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Technology transitions: identifying challenges for hydrogen vehicles*

Jeroen Struben
System Dynamics Group
MIT Sloan School of Management, Cambridge MA 02142
jjrs@mit.edu

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Abstract

Automobile firms are now developing alternatives to internal combustion engines (ICE), including hydrogen fuel cells and ICE-electric hybrids. Adoption/diffusion dynamics for alternative powered vehicles are more complex than those typical of most new products, due to the enormous size and importance of the automobile industry, the size and impact of the vehicle fleet, the presence of scale and scope economies, learning by doing and through research, and the critical role of complementary resources such as fueling and maintenance infrastructure. This paper describes a model for examining the diffusion dynamics for and competition among hydrogen, hybrid and ICE vehicles. Its focus is on the generation of consumer awareness of alternative propulsion technologies through feedback from driving experience, word-of-mouth and marketing, with a reduced form treatment of network effects and other positive feedback (subsequent papers will treat these in depth). Through detailed model analysis the existence of a critical threshold for sustained adoption of new propulsion technologies and its importance for the diffusion dynamics are shown. Finally, word-of-mouth from those not driving an alternative vehicle is important in stimulating adoption.

*I am indebted to John Sterman for continuous collaboration and advise

1 Introduction

1.1 Motivation

At the end of the $19th$ century New York, Boston and Pennsylvania were among the cities to welcome the clean and silent electric "horseless carriages" as alternatives to the polluting horse drawn carriage (Kirsch [2000]). There was huge enthusiasm among both users and inventors, including Thomas Edison, for the potential of electric vehicles. Though an electric car set the world speed record of 61mph in 1899, automobiles powered by internal combustion engines (ICE) surpassed electrics in sales early in the 20^{th} century and became the dominant design.

Today, mainly motivated by environmental pressures and increasing constraints on availability of energy resources, we face another potential transition - this time away from fossil-powered ICE vehicles. Uncertainties on how the transition will unfold are enormous. Many envision a hydrogen-powered fleet, while others call for ICE-electric hybrids. The boundary of relevance involves a multiplicity of stakeholders with conflicting interests and perspectives, and complexities of the problem are profound. First the enormous scale of the automobile industry provides tremendous opportunity for learning by doing and R&D experience. Second, ICE-vehicles are deeply embedded within the existing transportation- and urban infrastructures and a hydrogen system requires a different infrastructure. Not only would this transition require billions of dollars of (public) capital investment (Mintz *et al.* [2003]), but due to the importance of the automotive and fuel industry to the US economy many structures and institutions have co-evolved around the dominant system, making replacement even harder. For instance, in the case of natural gas as source for hydrogen generation, a delivery network of large distribution sites close to points of production would be preferable (Farrell *et al.* [2003]). This would require a significant change of refueling behavior patterns of the consumer. On the other hand, a distributed network would be feasible with sources such as solar energy, but this is not likely as technology lags and currently the oil companies have a great role in the hydrogen discussion.[1] Third, alternative propulsion technologies provide huge opportunities for new conceptions in design logic, choice of materials and the role of electronics and software. Some of these innovations will provide spillover opportunities to the dominant platforms. Finally, cars are an important symbol in society and a source of personal identity, status and emotional resonance.

[1] See for instance the California Fuel Cell Partnership http://www.cafcp.org/

Automobile purchase decisions are not the result of "cold" calculation. Efficacy and safety of designs and their features are shaped by historic events, experience and social interactions.

Conceptual and formal models of the product life cycle are useful starting points to consider the possible transition to alternative vehicles. Abernathy & Utterback [1978] emphasized the role of uncertainty on consumer choice and Klepper [1996] introduced a formal model that incorporates learning and scale economies. In addition, since Arthur [1989],[2] factors such as learning and externalities that drive reinforcing loops have become part of mainstream organizational and industrial literature (e.g., Katz & Shapiro [1985] on the formation of standards and the role of expectations; Loch & Huberman [1999] discuss technological diffusion in the context of network externalities). Farrell *et al.* [2003] discuss various factors that constitute a hydrogen propulsion platform and particularly highlights the distribution system and infrastructure.

For innovation systems such as these the relevance of several interacting self-reinforcing mechanisms has been acknowledged and in the context of hydrogen vehicles, the "chicken-and-egg" problem between vehicles and infrastructure is widely recognized. However, the situation is much more complex than that, while the co-evolution of a platform with all its key contextual factors has not been explicitly modeled as one system. For the individual study, many factors are at best stated as given "environment factors", but their interactions are essential to the dynamic behavior. Only by modeling and careful analysis can one learn what type of trajectories are likely or unlikely when the various reinforcing (and balancing) feedback mechanisms interact. This research intends to take a first step to do so for the vehicle propulsion platforms that face a transition with potentially dramatic implications for many industrial fields, with billions of dollars of capital and R&D investments, and social patterns. Its focus is on the endogeneity of consumer choice, institutional factors, and infrastructure for a fundamentally new technology in the context of competition between vehicle propulsion technologies. In particular, this paper focuses on adoption generated by consumer awareness through feedback from driving experience, word-of-mouth and marketing. What are the various adoption patterns that can emerge in the context of competing vehicle technology platforms, where consumer choice and attractiveness are endogenous? While this paper only briefly discusses the transition challenge that these technologies face and the full model boundary, subsequent papers will treat the role of learning, research, spillover, infrastructure, and supply-demand dynamics more explicitly and

[2] Arthur's seminal paper circulated beginning in 1983, but was only accepted for publication in 1989

in detail.

1.2 The transition challenge

The transition to the current ICE-dominated system in the early 19^{th} century provides insights into the challenges of a transition to a hydrogen-powered transportation system. Figure 1 shows the competition between horse and vehicle platforms in the US (Census [1975]). In 1900 there were about 18 Million horses and 8000 registered vehicles for a population of 76 Million. Automobiles had been introduced around 1870; however, the fleet consisted mainly of steam- and electric propelled cars. The internal combustion engine did not seriously enter the market before Carl Benz demonstrated 20 years later the first operating ICE vehicle (Westbrook [2001]). This is illustrated in figure 1 b) that shows a sample of electric, steam and ICE producing plants as fraction of total.[3]

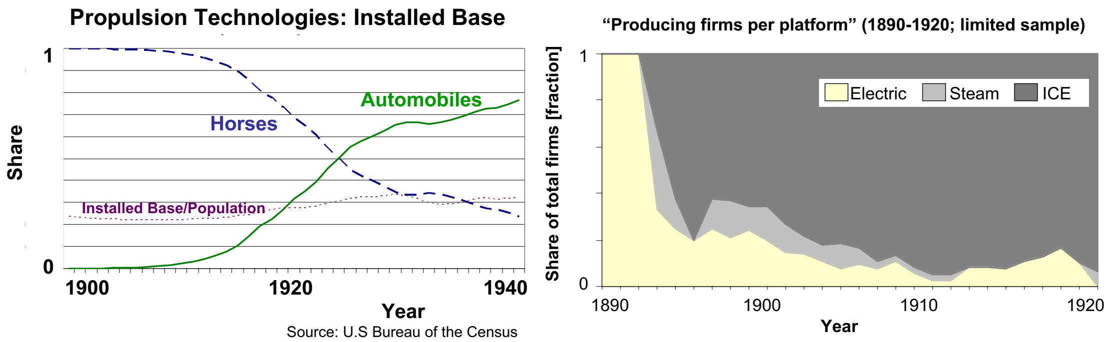

Figure 1: a) horse versus the automobile fleet 1900-1940.Source:U.S. Bureau of the Census, Historical Statistics of the United States-bicentennial edition b) Electric, steam and ICE producing plants as fraction of total - sample of 223 firms from Kimes & Jr. [1996]. Undersampled - additional data is being collected.

For several reasons the electric cars remained popular for a while: they proved extremely useful as a taxi-cabs and had various advantages over the ICE engines. Electrics were more quietly and easier to start than their ICE counterparts and they did not smell. There were several positive developments in battery-performance as well. However, in 1912 registered electric cars peaked at 30,000, while ICE vehicles had an installed base already 30 times greater. Why did the electric vehicle fail, despite supportive publicity and initial success? First, while expectations and potential were high,

[3]Drawn from Kimes & Jr. [1996] - illustrative only. Sample contains all 223 firms listed in the catalog that start with "A." Total sample size contains over 2500 plants

performance improvement in terms of cost (3 times that of a Ford) and driving range were slow. Second, by 1912 the vehicle designs had already evolved away from that of a classic carriage with the driver sitting up-front. It became clear that people preferred having the option of "touring," though this had not become common practice due to the poor quality of roads and the sparse infrastructure for both fuel and the frequent repairs needed. Horses could rely on a convenient and "cheap" network of water and food supply, while for the electric car the range was limited by the batteries.[4] Its use for short trips in urban areas provided little incentive for developing recharging stations in more remote areas. This lack of recharging stations fed back to limit the appeal of the electric cars in those areas, slowing diffusion further. In addition, little learning came from using batteries over longer ranges. The ICE vehicle initially faced a similar situation but its larger driving range implied that the network issue was much less pronounced and allowed for faster diffusion and development of an energy-distribution network (Kirsch [2000]). The demise of electric vehicles demonstrates the intimate interdependency between consumer choice and the evolution of technology. It also shows the many similarities between the current situation and that of 100 years ago. The emerging preferences for and possibility of long distance travel meant the doom of the popular electric vehicle. As growing production experience and scale led to spectacular improvements in ICE vehicles, ICE soon became dominant.

On the other hand,we also see an important difference in challenges between the new technologies at the end of the 19^{th} and those at the beginning of the 21^{st} century: in the first case proper roads were virtually non-existent, nor were conventions for driving. The "horseless-carriage" was often considered nothing more than hype (Westbrook [2001]), and horse traffic was initially well protected by regulation against the "race-devils" (Beasley [1988]). Moreover, the industry as a whole was not developed and awareness among the population was low. This situation allowed ICE to catch-up. More than 100 years later however, alternative vehicles face a mature industry, infrastructure and society oriented around ICE.[5]

This introduction illustrates the structural similarities between the current challenge for hydrogen and the horseless carriage transition in terms of "contextual factors." The differences, as potential speed of diffusion, and state of development of infrastructure on the other hand, are mainly para-

[4] To some extent the steam-engine could benefit from this network.

[5] While the electric car failed at that time, confidence in its efficacy did not disappear: it captured a considerable market niche for trucks in the 1930's and a revival was attempted to introduce it as a "citycar" by several Detroit manufacturers in the 1960's as well as more recently, but failed each time.

metric. The lasting enthusiasm for the electric vehicle also displays the enormous misconceptions in understanding the power of the co-evolution of such contextual factors as service and maintenance, infrastructure, and socialization in determining the successful or failing trajectories. A series of modeling exercises should shed a light on the typical challenges that are ahead for prospective contemporary vehicle propulsion system transitions.

