X) = \int_0^X \gamma_i(u)du$, with $s_i(0) = 0$ and $s_i'(X) = \gamma_i(X)$. Along any path $x_{1,t}$, making use of $s_i(\dot{X}_{i,t}) = \gamma_i(X_{i,t})x_i$ and integrating by part, the discounted cost of a clean fleet is:

  $$\int_0^{+\infty} e^{-rt}[s_1(X_t) + s_2(tN - X_t)]dt. \tag{20}$$

  We now prove the result by contradiction assuming that there is an interval $[s, u]$ over which $0 < x^*_{1,t} < N$ (even at the boundaries). We use infinitesimal variations: There exists a function h_t non-negative and positive over $[s, u]$ such that $h_t \leq x^*_{1,t} \leq N - h_t$ for all t. We denote H_t its integral ($H_0 = 0$) and consider the path $x^*_{1,t} + \epsilon h_t$ with $\epsilon \in [-1, 1]$.

  The total cost of a clean fleet along that path is

  $$f(\epsilon) = \int_0^{+\infty} e^{-rt}[s_1(X^*_{1,t} + \epsilon H_t) + s_2(tN - X^*_{1,t} - \epsilon H_t)]dt \tag{21}$$

  $f(.)$ is defined over $[-1, 1]$ and minimized at $\epsilon = 0$. The first order derivative is

  $$f'(\epsilon) = \int_0^{+\infty} e^{-rt}[\gamma_1 - \gamma_2]H_t dt$$

  and the second order derivative is negative:

  $$f''(\epsilon) = \int_0^{+\infty} e^{-rt}[\gamma_1' + \gamma_2']H_t^2 dt < 0$$

  It is negative because H_t is positive over an interval. Then f is strictly concave and not minimized at zero, leading to a contradiction.

- No switch :

  We prove the result by contradiction. Suppose that there is at least one switch at time $s > 0$ and that $x^*_{1,t} = N$ for $t \in [0, s[$ and $x^*_{1,t} = 0$ for $t > s$ over some interval.

  - Suppose there is only one switch, $x^*_{1,t} = 0$ for all $t > s$. At time zero, technology 1 is preferred, resulting in

    $$\int_0^s e^{-rt}\gamma_1(tN)dt + e^{-rs}\int_0^{+\infty} e^{-rt}\gamma_2(tN)dt \leq \int_0^{+\infty} e^{-rt}\gamma_2(tN)dt$$

    At date s the optimal path dominates a path in which technology 1 is first used during s periods:

$$\int_0^{+\infty} e^{-rt}\gamma_2(tN)dt \leq \int_0^{s} e^{-rt}\gamma_1(sN+tN)dt + e^{-rs}\int_0^{+\infty} e^{-rt}\gamma_2(tN)dt$$
$$< \int_0^{s} e^{-rt}\gamma_1(tN)dt + e^{-rs}\int_0^{+\infty} e^{-rt}\gamma_2(tN)dt$$

The previous inequality leads to a contradiction.

– Suppose there is a second switch at date u, $x^*_{1,t} = N$ for $t \in]u, v[$. Technology 1 is first used on $[0, s]$, then technology 2 on $[s, u]$, and eventually technology 1 again on $[u, v]$. A reasoning similar as before leads to a contradiction. One should consider annualized cost over each to take care of the different lengths of the three periods. If it is better to start with technology 1, then the annualized cost over $[0, s]$ must be lower or equal to the annualized cost over the period $[s, u]$. The latter must be lower than the annualized cost over $[u, v]$:

$$\frac{\int_0^s e^{-rt}\gamma_1(tN)dt}{1-e^{-rs}} \leq \frac{\int_0^{u-s} e^{-rt}\gamma_2(tN)dt}{1-e^{-r(u-s)}} \leq \frac{\int_0^{v-u} e^{-rt}\gamma_1(sN+tN)dt}{1-e^{-r(v-u)}}$$

However, the last annualized cost is strictly lower than the first because $\gamma_1(sN + tN) < \gamma_1(tN)$, which leads again to a contradiction.