1.3 Model boundary - full scope

We develop a model to examine the vehicle transition challenge. The model is designed to explore the possible transition from ICE to alternative propulsion technologies such as hybrids and fuel-cell powered vehicles, including scale, scope, learning, R&D, spillover, infrastructure, and consumer-choice.

Figure 2 shows the model boundary, displaying the main endogenous and exogenous factors. The fleet represents the installed base of n different platforms. Consumer choice among platforms depends on the relative attractiveness of each, which is a function of price, perceived performance, operating cost, safety, driving range, and of ecological impact. In addition, consumers will consider a particular option only when sufficiently familiar with it. Familiarity itself increases through social processes including word-of-mouth, direct exposure to the different platforms, marketing, and media attention.

The unit of analysis is the vehicle platform: the model does not disaggregate automobile OEMS or capture competition within platforms. Accumulated production leads to higher experience and scale economies and its sales provide the necessary funding for R&D. Complementary assets such as the service, maintenance, and fuel distribution infrastructure not only influence the attractiveness of the installed base (vehicles), but the attractiveness of the infrastructure is highly endogenous itself as well: only with a sufficient prospective installed base will infrastructure investments take off. R&D leads to improvement for an individual platform, but also leads to spillover, at least potentially, to other platforms. For example, improvements in software or lighter materials that are generated in a hydrogen research project will benefit ICE and hybrids as well. The same holds for the learning-by-doing processes. We consider the availability of energy resources and the state of the environment to be exogenous.

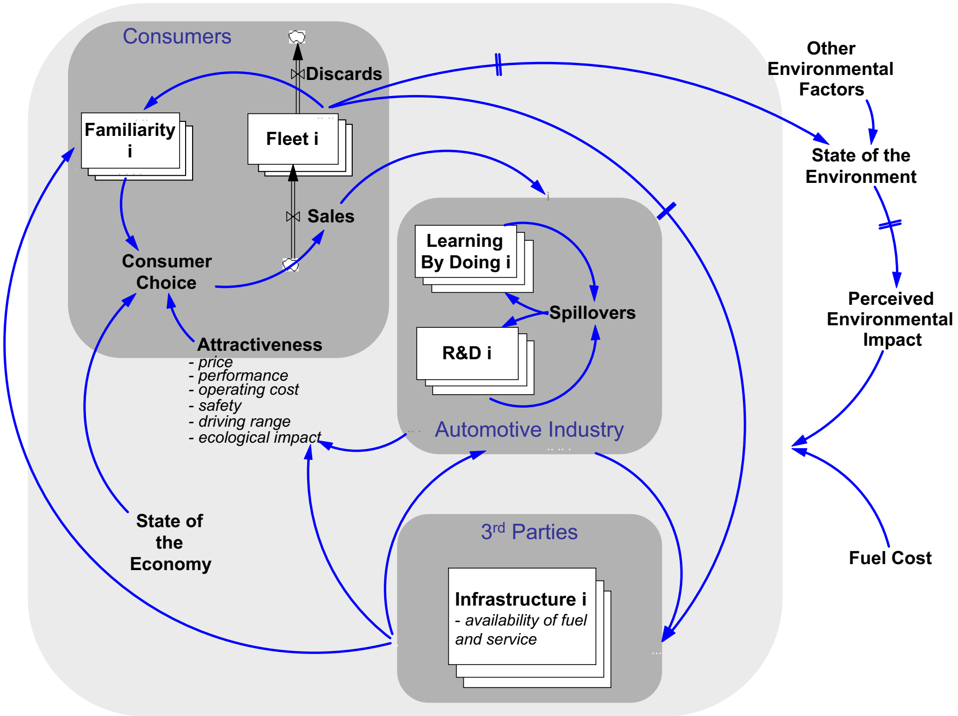

Figure 2: Model boundary and sectors

1.4 Dynamic hypothesis

Models of innovation date from the 1950's (Griliches [1957], Rogers [1995], Bass [1969]). The basic Bass model (Bass [1969]) with internal (word-of-mouth) drivers of adoption has been extended by Mahajan *et al.* [2000] to include effects of marketing & media attention. Sterman [2000] incorporates repurchases and Norton & Bass [1987] focus on substitution among successive generations of (the same or similar) technologies. All these models yield an S-shaped growth curve for the introduced product and are widely used, as many new products follow that basic pattern. This paper builds on the Bass-diffusion model and its variants, but revises it at critical areas: the transition to the horseless age suggests that we should expect other behavior patterns such as a "rise and demise" to be relevant as well. First, this paper introduces competition among platforms, second, familiarity is explicitly modeled with each platform. Finally the reinforcing loops on the supply side are incorporated.

The consumer adoption segment that is shown in figure 2 is the main focus of this paper. Figure 3 shows the dynamic hypothesis for this segment, which is partly based on the existing diffusion

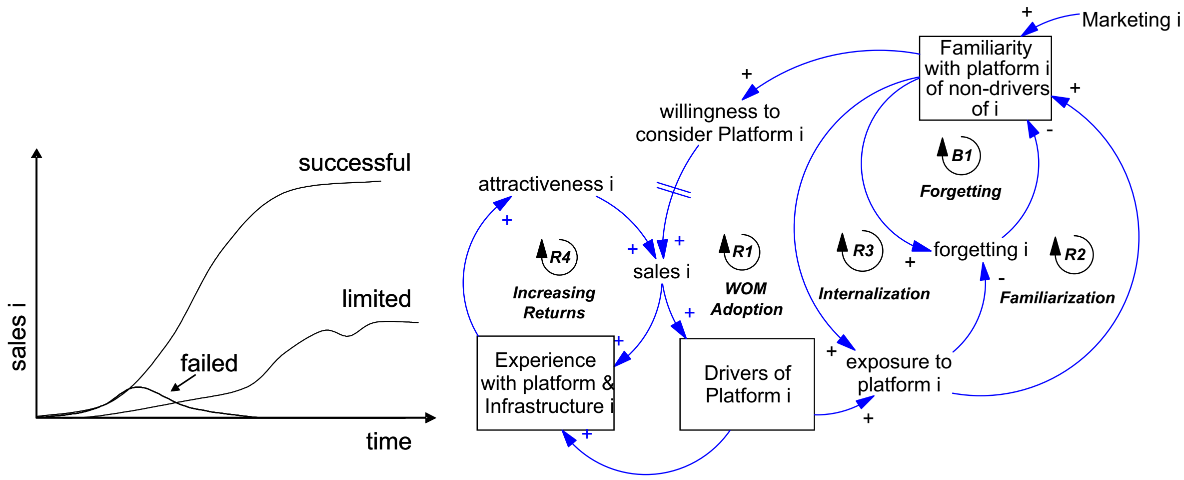

Figure 3: Dynamic hypothesis for the adoption of one platform

literature. However, the paper especially acknowledges the role emotional attachment, high media attention and slow replacement in the case of vehicles, referring to the historical events, specifically, the repeated attempts to introduce electric cars. A word-of-mouth adoption loop is active between drivers and sales as a growing installed base of a platform results in more direct exposures of non-drivers to the new technology. An increased exposure, either by seeing it constantly on the street or riding in or test-driving the neighbor's car, increases a person's willingness to consider that platform ($R1$).

On the other hand, initially adoption is very slow, and not only because of the long average life of a vehicle (as indicated with the delay marking between willingness to consider and sales): central in our hypothesis is the average person's familiarity with a platform, and while the population will generally be aware of the existence of each platform, taking one into account in one's "choice set" at time of purchase requires much more confidence or "familiarity". As vehicles are highly visible and emotional assets, familiarity of non-drivers with a platform increases through interaction with other non-drivers of that platform (the reinforcing word-of-mouth loop($R2$)). Note that this loop does not involve any adoption itself. Furthermore, attention is costly, and other phenomena (perhaps unrelated to vehicles) continuously compete for attention; thus people loose their interest over time, or "forget"($B1$). Once exposure is sufficiently intense, people unconsciously begin to accept this "once new" concept into the existence of daily life. People internalize the new technology in the sense that forgetting diminishes ($R3$). "Successful" adoption of a platform (figure 3) requires familiarity generation to exceed forgetting, until familiarity and adoption rise to a high enough level to be self-sustaining.

Adoption is a function of attractiveness, which is a function of costs (that are reduced by learning-by-doing), and efficacy and safety (increased with research & development, infrastructure for services and fuel distribution delivered by 3^{rd} parties): With sufficient adoption there is opportunity for learning and further investment for R&D; other parties also become involved to build infrastructure ($R4$). Including balancing loops of spillovers could yield successful transitions, but could also lead to demise as it is yet unspecified which of the technology platforms will benefit most. Thus we hypothesize that "failed" or "limited" adoption as depicted in figure 3, can already emerge from the demand structure. However, hypothesizing a critical behavior mode is only a preliminary step; first, it needs to be scrutinized in detail. Is this hypothesis internally consistent!? And if so under what circumstances will this typically emerge!? However from these non-linear highly coupled interactions the behavioral complexity is enormous and in order to address these questions, the paper resorts to analysis of dynamic non-linear mathematical models, as well as simulation. Second, including interaction with the industrial supply structures will be essential to obtain necessary insights about the behavior of the system as a whole and to understand what type of policies will allow for successful intervention. How much coordination among key players is required for a "successful" scenario!? Issues as these are critical, as billions of dollars are invested by companies from the automotive and energy sectors, as well as by governments. To set the stage for later research this paper lumps all structures that represent the supply dynamics into one endogenous attractiveness parameter, affected by one reduced form "learning" parameter that increases with increasing production experience. Ultimately this research should allow us to do dynamic calibration and scenario, strategic, and policy analysis and so addressing the issues raised.

2 The Model

Below the paper introduces a structure that portrays behavioral aspects of the customer segment of the vehicle market. To capture the main drivers of adoption as discussed in Rogers [1995] (chapter 6), three main sub-sectors are specified: consumer choice, familiarity (driven by various communication channels) and perceived attractiveness of the platforms. The full model is available from the author; in the appendix shorthand notation and definitions of all variables are provided.

2.1 Consumer choice of platforms

The fleet (installed base) of each platform accumulates car sales less age-dependent discards of existing vehicles (figure 4).

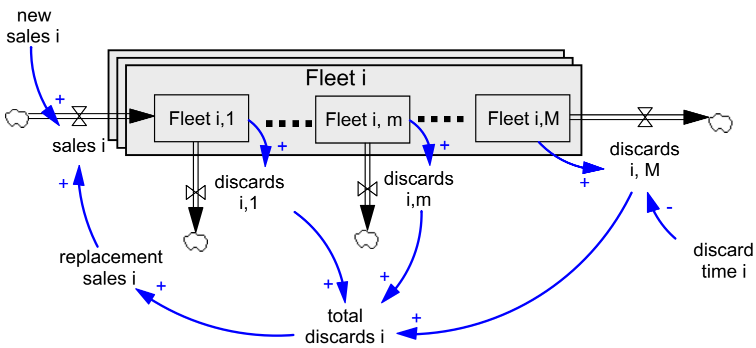

Figure 4: Overview of the fleet structure

Thus, each platform has a standard aging chain that follows Sterman [2000] (chapter 12); the discussion ignores the details of the aging chain. The fleet F_i evolves as

$$\frac{dF_i}{dt} = s_i - dc_i^T \tag{1}$$

where i is the index for fleet and s_i, dc_i^T are platform sales and total discard rate respectively, and

$$dc_i^T = \sum_{m=1}^{M} dc_i^m \tag{2}$$

with m being the m^{th} cohort of the aging chain.

Sales consist of replacement sales rs_i and new sales ns_i of each platform:

$$s_i = rs_i + ns_i \tag{3}$$

Replacement sales for a platform i is the summation over the contribution from each platform $rs_{j,i}$. Ignoring the time between discard and repurchase (as this is much shorter than any of the other time constants), the replacement sales is defined as

$$\begin{aligned} rs_i &= \textstyle\sum_{j=1}^{n} rs_{j,i} \\ rs_{j,i} &= \sigma_{j,i} * dc_i^T \end{aligned} \tag{4}$$

where $\sigma_{j,i}$ is the share of discards j that will go to i and n represents the total number of platforms.

To model the choice among platforms the model builds upon the multinomial logit formulation, but the formulation will be unpacked in several steps as the standard approach is modified for the purpose of this structure. First,

$$\sigma_{j,i} = \frac{ea_{j,i}}{ea_j^T} \tag{5}$$

with $ea_{j,i}$ and ea_j^T being respectively the effective attractiveness of platform i as perceived by an average driver of platform j and the total attractiveness of all platforms. The model differentiates drivers d and non-drivers nd of each platform i. All non-drivers of platform i perceive the same effective attractiveness ea_i^{nd} of that platform. This is equivalent to a perfect mixing assumption among the various non-drivers of a particular platform i .[6] However, actual drivers of platform i bring their own experience into their decision formation and thus have a different perception of attractiveness, ea_i^d. Thus

$$ea_{i,j} = \begin{cases} ea_i^d & \text{if } i = j \\ ea_j^{nd} & \text{otherwise} \end{cases} \tag{6}$$

Accordingly, total attractiveness ea_j^T for driver j is the sum of the effective attractiveness of the current platform, perceived as driver, and the effective attractiveness of all the alternatives, perceived

[6] The argument is that, as the average replacement time is large, one's experience with previously owned different platform will have faded away and mixed with new information by time of a new purchase

as non-driver. In vector notation this implies

$$\boldsymbol{ea_N^T} = \boldsymbol{I_{NN}} * \boldsymbol{ea_N^d} + [\mathbf{1} - \boldsymbol{I_{NN}}] * \boldsymbol{ea_N^{nd}} \tag{7}$$

where $\mathbf{ea_N^T}$ is a $1xN$ vector representing total attractiveness for drivers of each N platforms. Total effective attractiveness for a driver of platform j, ea_j^T is the j^{th} element of this vector; $\mathbf{I_{NN}}$ is an N-dimensional unitary diagonal matrix and $[\mathbf{1} - \mathbf{I_{NN}}]$ is its complement. Effective attractiveness $ea_i^q, q \in \{d, nd\}$ is derived by multiplying the perceived attractiveness a_i^q and the average familiarity with that platform fa_i^q(which will be discussed later):

$$ea_i^q = fa_i^q * a_i^q \tag{8}$$

Attractiveness a_i^q is a function of attributes l of the set L that comprises performance (e.g. maximum velocity, power, comfort, and spaciousness), price, operating cost (insurance and fuel expenditures), safety, driving range (number miles between refills), availability of fuel and service and emissions. To keep the model tractable, we assume multiplicative separability[7], and thus

$$a_i^q = f_1(x_{1,i}^q) * f_2(x_{2,i}^q) * ...f_l(x_{l,i}^q) * ...f_L(x_{L,i}^q) \tag{9}$$

where the $x_{l,i}^q$ are the attributes $l \in \{L\}$ for platform i, as perceived by group $q \in \{d, nd\}$. Following the logit formulation the individual attractiveness functions are exponential in the attributes

$$f_l(x_{l,i}^q) = exp\left(\alpha_l \frac{x_{l,i}^q}{x_l^*}\right) \tag{10}$$

Here $x_{l,i}^q$ is the particular state of attribute l as perceived by a driver or non-driver evaluating platform i. Further, x_l^* is the reference value for that attribute, which is the same for all platforms and α_l is the sensitivity to the particular change in the attribute value.

The discard rate represents the flow of vehicles that are scrapped (the used car market is not modeled).[8] Discards are the sum of discards that are replaced rd_i^m and those that adjust the total

[7]For instance an extremely poor score for driving range will almost certainly have a devastating impact on the judgement of the whole - therefore linear separability is clearly not appropriate.

[8]For this discussion we ignore vehicles that leave prematurely in earlier stages of the aging chain due to stock adjustments of the total fleet. Stock adjustments will be discussed below.

fleet downwards ad_i^m:

$$dc_i^m = rd_i^m + ad_i^m \tag{11}$$

and

$$rd_i^m = (1 - f_{s,i}^m) * F_i^m / \tau_c \tag{12}$$

where $f_{s,i}^m$ is the survival fraction of vehicles (fraction maturing to the next cohort), and τ_c is the cohort time. Using Little's law and setting $f_{s,i}^M \equiv 1$, we get for the average discard time $\tau_{d,i}$:

$$\tau_{d,i} = \sum_{m=1}^{M} \left(\prod_{n=1}^{m-1} \left(f_{s,i}^n \right) \right) * \tau_c \tag{13}$$

Net changes to the fleet (stock adjustments) follow the basic stock-adjustment structure (Sterman [2000]), modified for multi-product allocation. Positive adjustments towards the indicated fleet F^* occur through new car sales ns_i, with each platform receiving a share σ_i^{new} of the new sales:

$$ns_i = \begin{cases} \sigma_i^{new} * (F^* - F)/\tau_s & \text{if } (F^* - F) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

The indicated fleet is the current licensed driver population D multiplied by the current fractional vehicles per driver f_v, such that

$$F^* = f_v * D \tag{15}$$

Furthermore, the model assumes familiarity and attractiveness towards a platform to be idententical to that of the non-drivers and therefore the share of platform i from new drivers follows

$$\begin{aligned} \sigma_i^{new} &= \frac{ea_i^{nd}}{ea_i^{new,T}} \\ ea_i^{new,T} &= \sum_{j=1}^{N} ea_i^{nd} \end{aligned} \tag{16}$$

Negative adjustments ad_i^m occur proportionally with relative size of the fleet

$$ad_i^m = \begin{cases} 0 & \text{if } (F^* - F) > 0 \\ \frac{F_i^m}{F}(F^* - F)/\tau_s & \text{otherwise} \end{cases} \tag{17}$$

2.2 Familiarity with platforms

Vehicle types and their infrastructure have a high degree of observability (Rogers [1995]). Because of the economic and social importance of autos, people are made aware of new or proposed platforms through the media and marketing, even when they are mainly premarket (as is the case for the hydrogen, gasoline-electric hybrid and pure electric vehicles). This observability is much stronger for vehicles than for walkmans or many other new technologies at introduction, since then only limited numbers of social groups are reached. However, the technologies behind these platforms are complex and have low tractability (Rogers [1995]); for instance, few people understand the risk implications of on-board storage of hydrogen, as compared to, for instance on-board gasoline. This increases uncertainty about their social acceptability and suggests a strong "liability of newness," irrespective of awareness and attractiveness. Only after sufficient repetitive and direct exposure will people internalize a new alternative into their decision sets. For example, the revolutionary pacemaker technology faced enormous resistance by cardiologists and adoption was very low over a long period of the total adoption curve (Homer [1987]). We will use the term "familiarity" to specify the tendency of an individual to consider a platform in one's decision set. In addition, we need to incorporate the various channels for familiarity creation.

The characteristic of "familiarity" fa_i is modeled as an individual level characteristic that ranges from 0 to 1. The model distinguishes between familiarity for non-drivers and drivers of platform i. For the average familiarity of non-drivers familiarity of people that abandon a platform (figure 5) is traced. Drivers of platforms bring their familiarity with them when abandoning a platform. Conversely, drivers of other platforms that convert to platform i bring their familiarity as well and

$$\frac{dFA_i^q}{dt} = \text{sign}_q * (fs_{\sim i,i} - fs_{i,\sim i}) + fg_i^q - fl_i^q \tag{18}$$

where $fs_{\sim i,i}$ and $fs_{i,\sim i}$ account for the flows of familiarity that accompany drivers that respectively switch from another platform to i and those that switch from i to another. Thus, sign_q is $+(-)$ for drivers, with $q = d$ (non-drivers, with $q = nd$) respectively. fg_i^q and fl_i^q represent familiarity gain

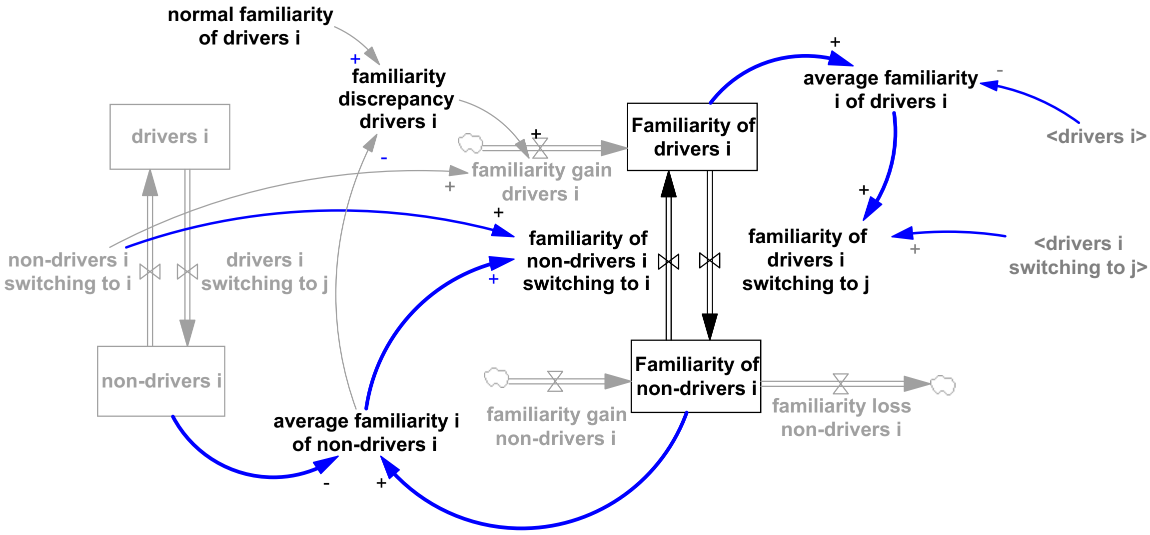

Figure 5: tracking familiarity with a nonconserved coflow structure for a single platform

and loss by individuals. Flows that track switching are defined as:

$$\begin{aligned} fs_{\sim i,i} &= \left(\sum_{j\neq i} rs_{j,i}\right)/f_v * fa_i^{nd} \\ fs_{i,\sim i} &= (rd_i - rs_{i,i})/f_v * fa_i^d \end{aligned} \tag{19}$$