Winning technology If the transition date is instantaneous, and only one technology is chosen for the transition, then there are only two choices of optimal trajectories.

$$\Gamma_1 = \int_0^{T_1} e^{-rt}[p_t^{CO2}N]dt + e^{-rT_1}\int_0^{+\infty} e^{-rt}C_1(tN, N)dt$$
$$\Gamma_2 = \int_0^{T_2} e^{-rt}[p_t^{CO2}N]dt + e^{-rT_2}\int_0^{+\infty} e^{-rt}C_2(tN, N)dt$$

We have $\Gamma^* = \min(\Gamma_1, \Gamma_2)$. The optimal technology is the one with which the discounted cost of a clean fleet is the lowest. Along the optimal trajectory, the optimal launch date can be easily found by cancelling the derivative of γ_i with respect to T_i.

C Exogenous technical change only

To simply illustrate the difficulties to handle analytically exogenous technical change we show here that even with a simple specification multiple switches can be optimal.

Consider the following specification of cost functions:

$$C_i(X_t, x_t, t) = [\underline{c_i} + (\overline{c_i} - \underline{c_i})e^{-\mu_i t}]x_{it}.$$

This cost function does not exhibit learning by doing and is linear respect to production. Therefore, determining the optimal deployment simply involve choosing the cheapest technology at each time period. Figure 6 illustrates an example in which the optimal deployment scenario consists in first switching to BEBs and then to FCEBs latter.

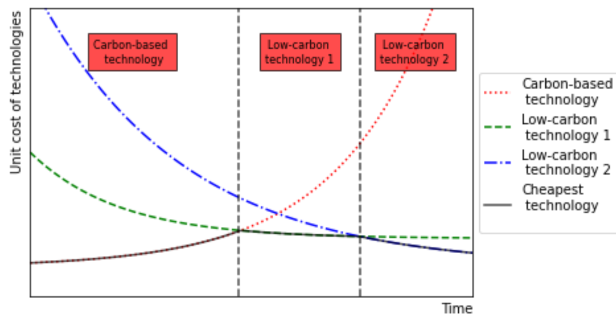

Figure 6: Illustration of a double-switch scenario

D Dynamic cost minimisation in discrete time

Dynamic cost minimisation program

$$\min_{x_i^j} \Gamma = \sum_t^T \left(\frac{1}{1+r}\right)^t$$
$$[(\underline{c_{BEB}} + \overline{c_{endo,BEB}} e^{-\lambda_{BEB} X_{BEB}(t)} + \overline{c_{exo,BEB}} e^{-\mu_{BEB} t})(x_{BEB}^{main}(t) + x_{BEB}^{niche}(t)) + dx_{BEB}^{niche}$$
$$+ (\underline{c_{FCEB}} + \overline{c_{endo,FCEB}} e^{-\lambda_{FCEB} X_{FCEB}(t)} + \overline{c_{exo,FCEB}} e^{-\mu_{FCEB} t})(x_{FCEB}^{main}(t) + x_{FCEB}^{niche}(t))$$
$$+ (c_0 + p_0 e^{rt})(N_{main} + N_{niche} - x_{BEB}^{main}(t) - x_{FCEB}^{main}(t) - x_{BEB}^{niche}(t) - x_{FCEB}^{niche}(t))]$$

Under the following constraints

$$X_i(t+1) = X_i(t) + x_i^{main}(t) + x_i^{niche}(t) \qquad \text{(Evolution of learning stock } i\text{)}$$
$$x_i^j(t+1) \leq x_i^j(t) + N_j/D_i \qquad \text{(Inertia in market } j \text{ for tech } i\text{)}$$
$$0 \leq x_i^j \leq N_j \qquad \text{(Size of market } j\text{)}$$
$$0 \leq N_j - x_1^j - x_2^j \qquad \text{(Saturation of market } j\text{)}$$

Notations

Variables
$x_i^j(t)$ the production of technology $i \in \{BEB,\ FCEB\}$ in market $j \in \{main,\ niche\}$ at time t
$X_i(t)$ the knowledge stock of technology i at time t
Parameters
T the time horizon of the problem
r the discount rate
$\underline{c_i}$ the long-term unit cost of technology i
$\overline{c_{endo,i}}$ the endogenous cost reduction potential of technology i
$\overline{c_{exo,i}}$ the exogenous cost reduction potential of technology i
λ_i the endogenous learning rate of technology i
μ_i the exogenous learning rate of technology i
d the cost penalty of BEBs on the niche market
c_0 the cash cost of diesel bus
p_0 the social cost of diesel buses emission in 2020
N_j the size of market j
D_i the transition duration associated with technology i