For tracking the familiarity, only the flow of vehicles that change owners are of interest and discards that are replaced by the same owner ($rs_{i,i}$) must be omitted. Further, $fa_i^d(fa_i^{nd})$ is the average familiarity of an individual driver (non-driver) of platform i, thus $fa_i^q = Fa_i^q/D_i^q$, where D_i^q is the number of people in each segment ($D_i^d = D_i = D * F_i/F$ and $D_i^{nd} = D - D_i$).[9] New drivers become instantly familiar once they convert to a different platform i and retain their familiarity throughout ,such that

$$\begin{aligned} fg_i^d &= (\textstyle\sum_{j\neq i} rs_{j,i})/f_v * (fa^{max} - fa_i^{nd}) \\ fl_i^d &= 0 \end{aligned} \tag{20}$$

with fa^{max} being the maximum familiarity of one. Figure 6 shows the structure for the familiarity update of non-drivers.

Familiarity increases due to endogenous socialization effects. It does so at a decreasing rate until

[9]Note that $D_i^{nd} + D_i^d = D$, and $\sum_i D_i^{nd} = (N-1) * D$, as people are "non-driver" of all platforms but the one they currently drive.

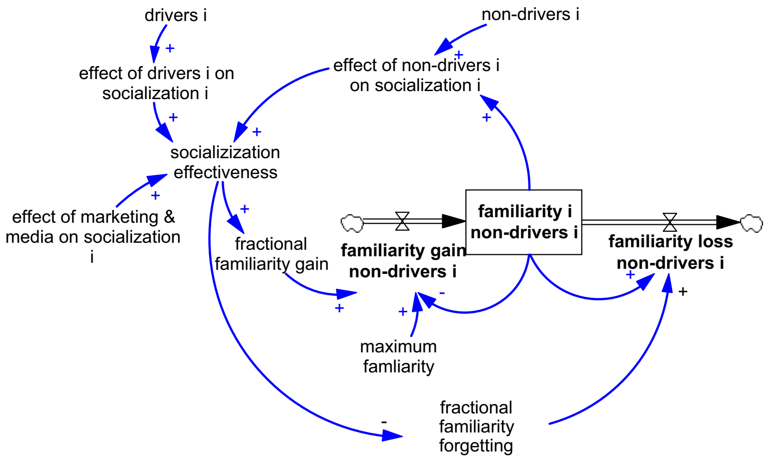

Figure 6: familiarity structure - the socialization process for non-drivers

the maximum level is attained:

$$fg_i^{nd} = \eta_i^s * (1 - fa_i^{nd}) * (D - D_i) \tag{21}$$

with η_i^s being the total socialization effectiveness for platform. i[10] Three sources are responsible for this effectiveness: marketing & media, word-of-mouth through users of the platform, and word-of-mouth through non-users of that platform that are themselves familiar with it. We assume linear additivity of these effects, which is reasonable as long as the socialization events are sufficiently dispersed in time in order to have limited overlap. This assumption might not hold when average familiarity is high, but in such cases saturation forces are strong, accounting for reduction of the strength (the balancing effect $1 - fa_i$ is strong). The total socialization impact for a non-driver of platform i, measured in fractional increase of familiarity per period, is:

$$\eta_i^s = \eta_i^m + c * p^d * fa_i^d * d_i + c * p^{nd} * fa_i^{nd} * (1 - d_i) \tag{22}$$

The first term, η_i^m represents the effect of exposure to marketing. The second term represents the word-of-mouth effect through drivers of the platform, c represents the contacts per year of an individual (with someone of the total driver population), p^d is the persuasiveness of a driver of a platform. $d_i \equiv \frac{D_i}{D}$ is the platform-specific driver density, with respect to the total driver population

[10] Note that the maximum familiarity fa^{max} is equal to 1; see equation 20 and discussion.

and represents the probability of meeting a non-driver of platform i conditional on meeting someone. The last term covers the word-of-mouth generated by non-drivers of a platform and is structurally similar to the second; p^{nd} is the persuasiveness of a non-driver of a platform, and $1 - d_i$ represents the probability of meeting a non-driver of i, conditional on an encounter with someone from the driver population. Since fa_i represents a person's familiarity with a platform, it also directly affects the likelihood that someone initiates discussion on that particular platform. This formulation suggests that (for low marketing effectiveness) the socialization effect might take off slowly, but with sufficient adoption the second term will become strong and familiarity could rise dramatically. Over the time horizon relevant to the transition to alternative vehicles, familiarity with a platform among those who do not drive it may decline. If exposure diminishes, familiarity will decay. This is the result of "forgetting." Forgetting can be seen as the process of gradual conscious or unconscious dismissal of an alternative as a serious purchase option, irrespective of its perceived potential qualities. The electric car has been launched several times (early 1900, 1960's and recently interest started again), each time unsuccessfully and each time the potential market had to be re-educated through marketing.

Alternatively, when exposure is high, these prospective alternatives become internalized and become a natural alternative in the range of choices. For instance, exposure to cell phones is so pervasive that even people without one will (perhaps unconsciously) consider the pro's and con's of acquiring service. Thus the fractional rate of familiarity loss is a (decreasing) function of the effective reminders from the socialization in equation 21. We obtain for the familiarity loss rate:

$$\begin{aligned} fl_i &= \lambda_i^f * FA_i \\ \lambda_i^f &= \lambda_0^f * \epsilon^s(\eta_i^s) \end{aligned} \tag{23}$$

where ϵ^s represents the effect of continuous reminders on forgetting, which is decreasing in η_i^s. Because familiarity itself cannot directly be observed, one can hypothesize several functional forms for the socializing effect on forgetting. However the following constraints are necessary for an expression to follow our arguments above:

$$\epsilon^s(0) = 1, \epsilon^s(\infty) = 0 \tag{24}$$

The forgetting fraction is at its maximum when there are no social exposures to the platform, and zero when there are constant exposures. In addition,

$$\epsilon^{s\prime} \leq 0, \epsilon^{s\prime}(\infty) = 0 \tag{25}$$

because forgetting is subject, at least eventually, to diminishing returns as exposures increase. Figure 7 displays how exposures influences familiarity loss. Figure 7)a shows potential relations between

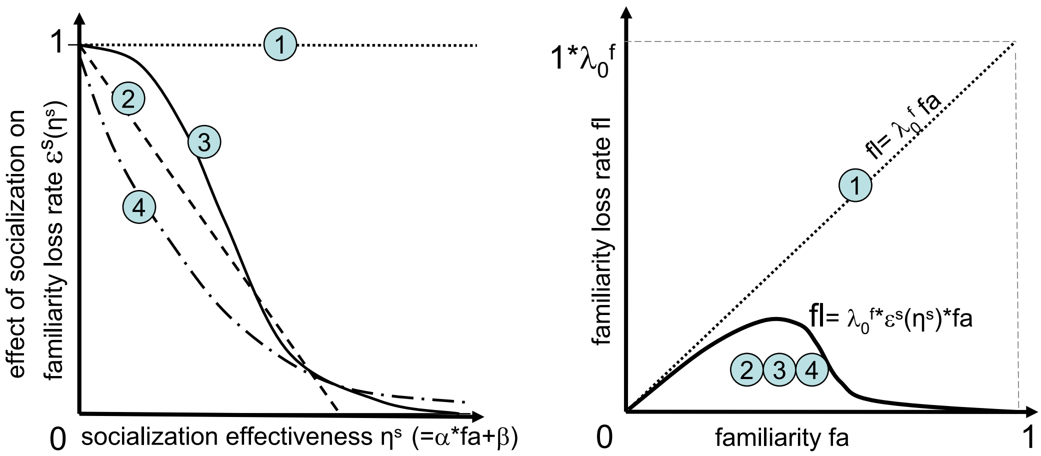

Figure 7: a) effect of socialization on forgetting rate. Displayed multiplicative effects of socialization on familiarity loss rate, are 1) no impact, 2) kinked-linear decreasing, 3) concave/diminishing with threshold, and 4) concave/diminishing; b) typical shape for resulting forgetting rate as function of familiarity for the different effects.

socialization and the effect on the forgetting rate. Plotted are a constant effect (1), a kinked-linear effect with zero as minimum (2), an S-shape relationship (3), and a curve with no inflection or threshold effect (4). Figure 7b shows typical hypothesized forgetting rates as a function of familiarity. For a given marketing effectiveness and driver pool, the socialization effect η^s is nonzero such that it can be written as: $\eta^s = \alpha * fa + \beta$ (platform indices i are omitted). The dotted line (1) represents a constant forget fraction, shape (1) in (a). The hump-shaped curve shows the effective forgetting rate when forgetting depends on exposures that obey equation *24) and (25), that is, shapes (2) to (4) in Figure 7a.[11]

The shape of preference should depend on the specifics of the technology, such as "perceived risk" of selecting an alternative from the mainstream. A broad range of curves can be approximated by

[11]For example the kinked-linear relationship will result in a symmetric, parabolic, shape (which is not likely to be an accurate approximation).

varying the parameters of the standard logistic curve (various subscripts omitted):

$$\epsilon^s = \frac{1}{1 + e^{[-4\alpha^s((\eta/\lambda_0) - \tilde{x_0})]}} \tag{26}$$

where α^s indicates the slope at the inflection point and $\tilde{x_0}$ the shift at the inflection point, while $(\alpha^s, \tilde{x_0}) = (2, 0.5)$ results in a symmetric and centered S-shape over the input range. The advantage of this approach is that we can test a variety of assumptions with only two parameters. Given our input range the dynamics are expected to be sensitive to the actual choice of the parameters that will change the characteristics of the effective curve.[12] Then, if we write

$$\tilde{x_0} \equiv x_0/\alpha^s \tag{27}$$

an increase in α_r implies an increase in the shoulder of an S-shape, while keeping the intercept of the curve fixed (and the inflection point floating). Varying (x_0, α^s) now yields a wide range of curves that fall within or close to the constraints of our assumptions to be tested.[13]

2.3 Learning about attractiveness

The actual state of the attributes of attractiveness as discussed in section 2.1 are not observed directly, but "learned" over time. Urban *et al.* [1990] examined subjects in clinics to understand their preferences for new vehicle introductions. They find that various sources have different impact under different conditions. They subsequently introduce a consumer-choice model for premarket forecasting that explicitly models effects of word-of-mouth (positive and negative), experience and marketing. In line with this, non-drivers learn gradually about the attractiveness of the latest model of a platform through social interactions with other people (drivers and non-drivers) and exposure to marketing and media. Each person's assessment of a platform's attractiveness depends on her perceptions of the product attributes. When a person switches from one platform to another, she will take her perception of the state of attractiveness with her, as depicted in 8, for one attribute. The perception $PX^q_{l,i}$ of a driver or non-driver $q = \{d, nd\}$ on attribute l for platform i, evolves as

[12] A large threshold can be interpreted as a particular strong "liability of newness" (or bias against newcomers)
[13] This includes shapes that are decreasing at decreasing rate - i.e. without any shoulder)

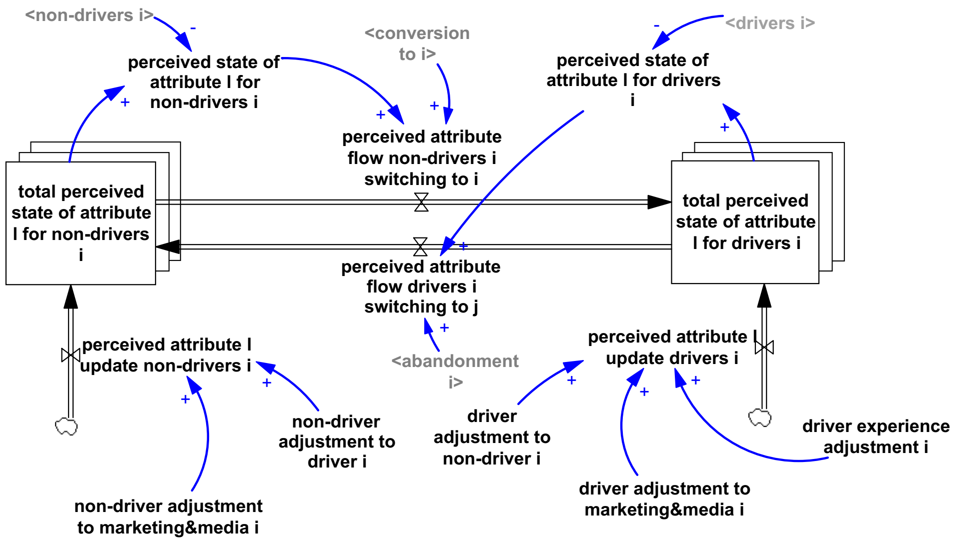

Figure 8: non-conserved co-flow formulation for perception on attributes as perceived by drivers and non-drivers of platform i

$$\frac{dPX_{l,i}^q}{dt} = \text{sign}_q * (xs_{\sim i,i} - xs_{i,\sim i}) + xu_i^q \tag{28}$$

where $xs_{\sim i,i}$ and $xs_{i,\sim i}$ account for tracking the flows of the perceived attributes accompanying drivers that respectively switch from another platform to i and those that switch from i to another. As before, sign_q is $+(-)$ for drivers (non-drivers) respectively, and $xu_{l,i}^q$ represents updating of the perceived state of an attribute by individuals.

Flows that track switching are defined as

$$\begin{aligned} xs_{\sim i,i} &= \left(\textstyle\sum_{j\neq i} rs_{j,i}\right) / f_v * px_{l,i}^{nd} \\ xs_{i,\sim i} &= (rd_i - rs_{i,i}) / f_v * px_{l,i}^{d} \end{aligned} \tag{29}$$

with $px_{l,i}^q = PX_{l,i}^q / D_i^q$ being the state of attribute l for platform i as perceived by an average person from the group q. Various independent sources drive updating of perceived state of an attribute, which we write as

$$xu_{l,i}^q = \sum_{k\neq q} \left(\gamma_l^{x,q,k} \eta_{l,i}^{s,q,k}\right) * D_i^q \tag{30}$$

where $k \in \{d, nd, m, e\}$ is an index for the source, which can be drivers (d), non-drivers (nd), marketing and media (m)or their own experience (e). $\eta_{l,i}^{s,q,k}$ is an shorthand expression that represents the socialization mechanism for each type of interaction or, the effect of source k on group q from platform i with respect to attribute l. This is similar to the familiarity formulation in equation 21. $\gamma_l^{x,q,k}$ is a multiplier for the strength. For instance, because drivers experience their own platform intensely, they will not be very open to non-drivers for updating their opinions and thus $\gamma_l^{x,d,nd}$ must be low in value. In general, we expect γ to be smaller than 1, indicating that updating of familiarity is faster than updating of opinions. With the previous discussions in mind the updating mechanisms η and strengths γ are summarized as follows:

source	socialization mechanism	relative strength of effect	
(k)	$(\eta_{l,i}^{s,q,k})$	$(\gamma_l^{x,nd,k})$	$(\gamma_l^{x,d,k})$
drivers (d)	$(c * p^d * fa_i^d * d_i * (px_{l,i}^d - px_{l,i}^q)$	$\gamma_l^{x,*}$	0
non-drivers (nd)	$(c * p^{nd} * fa_i^{nd} * (1 - d_i) * (px_{l,i}^{nd} - px_{l,i}^q)$	0	$\gamma_l^{x,d,nd}$
marketing (m)	$\eta_i^m * (x_{l,i}^m - px_{l,i}^q)$	$\gamma_l^{x,*}$	$\gamma_{l,d,m}^x$
experience (e)	$(1/\tau_e) * (x_{l,i}^e - px_{l,i}^q)$	0	1

The first and second row represents peoples (of group q) updates of their belief on the state of an attribute through drivers and non-drivers. While $q \in \{d, nd\}$ as before, also contains drivers and non-drivers. The third row shows how people learn about the technologies in the margin $x_{l,i}^m$ through marketing and media channels. Finally, drivers also update their beliefs through their own experience (row 4,x_i^e), a process which is typically much faster than the alternative influences. τ_e represents the time to update one's experience with a technology in use.

This completes the formulation of the consumer choice sector. The sectors that will cover the automobile industry and for the 3^{rd} parties, model the endogenous change in the state of attributes of each new vehicles platform, $x_{l,i}^m$, and the average for the existing fleet $x_{l,i}^f$. These are functions of the technology (fuel efficiency, performance and price) and infrastructure. These characteristics evolve through R&D, learning, spillovers, and 3^{rd} party activities to provide infrastructures. This will be discussed in a later paper. Below we perform partial model analysis on the consumer sector.

3 Analysis

Thorough analysis will allow to understand both, whether the hypothesized behavior is generated for realistic parameters, and what other modes of behavior might result. The order of the model as discussed is at least$N(3+M+3L)-1$ (N being the number of platforms, M the number of levels in the aging chain and L is the number of attributes). Analytic solutions to such high order non-linear systems of differential equations cannot be found, but the model can be simulated for any set of parameters. In addition, to gain insight into the system's behavior, a combination of partial and reduced model tests is used. While analysis of partial models lowers the risk of misinterpretation or misattribution of behavior (Homer [1983]), reduction (to lower order) allows for compact graphical representations and analysis of behavior and closed form analysis of approximate structures. In the discussions below we will keep the driver population P and vehicles per household f_v constant, implying a fixed population.

3.1 A first order model: familiarity

The fundamental dynamics of the forgetting structure become apparent in a one stock version of the model that emerges through a thought experiment. First assume a fixed driver pool. This decouples the dynamics of familiarity with the various platforms, as the only link is through market share (equation 5). We can thus limit the analysis to that of one individual platform. Second, assume that attractiveness of each platform is fixed. In line with earlier discussions, familiarity of drivers, fa^d equals 1. Then, the full dynamics of this system are then captured by the following first order differential equation:[14]

$$\frac{dfa}{dt} = \eta^s(fa) * (1 - fa) - \lambda * fa \tag{31}$$

where socialization effectiveness η^s and forgetting fraction λ are defined as in section 2.2:

$$\begin{aligned} \lambda &= \lambda_0^f * \epsilon^s(\eta^s) \\ \eta^s &= \eta^m + c * (p^d * d + p^{nd} * fa * (1 - d)) \end{aligned} \tag{32}$$

[14]we omit index i for familiarity fa and driver density d of a platform

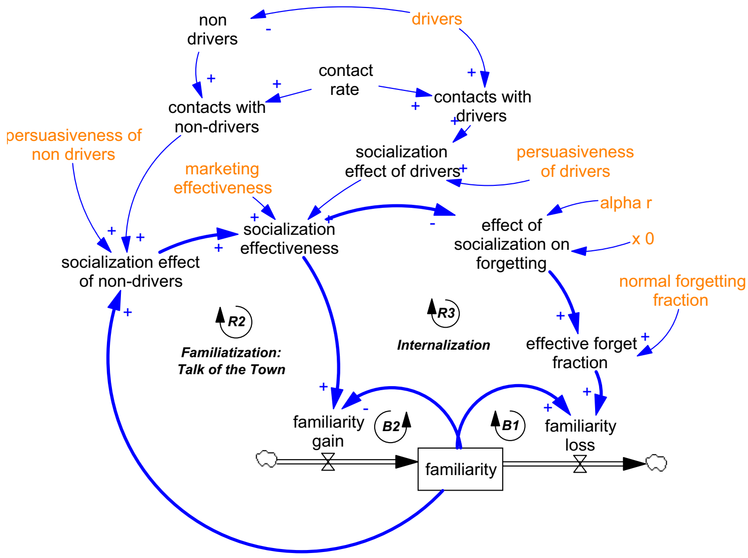

Figure 9: first order abstraction of the model - installed base (drivers d) is fixed. Loop numbers correspond, where relevant, with those of dynamic hypothesis

Note that η^s is linearly increasing in familiarity fa. As the "effect of socialization on forgetting," ϵ^s, decreases with the socialization effectiveness, the forgetting fraction decreases with increasing familiarity as well. At low familiarity we can expect the reinforcing loop ($R2$, talk of the town) to be strong, while at high familiarity, internalization $R3$ might be effective.

Figure 10 shows a phase plot familiarity fa against its rate of change $dfadt$ of the non-linear ϵ^s, that is, ϵ^s is defined as in equation 26). Parameters are: contact rate $c = 200[dmnl/year]$, persuasiveness of non-drivers $p^{nd} = 0.001[dmnl]$ and drivers $p^d = 0.003[dmnl]$, marketing effectiveness $\eta^m = 0.01[dmnl/year]$. These parameters are roughly estimated guesses based on calibration of other diffusion cases (e.g., VHS-adoption in Sterman [2000]), while persuasiveness parameters are adjusted downward. Normal forgetting rate $\lambda_0^f = 0.5[dmnl/year]$ and, for determining the shape of $epsilon^s$, $\alpha^s = 4$ and $x0 = 0.75$, implying a short threshold. Driver density d is 0.075. At zero familiarity, familiarity gain fg is nonzero, as a result of marketing and word-of-mouth effect from drivers. With increasing familiarity, initially the effect of exposures dominates, but eventually saturation takes over, resulting in the parabolic shape. The forgetting rate is zero when familiarity is zero. For low familiarity, the (negative) familiarity loss fl increases with rising familiarity as the fractional forgetting is nearly constant. However, for sufficient familiarity the exposure leads to a damping on

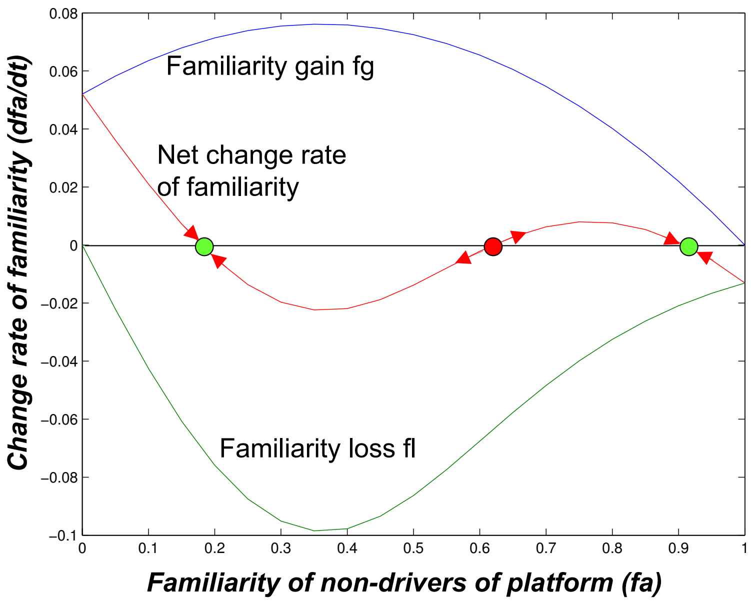

Figure 10: Phase plot of familiarity against its change rate exhibiting three fixed points

the fractional forgetting, sufficiently large that the net effect results in a decrease of the loss rate. The resulting net change rate of familiarity has three fixed points (equilibria) - the low and high points are stable.

Figure 11 shows the same parameters, but now driver density d is used as an independent parameter which we vary from 0 to 0.2. Note first that, as marketing effectiveness is constant and positive, zero familiarity implies a positive net change rate for all platform/drivers densities. We have already discussed the case for a driver density of 0.075. We observe that a tipping point exists for any driver density around this point. However, at very low densities (e.g. $d = 0$), there is very little word of mouth through very limited driver exposure and the net familiarity loss continues to be dominant, even for high familiarity. This results in one stable fixed point at low familiarity. Alternatively, at very high driver penetration (> 0.15), forgetting is close to zero, even for low familiarity. This yields again one equilibrium point, but now at maximum familiarity. In this case dynamics are similar to those of the SI epidemic model with advertising effectiveness, where effectiveness is sufficient as discussed in Sterman [2000].

Knowing the fixed points and their respective characteristics allows one to identify the model behavior in great detail. However, thus far we have only discussed results for one set of parameters and

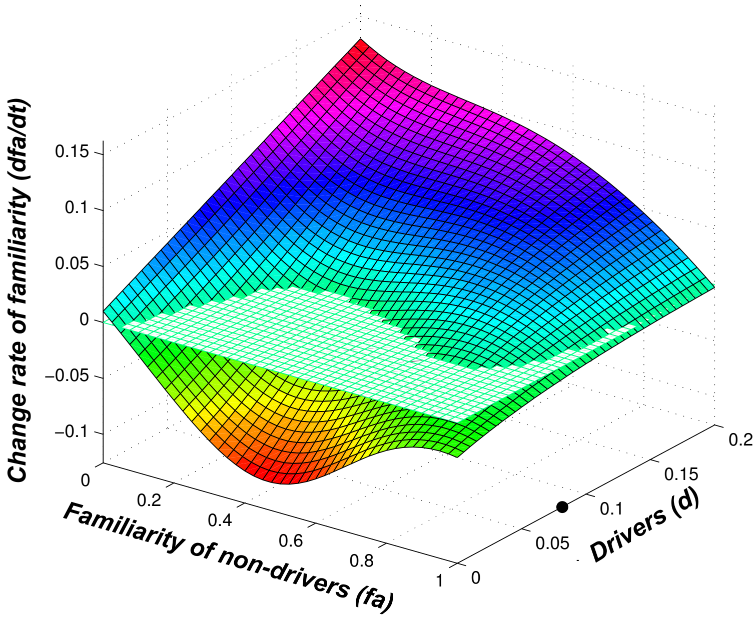

Figure 11: Phase plot of familiarity against its change rate for a range of driver density; non-linear case.

existence and locus of fixed points can depend very much on these factors. To avoid searching the full parameter-space, we considered the (piecewise) linear case for the retention effect on forgetting ϵ^s, conform the linear shape (2) in figure 7:

$$\epsilon^s \quad = \max(0, 1 - \alpha^s * \eta^s / \lambda_0^f) \tag{33}$$

Which results in the following expression for the familiarity state equation:

$$\begin{aligned} \frac{dfa}{dt} &= \eta^s * (1 - fa) - \max(0, \frac{\lambda_0^f - \alpha^s * (\eta^s)}{\lambda_0^f}) * \lambda_0^f * fa \\ \eta^s &= c(p^{nd} fa(1 - d) + p^d d) + \eta^m) \end{aligned} \tag{34}$$

While this linear shape is naive as representation of actual behavior, it is quite convenient for analysis. We are interested in the parameter space that contains multiple fixed points. While for similar parameters, phase-space for the linear and nonlinear case are close, we can characterize fixed points analytically for expression 34. For instance, when $\alpha \leq 1$, it can be shown that only one equilibrium exists[15]. We further find that for a wide range of parameters the multiple equilibria

[15]we will not show this here. It does make intuitively sense: for $\alpha = 1$, the structure reduces to one that has a bi-linear word-of-mouth effect, including forgetting.

conditions are satisfied.

3.2 A second order model: familiarity versus adoption

In this section the sophistication of the model is increased by introducing competition for adoption among platforms. Consider the case of two competing platforms where one is dominant (driver density and familiarity are 1, corresponding to the current dominance of ICE). Assume further that attractiveness is fixed as in the previous case, and that attractiveness of the new platform is not larger than that of the dominant platform. Under these conditions, market share of the dominant design will remain sufficient such that familiarity remains high. Finally, assuming a first order aging chain of the fleet ($M = 1$) results in the following set of equations that fully determine the dynamics:

$$\begin{aligned}
&\tfrac{dfa_2}{dt} = \eta_2^s(1 - fa_2) - \lambda_0^f(1 - r(\eta_2^s))fa_2 + (1 - fa_2)\tfrac{dd_2}{dt}\tfrac{1}{1-d_2} \\
&\tfrac{dfa_1}{dt} = 0 \\
&\tfrac{dd_2}{dt} = (\tfrac{at_{21}}{at_{21}+1}d_2 + \tfrac{1}{fa_2 at_{21}+1}d_1 - d_2)/\tau dc \\
&d_1 = 1 - d_2 \\
&\eta_2^s = c(p^{nd}fa_2(1 - d_2) + cp^d d_2) + \eta_2^m \\
&at_{21} \equiv at_2/at_1.
\end{aligned} \tag{35}$$

As d_2 and d_1 are interdependent a 2^{nd} order system remains. Compared to the previous analysis, this system has one additional 2^{nd} order reinforcing loop (through familiarity, market share, drivers and familiarity) and one additional 1^{st} order balancing loop (through drivers and discards). We can expect similar dynamics, as adoption and familiarity are strongly coupled. Again we can perform phase-space representations, now in two dimensions (fa_2, d_2) (we will omit index 2 from now). The analysis here uses identical parameter values as before to illustrate typical behavior of this structure for the non-linear, inverted S-shape effect of socializing on forgetting. Figure 12 introduces the basic idea. The dotted line are the "nullclines", that is, the represent the curves for which the rates of changes for familiarity (fa), respectively drivers (d) are zero. Parameters are the same as in the previous case - we see an identical intercept for $dfadt = 0$. Fixed points emerge where nullclines

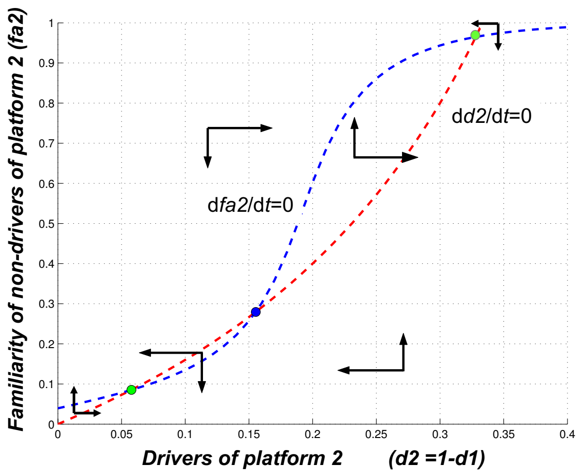

Figure 12: nullclines and fixed points in (fa,d)-phase-space

intersect (large dots). The dark dot is a saddle point.[16], the other two are stable[17] Starting from an arbitrary point at time 0, a deterministic trajectory will unfold that must end up at one of the fixed points. Since signs of the derivatives for fa and d can only change at their respective nullclines, we can sample one direction and then indicate the direction in terms of "north, south, east or west" (big arrows). Without any simulation, we have qualitatively characterized the full behavior for all initial conditions. Three observations can be made: first we see that the initial assumption of $fa_1 = 1$ is justified: once in the upper right corner of the plane, it will always stay there. Second, the high equilibrium allows for the platforms to coexist, with the relative share of the total installed base being equal to the relative attractiveness (in this case 1/3 for technology 2). Finally and most important we see that a large basin of attraction exists for the lower equilibrium: any initial condition in the bottom left region will be drawn to this fixed point. Figure 13 shows an actual set of trajectories for various sets of initial conditions. Graphs a) and b) only differ in marketing effectiveness: in a) $\eta^m = 0.01$, resulting in three fixed points (identical to before). The basin of attraction for the low equilibrium is clearly marked. For each trajectory, vectors are separated by 0.1 years. In b) $\eta^m = 0.02$, which results in one high, stable equilibrium. This might be seen as good news for the entrant technology. However, starting at a point in the region defined as the basin of attraction of

[16]For an n-dimensional system, each fixed point has $2n$ different directions of approach. For a linear system, these are the n eigenvectors (that each determine one pair of approaching trajectories. The saddle point (2-dimensional) implies that it acts as an attractor when approached along one of the eigenvectors, but as a repeller from the other

[17]Locus and classification of the dots are derived through linearization, solving for the fixed points and matrix analysis. Nullclines are derived by euler sampling of the continuous function.

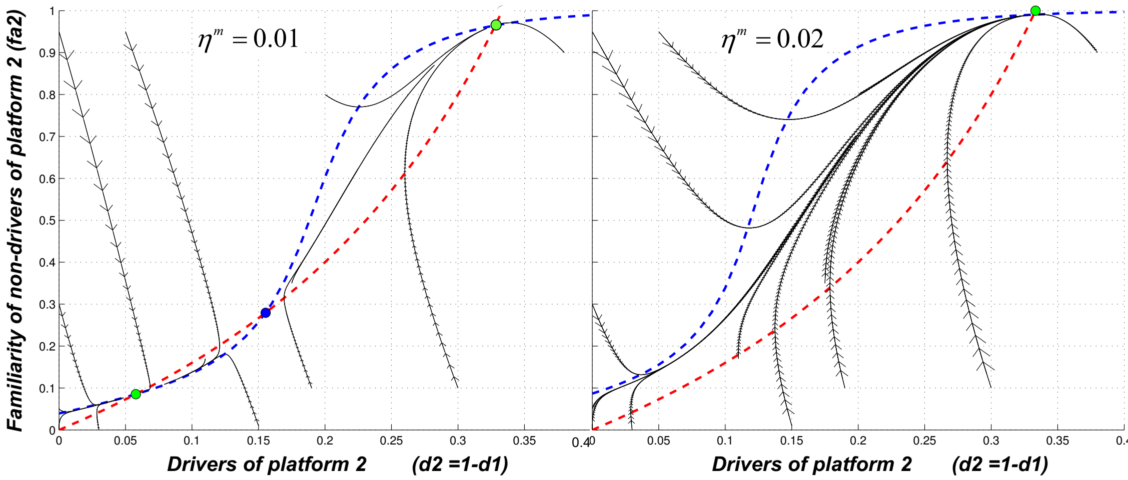

Figure 13: Figure 4 a,b - trajectories and market shares, nullclines and fixed points in (a,d)-phase-space: a) low marketing effect resulting in 3 equilibria (2 stable, 1 unstable) and b) high marketing effectiveness resulting in 1 stable equilibrium.

a), we see that it takes a long time before this area is surpassed in b[18]. This is especially the case for low initial driver density (the natural case). We can now study the effect of temporary marketing shocks at the launch of a new platform. For instance, how long must one "subsidize" a new platform, before the trajectory towards high market share becomes self-supporting?

Figure 14 shows the dynamics over time for the same parameter sets. Each line represents market share (a) or familiarity (b) for various durations of high marketing effectiveness ($\eta^m = 0.02$), as deviation of the base marketing ($\eta^m = 0.01$). Marketing shocks start at $t = 5$ years and duration $T^m \in [0, 50]$ years. As long as marketing is high , the trajectory towards the high equilibrium point is followed (conform case b) of figure 13). When the marketing shock seizes, the trajectory follows case a) of figure 13), from that point on. The critical point for continuation towards the high trajectory is in this case is around 20 years of intensive marketing.

[18]An increasing (decreasing) distance between vectors, along the axis for one state (familiarity or driver density), implies that a reinforcing (balancing) loop is dominant for that particular state. We see that the approach towards the high equilibrium is dominated by a balancing loop and the trajectory is slow

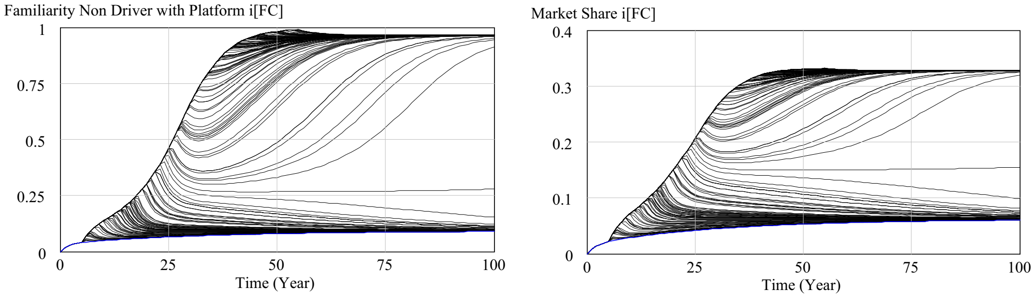

Figure 14: simulation of familiarity fa_2 and marketshare 2 for same parameters as 13. Duration of a high marketing effectiveness shock of $\eta^m = 0.02$ is varied between 0 and 50 years

3.3 Towards a full model: a proxy for learning, scale and infrastructure effects

This section extends the scope further by allowing for endogenous platform attractiveness. This requires closing the loop between the fleet and attractiveness 2. This first implies incorporating reinforcing dynamics, driven by production experience, scale, and production activities (as popularized in the strategic literature since Arthur [1989]). Second, the balancing loops that involve spillovers between platforms and the effects of infrastructure will be important. As argued in the introduction, for sufficient learning about the transition challenge, it will be essential to capture these dynamics carefully, and we will do so in a subsequent paper. To obtain basic qualitative insights from the dynamics that include a notion of an endogenous supply side, we lump all L attributes into one abstract attribute x_i that improves through production experience, acting as a proxy for scale, learning, R&D, and infrastructure effects.

For the formulation of the attribute x_i, we follow standard learning curve theory, which says that performance x relates to effective production experience $\widetilde{pe_i}$ as follows (see Zangwill & Kantor [1998] and Sterman [2000], especially chapter 12):

$$\begin{aligned} x_i^m &= x^* * \widetilde{pe}_i^z \\ z &= log_2(1 + f_x) = ln(1 + f_x)/ln(2) \end{aligned} \tag{36}$$

where the exponent z determines the strength of the learning curve, set to provide a fractional improvement f_x in performance per doubling of effective experience. Effective production experience

$\widetilde{pe}_i$ is a function of cumulative experience but should also incorporate spillover effects from the other platforms:

$$\widetilde{pe}_i = g(pe_i; so_i^{\sim i}) \tag{37}$$

where $so_i^{\sim i}$ is a vector that includes all platforms except i. There are several ways to incorporate spillovers in a tractable way. Jovanovic & Macdonald [1994] propose a model where leaders improve performance through learning, while laggers improve by closing the gap over time with those that perform better. This would imply a strong assumption of unidirectional spillover from the better to the worse performers. Here we proceed differently and assume that a certain fraction of the experience gets spilled over with a lag, corresponding with the model proposed by Cohen & Levinthal [1989]. Thus $so_i^{\sim i}$ is defined as a vector of lagged effective production experiences of the other platforms

$$so_i^{\sim i} = \{LPE_1, ..., LPE_{i-1}, LPE_{i+1}, ..., LPE_N\} \tag{38}$$

and the effective total production experience is, in vector notation

$$\boldsymbol{\widetilde{pe}_N} = \boldsymbol{G_{NN}^{so}} * [\boldsymbol{I_{NN}} * \boldsymbol{pe_N} + [\boldsymbol{1} - \boldsymbol{I_{NN}}] * \boldsymbol{LPE_N}] \tag{39}$$

where $\mathbf{\widetilde{pe}_N}$ is the N-dimensional vector with elements $\widetilde{pe}_i$, for all platforms i, $\mathbf{G_{NN}^{so}}$ is the spillover matrix of which elements γ_{ji}^{so} represent the fractional spillover from platform j to i. The strength depends on the similarity between technologies. $\mathbf{LPE_N}$ is the vector of all lagged performance experiences LPE_i. Further, lagged performance experience evolves as:

$$\frac{dLPE_i}{dt} = (pe_i - LPE_i)/\tau_{so} \tag{40}$$

where τ_{so} is the time to spillover, which depends on the transparency of information and complexity of the technologies. Effective production experience pe_i is normalized:

$$pe_i = P_i/pe^* \tag{41}$$

where pe^* is a reference experience. Normal experience integrates production minus loss of experience as previous learning decays or becomes obsolete:

$$\frac{dP_i}{dt} = rs_i + ns_i - \lambda^e * P_i \tag{42}$$

where λ^e is the experience decay rate. Finally, the attributes that define the attractiveness and that are the subject of learning, need to be identified. Equation 30) and the subsequent table reveal to exogenous input for that segment. First, marketing and media (index $k = m$ in equation 30), communicate the attributes of the technology in the margin (x^{new}). Second, experience of performance is one of the factors influencing drivers' perception ($(k = e)$ in equation 30). To assess their expectation of the latest technology, drivers project their experiences of their platform (of the current fleet x_i^f):

$$x_i^e = f_e(x_i^f) \tag{43}$$

We assume for now $f_e(x_i^f) = x_i^f$. Note that drivers weigh this experience with other influences (see discussion of 30). The average performance in the fleet, x_i^f, evolves as:

$$\begin{aligned} \tfrac{dX_i^f}{dt} &= rs_i * x_i^{new} - dc_i^T * x_i^f \\ x_i^f &= X_i^f / F_i \end{aligned} \tag{44}$$

where X_i^f is the performance of the whole fleet. For the rest of the paper we assume that $f_e(x) = x$.

Figure 15 shows the time trajectories for adoption for increasing complexity over 100 years. There are two platforms. For each trajectory, the incumbent initially has 100% of the total installed base and its familiarity is 1; the entrant technology has 0 familiarity. ICE and hydrogen face exactly such a situation. Constant parameters are similar as the non-linear case of forgetting discussed in section 3.3.

A marketing investment shock starts at $t = 5$ and lasts 65 years and its effectiveness $\eta^m = 0.025$, for the rest $\eta^m = 0.01$. We trace the entrant platform (which we give the name hydrogen), left shows familiarity, right the fraction of the total installed base. The first run (base adoption, (1)) has only the standard diffusion loop active ($R1$ in figure 3). There are no increasing returns on the supply side, nor is there feedback through non-drivers. In this case the technology does not take-off. In fact, it seems that an infinite duration of the marketing shock would not be sufficient for take-off,

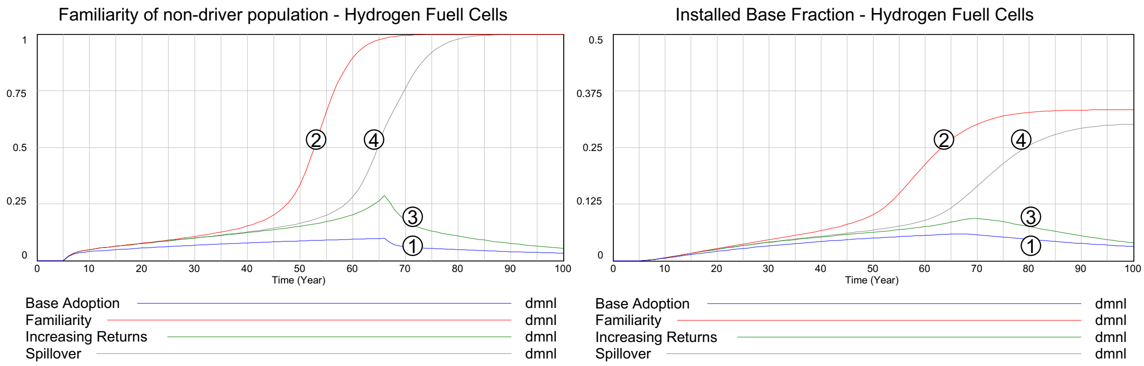

Figure 15: 100 years simulations for increasing complexity: (1) base adoption, (2) familiarity, (3) increasing returns and (4) spillovers

as we see from the apparent saturation of familiarity. The second run includes the feedback through non-drivers ($R2$). The structure of relevance for this scenario is identical to that of section 3.3. Duration of the marketing shock is well above the critical threshold as depicted in figure 14 and marketing effectiveness is higher than for those scenarios, so a high equilibrium must be attained. The third case includes increasing returns (loop $R4$) on top of the non-driver feedback of the 2^{nd} run. Learning effectiveness $f_x = 0.3$, yielding a 30% performance improvement for every doubling of effective experience. We assume that the initial effective experience of hydrogen is 1/100 of the reference experience - thus it faces a very steep segment of the learning curve, while ICE has an initial experience of 10 times the same reference experience, facing a flat curve. Counterintuitively, the situation is worse than for run 2: with the great difference in market share early on, ICE is able to make more use of the increasing returns and its faster performance improvement turns out to be critical for keeping Hydrogen within the "basin of attraction" for the the low equilibrium. The last scenario includes spillovers $\gamma_{ji}^{so} = 0.5$ for $j \neq i$ in addition to the other effects, which improves the situation for hydrogen, relative to the previous case.

For these parameter sets, all effects have important and different impacts on the behavior. We examine more closely the effect of performance improvements through learning and spillovers on the critical behavior. For this, we first define a proxy for marketing investment MI as:

$$MI = \eta^m * T^m / MI^* \tag{45}$$

where η^m is the known effectiveness of marketing & media and T^m is the duration of the effect. Figure 16 plots the fractional installed base for hydrogen attained after 100 years, for varying levels of learning effectiveness f_x and marketing investment proxy MI.[19] Reference value $MI^* = 1$ is defined such that, MI is 1 for $\eta^m = 0.02$ and $T^m = 50$, the parameters for the "base run". Parameters are similar as before. a) displays the result without cross platform spillover. The dark spot at $f^x = 0.3$

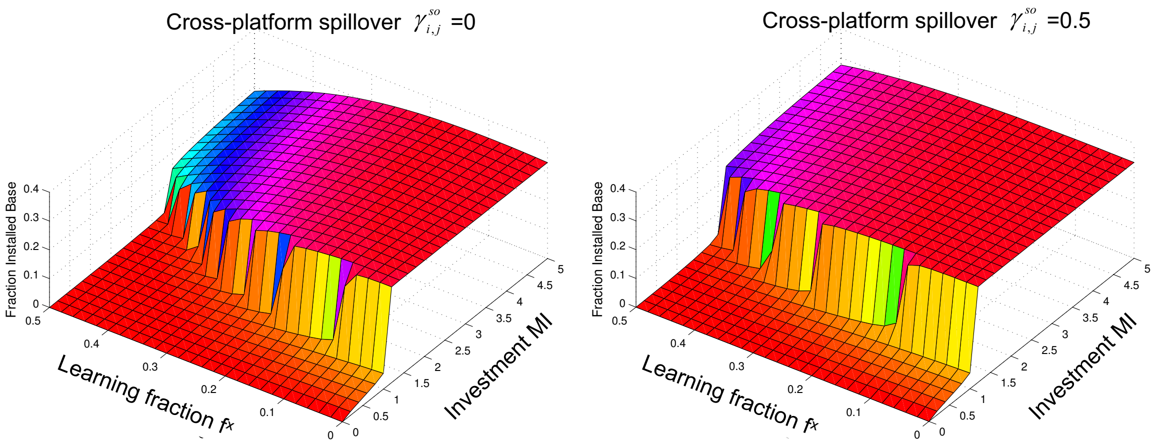

Figure 16: Equilibrium installed base against marketing investment and learning. a without and b with spillover ($\gamma^{so}_{ji} = 0.5$for$j \neq i$,$\gamma^{so}_{ii} = 1$). Zero learning corresponds with earlier discussion, investment level = 1

and $MI = 1.5$ shows case 3 of scenario (3) in figure 15. The critical point still exists for similar parameters: zero learning effectiveness corresponds with section 3.3's the two state problem, for which we normalize the critical investment level to 1. Increasing learning effectiveness makes entry more difficult, while, all else equal, learning provides an opportunity to catch up; a low market share early in the competition will mainly work for the benefit of the dominant player, thus increasing the gap. For large learning fraction, also the equilibrium share falls. Eventually an initial rise of the entrants' share may thus result in demise. Figure 16b) shows the effect of strong and symmetric spillover effect ($\gamma^{so}_{ji} = 0.5$ for $j \neq i$), equal to scenario 4 of the time trajectory. In this case the investment threshold is reduced, but the effect is limited.

Thus the "liability of newness" that the entrant faces has several layers: the emotional consumer choice and slow potential replacement result in a low-level stable equilibrium. This can be overcome through sufficient marketing or media attention. The role of the non-driver population is significant,

[19] As the equilibrium values are very insensitive to the different combinations of a linear increase of I was done by increasing simultaneously the square root of that same value η_m and T^m.

but making use of this is more problematic when the maximum potential replacement rate is slower. The reinforcing loops that link the supply side will likely make the situation worse. Spillover could mitigate the problem, but one can doubt if spillover is symmetric and if not, in favor for the new technology. Finally, the infrastructure loop (figure 2) will slow penetration further.

4 Conclusion and Discussion

4.1 On model and analysis

This paper analyzed the various adoption patterns that can emerge in the context of competing vehicle technology platforms where consumer choice and attractiveness are endogenous. The presented model focused on one of the three sectors of a full model that we will discuss in subsequent papers. The result was a basic consumer-adoption model that generates the patterns according to the reference mode.

The model extends existing Bass-diffusion models that are applied to adoption of technologies to incorporate two characteristics that are typical of technological systems as vehicle propulsion platforms: first, the maximum diffusion rate is slow due to the physical characteristics - thus competition for attention is more complicated than usual; second, adopters face a choice among a variety of technologies, of which performance is endogenously affected by adoption. A diffusion model resulted with individual level familiarity, non-linear decay of familiarity, and endogenous attractiveness.

Phase-space analysis showed the fixed points and dynamic trajectories that can result from the proposed structure. For analyzing the relevant dynamic behavior, a richer model is necessary. However, the essence of the structural characteristics behind our hypothesis is well captured in a 1^{st} order model that is also analytically tractable. The biggest challenge is to understand more deeply the exact relation between socializing and the gain and loss of familiarity. What is the exact interplay between exposure, socialization and choice sets? To what extent is the effect of socialization on the fractional increase of attention non-linear? These sociopsychological interrelations are not directly observable (signal and response are not closely related in time) and are hard to estimate. Rather, they will have to be carefully synthesized out of calibrations. Parameter sensitivity tests based on various real-life cases of adoption will help improve this basic structure. The model has been formulated such that this is feasible.

4.2 Implications and future work

Obviously the scope of the current model is limited and much further work is needed. Yet several questions already present themselves. Currently there is huge positive exposure for the hydrogen/fuelcell platform. Even in a broader context, hydrogen is portrayed as the “freedom fuel” that brings a new-economy. But even when its perceived future performance is superior to alternatives, what are challenges for take off!? First, as this research reveals, there are little benefits to reap from the attention, as long as potential adoption rate is low. Moreover, performance of a technology is not objective or a given fact - its developments are to large extent a function of a complex processes of socialization that involves both learning about its qualities and evolution of preferences of consumers, while its actual adoption drives developments of complementary assets that in turn feed back to attractiveness. Acceptance will demand a process that allows building “trust” in the new technology and “confidence” through actual experience and intimate exposure. There are strong feedbacks that operate around the *perception* of performance: while expectations are currently high the platform experiences a lot of “free” media attention. This effect will gradually disappear when performance improvement is slow. Eventually, any focus could solely be directed to incidents of failure, thus turning a virtuous cycle in a vicious one. Second, limited performance improvement can limit the adoption rate as well, which in turn further reduces the opportunity for learning-by-doing. A recent MIT report by Heywood *et al.* [2003] estimates that performance of hydrogen vehicles will not equal that of ICE, gas-electric hybrids or diesel engines, within 20 years. In the mean time, the dominant internal combustion engine has the opportunity to “free ride” on innovative ideas that emerge out of the hydrogen platform.

This paper shows how a combination of familiarity and the self-reinforcing effects such as learning-by-doing, and spillovers can lead to perverse dynamics, even under much more friendly initial conditions.

However, much more work is to be done as the hydrogen/fuelcell technology is part of a complex platform of emerging complementary technologies, infrastructures and institutions. How long will it take before there are sufficient hydrogen distribution stations to form a critical threshold for adoption? This depends on the penetration level of the vehicles themselves. The electric vehicles never established a network that was wide enough to allow for touring, yet dense enough to provide sufficient coverage. Critical for successful adoption are availability of (central/distributed) fuel distribution systems. There are several visions about alternative distribution methods (for instance per individual household), but development of these radical alternatives also depends on the expected viability: the hydrogen vehicle here forms an important complementary asset to this industry.

This transition challenge is larger for technologies such as vehicle propulsion systems that are more dependent on co-evolution of infrastructures, energy supply/demand dynamics and institutions and that face slow inherent replacement rates (e.g. long life time): the longer the adoption process the larger the likelihood of negative occurrences. Likewise, the higher the initial expectations, the more potential disappointment, when improvement is slow. Managing the transition trajectories of these socio-technical systems is a delicate - without a “fertile supportive environment”, early marketing and media attention will not be a leverage point for replacement. High prospective performance is not a guarantee for success and managing expectations does not necessarily imply ”more is better”. Subsequent work will develop a more complete structure that incorporates the complexities of organizational learning, fuel distribution system, fuel/service infrastructures, and supply/demand in detail. This might provide insights necessary for understanding the counterintuitive risks we addressed above and subsequently high leverage policies.

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